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Learning by explaining to oneself and a peer enhances learners' theta and alpha oscillations while watching video lectures

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Abstract

In the present study, we tested the effectiveness of three learning strategies (self-explanation, learning by teaching and passive viewing) used by students who were learning from video lectures. Effectiveness was measured not only with traditional measures, but also with electroencephalography (EEG). Using a within-subjects design, 26 university students viewed three sets of short lectures, each presenting a different set of English vocabulary words and were asked to use a different learning strategy for each set of lectures. Participants' EEG signals were assessed while watching the videos; learning experience (self-reported motivation and engagement) and learning performance (vocabulary recall test score) were assessed after watching the videos. Repeated measures ANOVAs showed that the self-explaining and teaching strategies were more beneficial than the passive viewing strategy, as indicated by higher EEG theta and alpha band power, a more positive learning experience (higher motivation and engagement) and better learning performance. However, whereas the teaching strategy elicited greater neural oscillations related to working memory and attention compared to the self-explanation strategy, the two groups did not differ on self-reported learning experience or learning performance. Our findings are discussed in terms of potential application in courses using video lectures and in terms of their heuristic value for future research on the neural processes that differentiate learning strategies.

Keywords: video lectures, EEG oscillations, learning strategy, self-explaining, learning by teaching

Zhongling Pi and Yi Zhang are first coauthors.

Practitioner Notes

What is already known about this topic

- Watching video lectures does not always result in learners actively making sense of the learning material.
- Self-explaining facilitates deep learning from viewing video lectures and in traditional educational settings.
- Learning by teaching also facilitates deep learning in traditional educational settings.

What this paper adds

- Learning by teaching resulted in the highest theta and alpha band power in EEG assessment while viewing video lectures.
- Compared with passive viewing, learning by teaching enhanced students' motivation to try to understand the material; in addition, both learning by teaching and self-explaining enhanced the amount of mental effort students put into understanding the material.
- Learning was increased via both self-explaining and teaching strategies after viewing video lectures.

Implications for practice and/or policy

- Learners are encouraged to generate explanations during pauses in video lectures or after viewing them, in order to increase learning.
- Learners are also encouraged to learn by teaching, as this strategy can increase learning and also increase neural oscillations associated with memory and attention.

Introduction

Video lectures have become a very popular way to teach learners of a wide range of ages (Jung & Lee, 2018). Therefore, the question of how to effectively learn from video lectures has attracted much attention from researchers and educators. Many attempts have been made to apply design principles in creating videos that will maximize learning (Fiorella & Mayer, 2018; Fiorella, Stull, Kuhlmann, & Mayer, 2019; Pi, Xu, Liu, & Yang, 2020). For example, although many video lectures present only slides on the screen, empirically based designs informed by the principles of multimedia learning (Mayer, 2014) present the teacher's image to motivate learners' social response and direct their attention to important information. However, relatively little attention has been paid to the learning strategies that learners use when watching video lectures.

Learners who watch a video lecture are not necessarily actively making sense of the learning material by selecting important information, organizing it into a coherent mental model and integrating it with their prior knowledge (Fiorella, Stull, Kuhlmann, & Mayer, 2020). These learning behaviors may be more common in traditional classrooms, where interaction and immediate feedback are more accessible than they are when watching video lectures (Lin & Kao, 2018). In traditional classrooms, a teacher can use speech (eg, praise, encouragement, inquiry) or nonverbal cues (eg, smile, head nod, body contact) to motivate learners and actively engage them in learning; the teacher can also judge learners' engagement by observing learners' nonverbal cues (eg, furrowed brow, head scratching, note taking) and thus, adjust their teaching accordingly. Because video lectures lack these features, it is harder for learners who watch a video lecture than for those who learn in traditional classrooms to process information needed for learning (Lin & Kao, 2018).

Generative learning strategies (that is, non-passive) have been shown to promote learning in traditional contexts (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; De Backer, Van Keer, & Valcke, 2012) and may also be helpful when learning from video lectures (Fiorella *et al.*, 2020; Fiorella & Mayer, 2016). One generative learning strategy is learning by explaining. Using this strategy, learners generate statements to clarify the meaning of the learning material by integrating information from various sources and relating it to their prior knowledge (Chi *et al.*, 1989). One use of the explaining strategy is self-explaining, which facilitates deep learning from video lectures (Fiorella *et al.*, 2020; Fiorella & Mayer, 2016; Mayer, Fiorella, & Stull, 2020). In a recent study (Fiorella *et al.*, 2020), college students viewed a 12-minute narrated video lecture on how the human kidneys work. The video was broken into five segments and after each segment the participants either re-watched the video (control group) or wrote an explanation (self-explaining group). The results showed that the self-explaining group outperformed the control group on recall and transfer tests.

Learning by explaining can also be accomplished by explaining to peers (Roscoe, 2014; Roscoe & Chi, 2008), also called learning by teaching (Fiorella & Mayer, 2016). Learning by teaching is considered a powerful learning strategy (Fiorella & Mayer, 2013; Kobayashi, 2019a; Roscoe & Chi, 2008). It involves not only generating explanations, but also giving the explanations to others and both components appear to contribute to the teacher's learning (Hoogerheide, Deijkers, Loyens, Heijltjes, & van Gog, 2016; Kobayashi, 2019a, 2019b; Roscoe & Chi, 2008). Learning by teaching can be accomplished in multiple ways, for example explaining to an imaginary or anonymous learner (eg, creating a lecture video, providing written explanations), explaining to a passive and anonymous learner who just listens and teaching a learner face-to-face by asking and answering questions (Fiorella & Mayer, 2013; Kobayashi, 2019a).

The benefits of learning by teaching are called peer tutoring effects. These include cognitive and metacognitive benefits, as well as motivational benefits (Kobayashi, 2019b; Roscoe & Chi, 2008). Regarding cognitive and metacognitive benefits, learners engage in more integration of new and prior knowledge, as well as more monitoring and reconstruction of their own understanding, when teaching peers (Roscoe & Chi, 2008). For example, the effects of learning by teaching were tested in a sample of elementary school students who were learning to problem solve in mathematics (Muis, Psaradellis, Chevrier, Di Leo, & Lajoie, 2016). Participants were given situational problems, such as to create a seven-sided polygon for a racetrack design that ranged in length between 4.5 km to 5 km. After they were given the problems, participants were randomly assigned to a control condition in which they created a concept map and completed the problem or an experimental condition in which they additionally taught others about the learning activities. The results confirmed the peer tutoring effect by showing that compared to the control group, the learning-by-teaching created higher quality concept maps, had higher task achievement and engaged in more metacognitive processing.

Learners who learn by teaching have also been shown to have more motivation, put more effort into learning and spend more time engaging in learning activities both in traditional educational settings (Al-Hebaishi, 2017; Cristina *et al.*, 2018) and in multimedia learning (Chase, Chin, Oppezzo, & Schwartz, 2009; Zhao, Ailiya, & Shen, 2012). For example, Chase *et al.*(2009) developed Betty's Brain software, a computer-based learning environment in which children could work independently or instruct a Teachable Agent, using concept mapping activities. In a sample of 5th graders who were learning about physiological responses to fever, students who learned by teaching spent more time on the learning activities compared to the independent learners, suggesting greater motivation. This motivation may result from the need to give relevant, coherent, complete and accurate explanations to someone else (Kobayashi, 2019a, 2019b).

Although there appears to be wide utility of explaining to oneself and to peers across a range of information sources (eg, classroom activities, text, static diagrams, animations), the effects of these two learning strategies have only recently been examined in relation to the content of video lectures (Chi, Kang, & Yaghmourian, 2017; Fiorella *et al.*, 2020; Kobayashi, 2019a, 2019b). According to the self-explanation principle in multimedia learning, self-explaining facilitates deep learning from video lectures by prompting active engagement (ie, selecting, organizing and integrating; Wylie & Chi, 2014). Therefore, learning by self-explaining might foster greater cognitive engagement than passively viewing video lectures and thus, promote better learning performance.

However, there is also reason to expect that not only self-explaining, but also explaining to a peer would be helpful in learning from video lectures (Fiorella & Mayer, 2013; Kobayashi, 2019a; Roscoe & Chi, 2008). Learning by teaching not only includes generating explanations, but also giving the explanations to others. The various benefits of learning by teaching might be due both to generating explanations and to sharing the explanations with others (Hoogerheide *et al.*, 2016; Kobayashi, 2019a, 2019b; Roscoe & Chi, 2008). Therefore, it is reasonable to assume that compared with self-explaining, teaching would have the additional benefit of increasing the motivation to learn from video lectures. As a result, the benefits of learning by explaining appear to be stronger when learners are teaching a peer than when they are only explaining to themselves.

One limitation of the literature on learning from video lectures is that assessments of learning experience (motivation, engagement) and learning performance (typically recall and transfer) are made after watching the lecture. This means that little is known about the process by which different learning strategies might affect outcomes. Although self-reported motivation could be used to infer something about this process, the fact that it is assessed after learning limits its utility for this purpose. Detection of electroencephalography (EEG) signals enables a direct examination of neural oscillations in real time (Perry, Stein, & Bentin, 2011; Puma, Matton, Paubel, Raufaste, & El-Yagoubi, 2018). Studying the neural underpinnings of the strategies of self-explaining and learning by teaching could provide information about the underlying processes by which these strategies are associated with learning performance.

EEG signals at certain frequencies provide indirect evidence of processes related to memory and attention, which are key components of learning (Narimani & Soleymani, 2013). Neural oscillations in the theta frequency band (4–8 Hz) are well known to correlate with memory (Herweg, Solomon, & Kahana, 2020). Specifically, increases in theta oscillations indicated by power values are associated with high working memory activity, successful memory encoding (Miller *et al.*, 2018) and retrieval (Solomon, Lega, Sperling, & Kahana, 2019). Neural oscillations in the alpha frequency band (8–12 Hz) are associated with increases in internal attention-demanding cognitive processes (Fink & Benedek, 2014; Klimesch, 2012). Importantly, the link between theta power and memory and the link between alpha power and attention, are more evident in some regions than others. The link between theta oscillations and memory is most prominent in the frontal and central regions (Castro-Meneses, Kruger, & Doherty, 2020; Wang, Antonenko, Keil, & Dawson, 2020), whereas the link between alpha oscillations and attention is most pronounced in the occipital and parietal regions (Jensen, Gelfand, Kounios, & Lisman, 2002; Whitmarsh, Oostenveld, Almeida, & Lundqvist, 2017).

In the present study, we tested the effects of three assigned learning strategies (passive viewing vs. self-explaining vs. teaching), with the effects being measured in terms of EEG oscillations in theta and alpha band power while watching video lectures; self-reported learning experience (motivation and engagement) after the video lectures; and learning performance. The videos taught English vocabulary words. In the passive viewing condition, participants watched the video and viewed and read out loud pre-written sentences containing each word; in the self-explaining condition, participants watched the video, created sentences containing each word and read the sentences out loud; and in the teaching condition, participants watched the video, created sentences containing each word and orally shared the created sentences as a way to teach a peer face-to-face. The peer was a male research assistant and was similar aged with participants.

We adopted the self-explanation principle in multimedia learning (Wylie & Chi, 2014) to inform our hypotheses about learning through self-explaining and used empirical evidence of the peer tutoring effect in traditional learning environments to inform our hypotheses about learning by explaining to a peer (Fiorella & Mayer, 2013; Kobayashi, 2019a; Roscoe & Chi, 2008). We expected that learning by self-explaining and learning by teaching would enhance learners' EEG oscillations, learning experience and learning performance relative to passive viewing and that learning by teaching would be the most effective strategy. Specifically, we posed the following hypotheses.

Hypothesis 1 Learners will show higher power of theta and alpha when using the strategy of learning by teaching, followed by learning by self-explaining and then, learning by passive viewing. Furthermore, higher power of theta will be most prominent in frontal and central regions; higher power of alpha will be most prominent in occipital and parietal regions.

Hypothesis 2 Learners will report greater motivation and engagement when using the strategy of learning by teaching, followed by learning by self-explaining and then, learning by passive viewing.

Hypothesis 3 Learners will show better learning performance when using the strategy of learning by teaching, followed by learning by self-explaining and then, learning by passive viewing.

Method

Participants and design

We recruited 26 healthy participants (five men) from a Chinese university. Participants were undergraduate and graduate students. Their ages ranged from 19 to 28 ($M = 22.54$, $SD = 2.18$). By self-report, all participants were right handed, had normal or corrected-to-normal vision and hearing and had no history of neurological or psychiatric disorders. Because the learning content was English vocabulary words from the Graduate Record Examination (GRE), the participants were required to have passed the College English Test-6 (CET-6), which is a national English examination in China. All participants provided written informed consent after being provided information about the experimental procedures. Participants received 70 RMB (about 10 US Dollars) for taking part in the study.

The experiment used a within-subjects design. Each participant was asked to watch 120 short video lectures to learn 120 English vocabulary words (three sets of 40 words), using three different strategies. The strategies were assigned to each participant in a counterbalanced order. (1) In the passive viewing strategy condition, the participant was asked to view a set of short video lectures on a set of 40 English words. After each video they viewed a sentence containing the vocabulary word for 10 seconds. After the 10 seconds, they read the sentence out loud. (2) In the self-explaining strategy condition, the same participant was told to watch a different set of short video lectures on a different set of 40 English words. After each video they created a sentence containing the vocabulary word in 10 seconds and then, after the 10 seconds, spoke the created sentence out loud. (3) In the teaching strategy condition, the same participant was told to watch another set of short video lectures on another set of 40 English words. After each video they created a sentence for each word in 10 seconds and then, after the 10 seconds, spoke the created sentence out loud in the presence of a peer. The peer was a male research assistant and was a master's degree student. He was of a similar age as the participants. This activity was the same as in the self-explaining condition, but in the teaching condition the participant spoke the created sentences out loud presumably to help another learner. Participants and the peer did not know each other before the study and sat face-to-face. The peer just listened to participants' created sentences and did not ask questions. In each condition, after speaking the sentence out loud, the participant pressed the "Enter" key to advance to the next word.

Video lectures

We created 120 short video lectures, each focused on one of 120 English vocabulary words. The videos were then randomly divided for use in the passive viewing strategy condition, self-explaining strategy condition and teaching strategy condition (40 short video lectures for each condition). The average duration of each short video lecture was 3045 ms (duration range: 2960–3054 ms). In each video, the same female teacher explained the English pronunciation of the word, its part of speech and its corresponding Chinese meaning. Figure 1 shows a screenshot from one of the video lectures, showing the teacher, the vocabulary word ("contort"), its part of speech ("verb") and the Chinese meaning of the word.

To ensure that the English vocabulary words in the three set of short video lectures were equally difficult, we invited 10 undergraduate and graduate students from different majors to individually watch the three sets of short video lectures. In an informal interview they reported that the difficulty of the vocabulary words in the three set of short video lectures was the same.

Figure 1: A screenshot from one of the short video lectures, with added explanations in red that were not seen by the participants
[Colour figure can be viewed at wileyonlinelibrary.com]

EEG recording and EEG data analysis

EEGs were simultaneously recorded using a 64-channel amplifier (ANT Neuro EEGO). Sixty-three scalp sites (FPZ, FZ, FCZ, CZ, PZ, POZ, OZ, FP1, FP2, AF3, AF4, AF7, AF8, F1, F2, F3, F4, F5, F6, F7, F8, FC1, FC2, FC3, FC4, FC5, FC6, FT7, FT8, C1, C2, C3, C4, C5, C6, T7, T8, CP1, CP2, CP3, CP4, CP5, CP6, TP7, TP8, P1, P2, P3, P4, P5, P6, P7, P8, PO3, PO4, PO5, PO6, PO7, PO8, O1, O2, M1, M2) were mounted in a cap using the 10–20 system (Homan, Herman, & Purdy, 1987). Two electrodes were placed above and below the left eye for recording the vertical electrooculogram (EOG) and the electrodes were placed to the left and right of the external canthi for recording the horizontal electrooculogram. The CPZ electrode was used as a reference and the GND electrode served as the ground. Electrode impedance was kept under 10 kΩ for all signal recordings. EEGs were recorded and digitized at a rate of 1000 Hz and re-sampled at a rate of 250 Hz for offline analysis.

EEG data analysis was conducted using Brain Vision Analyzer 2.1 software (Meadows, Gable, Lohse, & Miller, 2016). In the EEG data preprocessing, all of the original EEG data were re-referenced offline to the average mastoids to prevent a laterality bias (Teplan, 2002). First, we applied a 0.1 Hz high pass filter and a 30 Hz low pass filter. Second, we corrected ocular artifacts (vertical eye movements, horizontal eye movements). Independent component analysis (ICA) was adopted to remove EOG components from the EEG signals (Subasi & Gursoy, 2010). Third, we used algorithms in the software to flag and remove the epochs that contained artifacts. Fourth, EEG epochs were re-segmented into a time window of 3960 ms (−1000 ms pre-video to 2960 ms post-video) for spectral analysis. Then, baseline correction was performed using the pre-video interval (−1000 to 0 ms).

For outcome analysis, we clustered the scalp electrodes according to six corresponding brain regions (see Figure 2): (1) Frontal: F1, F2, F3, F5, F7, AF3, AF4, AF7, AF8, FP1, FPZ, FP2, FZ, F4, F6, F8; (2) Left temporoparietal: FT7, FC5, T7, C5, TP7, CP5, P7; (3) Fronto-central: FC3, FC1, FCZ, FC2, FC4, C3, C1, CZ, C2, C4; (4) Right temporoparietal: FC6, C6, CP6, FT8, T8, TP8, P8; (5) Parietal: CP3, CP1, CP2, CP4, P5, P3, P1, PZ, P2, P4, P6; (6) Occipital: PO7, PO5, PO3, POZ, PO4, PO6, PO8, O1, OZ, O2 (Jahng, Kralik, Hwang, & Jeong, 2017). Finally, the EEG data were spectrally analyzed using a fast Fourier transform (FFT; Golden, Wolthuis, & Hoffler, 1973) and power was computed as μV^2 for the theta (4–8 Hz) and alpha (8–12 Hz) frequency bands via averaging the power of all scalp electrodes (Fink, Grabner, Neuper, & Neubauer, 2005; Jacobs, Hwang, Curran, & Kahana, 2006).

Measurements

Learning experience questionnaire (motivation and engagement)

The self-reported learning experience questionnaire (Stull, Fiorella, Gainer, & Mayer, 2018) was used to measure motivation (six items) and engagement (two items). The six motivation items assessed participants' enjoyment, willingness to learn in this way in the future, understanding of the learning materials, desire to learn more about the content, finding the lesson useful and motivation to learn the content. The two engagement items assessed participants' perception of the difficulty of the learning material and their mental effort. Participants rated all items on a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"), with the exception of the item on mental effort "I felt that the subject matter was difficult," which was reverse-scored. In the current study, Cronbach's alpha for the learning experience questionnaire was 0.85.

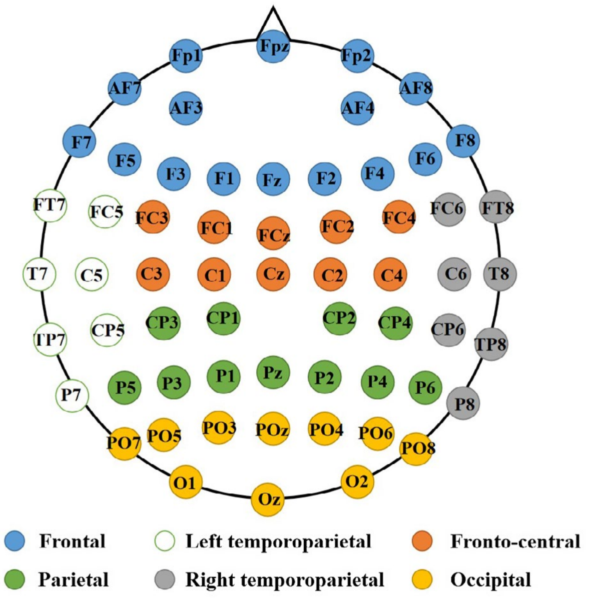

Figure 2: The clustered scalp electrodes. There were 63 electrodes, clustered in six brain regions [Colour figure can be viewed at wileyonlinelibrary.com]

Learning performance tests

Three learning performance tests, one for each set of 40 words, were used to assess the participants' mastery of the GRE words. Two university English professors worked together to develop the learning performance tests. Each test consisted of 40 multiple-choice questions. There were four answer choices for each question, only one of which was correct and the three incorrect choices were words that were also learned in the videos. For example, "Your face has nine muscles beneath your skin that you, flex, and move." The four choices were: A. contort; B. gurgle; C. conciliate; D. asymmetry. Participants were given 1 point if their answer was correct and 0 points if their answer was incorrect. Participants could score up to 40 points on each learning performance test. Cronbach's alphas for the 40 words tested after the passive learning condition, the 40 words tested after the self-explaining condition and the 40 words tested after the teaching condition were 0.76, 0.71 and 0.85 respectively.

Procedure

Before starting the experiment, all participants washed their hair to lower the impedance. Then, they filled out the demographic information form (eg, age, gender and major) and learned about the experimental procedure. The three sets of 40 short video lectures (one English vocabulary word per video) were counterbalanced. Participants' EEGs were recorded for the entire duration (including watching each video, reading/creating and speaking the sentences out at the end of the video). Participants filled out the learning experience questionnaire and the corresponding learning performance test after each set of 40 words. The whole experiment lasted for 1 hour and 40 minutes (see Figure 3).

Results

EEG oscillations

Two 3 × 6 repeated-measures ANOVAs were conducted with the within-subjects factors of Learning Strategy (passive viewing, self-explaining, teaching) × Region (frontal, left

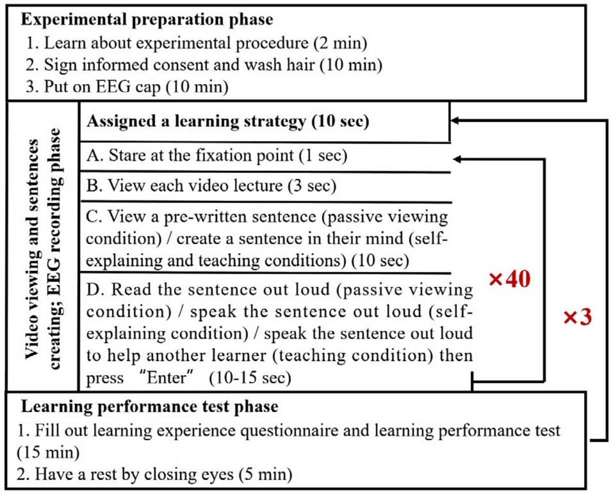

Figure 3: Experimental procedure. The experiment used a within-subject design in which participants used three learning strategies in counter-balanced order. In each condition, the learning content was presented in 40 short videos
[Colour figure can be viewed at wileyonlinelibrary.com]

temporoparietal, fronto-central, right temporoparietal, parietal, occipital) and theta power (4–8 Hz) and alpha power (8–12 Hz) as the dependent variables. Effect sizes were measured by η_p^2 for the ANOVAs, with $\eta_p^2 = 0.01$ considered a small effect, 0.06 a medium effect and 0.14 a large effect (Cohen, 1988).

Theta power (4–8 Hz)
There were significant main effects of Learning Strategy and Region (respectively, $F(2, 50) = 13.00$, $p < .001$, $\eta_p^2 = 0.34$; $F(5, 125) = 48.92$, $p < .001$, $\eta_p^2 = 0.66$) on theta power. In addition, the Learning Strategy × Region interaction was significant ($F(10, 250) = 3.27$, $p = .001$, $\eta_p^2 = 0.12$; see Figure 4). Simple slope tests using $p < .05$ to indicate significance showed that in the fronto-central, right temporoparietal, parietal and occipital regions, participants had significantly higher theta power when learning by teaching than by self-explaining, which in turn had significantly higher theta power than when learning by passive viewing. However, in two regions, namely frontal and left temporoparietal, the self-explaining condition and the passive viewing condition did not differ significantly in theta power.

Alpha power (8–12 Hz)
There were significant main effects of Learning Strategy and Region (respectively, $F(2, 50) = 15.84$, $p < .001$, $\eta_p^2 = 0.38$; $F(5, 125) = 15.54$, $p < .001$, $\eta_p^2 = 0.39$) on alpha power. More importantly, the Learning Strategy × Region interaction was significant ($F(10, 250) = 5.17$, $p < .001$, $\eta_p^2 = 0.17$; see Figure 5). Using $p < .05$ as the indicator of significance, simple effects analyses showed full support for the hypotheses in the frontal, left temporoparietal, right temporoparietal and occipital regions. In these regions participants had significantly higher alpha power when learning by teaching than by self-explaining, which in turn had significantly higher alpha power than when learning by passive viewing. However, in two regions, namely fronto-central and parietal, the self-explaining condition and the teaching condition did not differ significantly in alpha power.

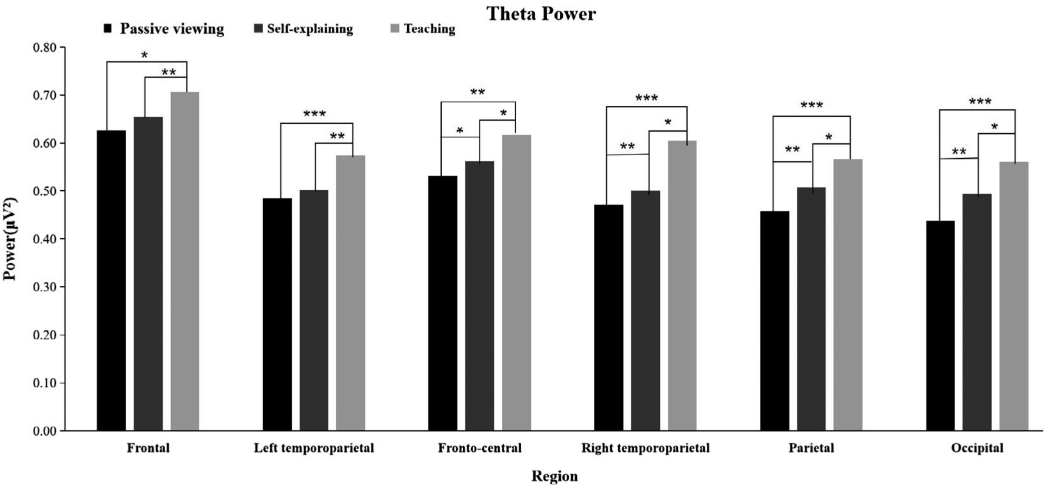

Figure 4: Theta oscillations power for the six brain regions in the passive viewing, self-explaining and teaching conditions while watching video lectures ($^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$)

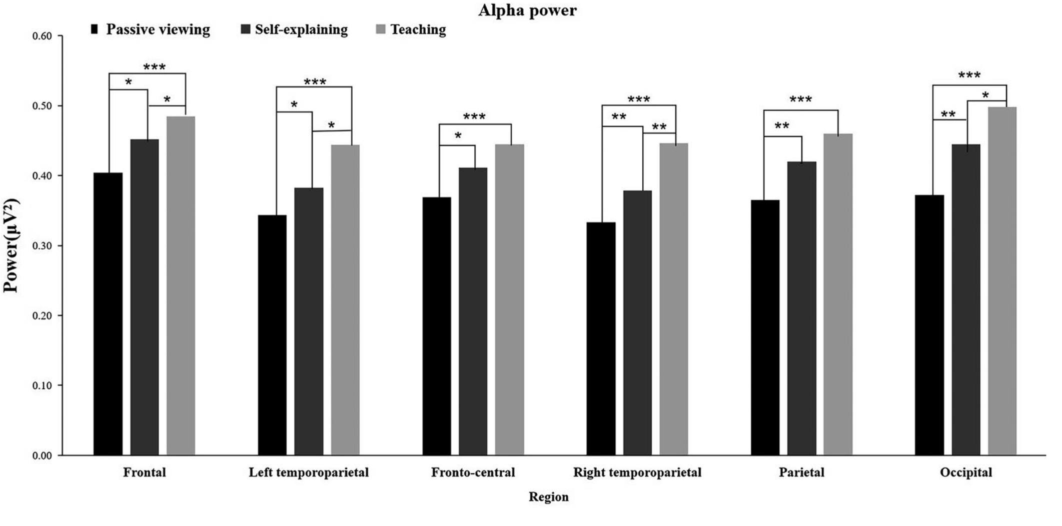

Figure 5: Alpha oscillations power for the six brain regions in the passive viewing, self-explaining and teaching conditions while watching video lectures ($^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$)

Taken together, the results were mostly but not completely consistent with our first hypothesis regarding the effects of learning strategies on learners' EEG oscillations. In most regions, as hypothesized, learners showed higher theta and alpha band power in the teaching condition, followed by the self-explaining condition and finally in the passive viewing condition. However, the expected results were not found in all brain regions.

Learning experience (motivation and engagement)

To test differences in motivation and engagement across the three learning strategies, a series of repeated measures analyses of variance (ANOVAs) was conducted on each of the eight items on

Table 1: Mean ratings, standard deviations and ANOVA results for learning experience items

	Passive viewing		*Self-explaining*		*Teaching*		
Item	*M*	*SD*	*M*	*SD*	*M*	*SD*	*ANOVA*
Enjoyment—I enjoyed learning this way	3.73	1.59	4.12	1.82	3.81	1.63	$F(2, 50) = 0.59$, $p = .560$, $\eta_p^2 = 0.02$
Willingness—I would like to learn this way in the future	3.35	1.70	3.62	1.86	3.81	1.79	$F(2, 50) = 0.68$, $p = .513$, $\eta_p^2 = 0.03$
Understanding—I feel like I have a good understanding of the material	3.81	1.20	3.54	1.48	3.73	1.54	$F(2, 50) = 0.53$, $p = .591$, $\eta_p^2 = 0.02$
Interest—After this lesson, I would be interested in learning more about the material	3.54	1.65	3.77	1.66	3.69	1.87	$F(2, 50) = 0.24$, $p = .785$, $\eta_p^2 = 0.01$
Useful—I found the lesson to be useful to me	4.19	1.58	4.27	1.69	4.00	1.77	$F(2, 50) = 0.42$, $p = .657$, $\eta_p^2 = 0.02$
Motivation—I felt motivated to try to understand the material	4.08	1.55	4.50	1.50	5.08	1.87	$F(2, 50) = 4.37$, $p = .018$, $\eta_p^2 = 0.15$
Difficulty—I felt that the subject matter was difficult	4.58	1.17	4.42	1.39	4.92	1.41	$F(2, 50) = 2.56$, $p = .087$, $\eta_p^2 = 0.09$
Effort-Please rate the amount of mental effort you put into understanding the material	5.39	0.94	5.81	0.94	6.08	0.80	$F(2, 50) = 6.51$, $p = .003$, $\eta_p^2 = 0.21$

Note: In the passive viewing condition, participants viewed a sentence and read it out loud after they viewed each lecture; in the self-explaining condition, participants created sentences alone and spoke the sentences out loud after they viewed each lecture; in the teaching condition, participants created and spoke the sentences out loud to a peer face-to-face to help her/him learn after they viewed each lecture. The two explaining conditions produced significantly higher scores than the passive viewing strategy, but did not differ from each other. For the item "Motivation," scores were significantly higher when participants learned by teaching than by passive viewing; for the item "Effort," scores were significantly higher when participants learned by self-explaining and learned by teaching than by passive viewing.

the learning experience scale, with Learning Strategy (passive viewing, self-explaining, teaching) as the within-subjects factor. Descriptive results and the ANOVA results for each item are presented in Table 1.

Concerning the six motivation items, only one item, "I felt motivated to try to understand the material," showed a significant difference across groups ($F(2, 50) = 4.37$, $p = .018$, $\eta_p^2 = 0.15$). When using the teaching strategy, participants had significantly higher scores on this item than when they used a passive viewing strategy (see Figure 6; $MD = 1.00$, $p = .018$). The other pairwise comparisons were nonsignificant (ps > .05). The three learning strategies did not differ significantly on other ratings related to motivation, namely promoting enjoyment, willingness to learn in this way in the future, understanding the learning materials, desire to learn more about content or finding the lesson useful (ps > .05).

Concerning engagement, when participants learned by self-explaining and teaching they reported investing significantly more mental effort than when they learned by passively viewing (see Figure 4; $MD = 0.42$, $p = .046$; $MD = 0.69$, $p = .002$). However, participants' perceptions of the difficulty of the material did not differ across the three learning strategies ($F(2, 50) = 2.56$, $p = .087$, $\eta_p^2 = 0.09$). Thus, the results based on the motivation item and the mental effort item from the learning experience scale provided support for our second hypothesis regarding the effects of learning strategies on learners' self-reported motivation and engagement.

Learning performance

To test differences in learning performance scores across the three learning strategies, a repeated measures ANOVA was conducted, with Learning Strategy (passive viewing, self-explaining and teaching) as the within-subjects factor. The ANOVA results showed significant differences in learning performance across the three learning strategies ($F(2, 50) = 4.04$, $p = .024$, $\eta_p^2 = 0.14$). Post hoc tests (*LSD*) found that participants showed higher learning performance when learning by self-explaining and teaching than when learning by passive viewing (respectively, $MD = 2.65$, $p = .009$; $MD = 2.23$, $p = .041$); there was no significant difference in learning performance

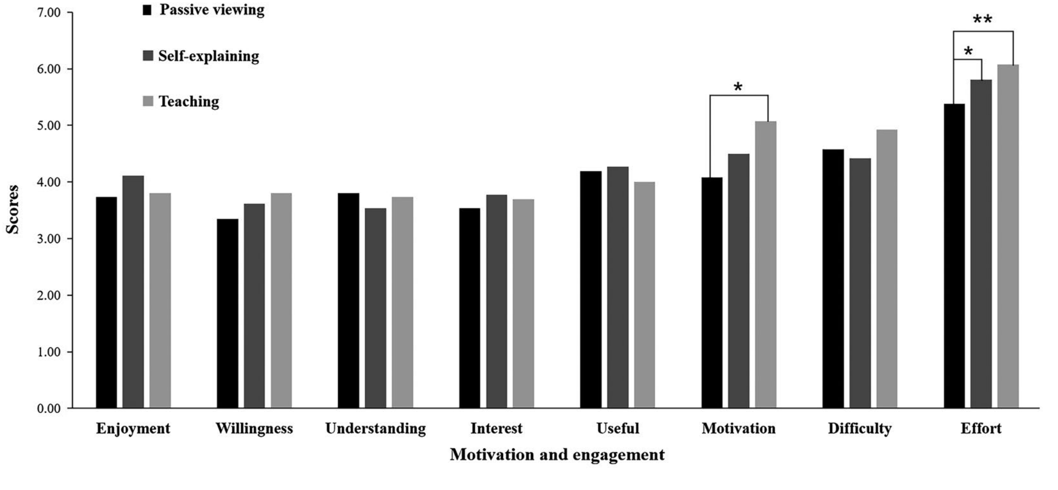

*Figure 6: Eight items from the learning experience scale across the three learning strategy conditions. The items designed to assess participants' enjoyment, willingness, understanding, interest, useful and motivation were the six motivation items. The items designed to assess participants' perception of difficulty and mental effort were the two engagement items (*p < .05, **p < .01)*

between the teaching and self-explaining conditions (MD = 0.42, p = .684; see Figure 7). The results partially supported our hypothesis; both the self-explaining and teaching strategies were more effective than the passive viewing condition, although teaching did not produce more benefits than self-explaining.

Discussion

This study tested whether the learning strategy of explaining—either self-explaining or explaining to a peer (teaching)—would be more beneficial than passive viewing when learning from video lectures. Both types of explaining were more helpful than passive viewing: EEG oscillations indicated more neural activation related to memory and attention, there was more self-reported motivation and engagement and learning performance scores were higher. Comparisons between the two explaining strategies showed oscillations related to memory and attention were more activated by teaching than by self-explaining; however, the two groups did not differ on traditional outcome measures. This suggests that EEG detected subtle information that was otherwise undetectable. This is the first study to examine the learning strategy of teaching a peer when learning from a video lecture and the first to use EEG to provide insight into the neural processes underlying learning strategies in this educational context.

The EEG frequencies under study were in the theta band, associated with working memory and in the alpha band, associated with attention. These two cognitive functions are important for learning (Narimani & Soleymani, 2013). For example, learners show higher theta power during the presentation of successfully remembered versus forgotten learning materials (Khader, Jost, Ranganath, & Rösler, 2010). Similarly, studies on learning from video lectures have shown that higher theta power over frontal and central cortex is related to increased working memory activity during the video presentation (Castro-Meneses *et al.*, 2020; Wang *et al.*, 2020). Deep processing of learning material in working memory may thus allow successful encoding of memories (Khader *et al.*, 2010; Lin *et al.*, 2017) and working memory maintenance may predict long-term memory (Hsieh & Ranganath, 2014; Ranganath, Cohen, & Brozinsky, 2005).

Whereas theta power is an indirect indicator of working memory processing, alpha power is an indirect indicator of inhibition of sensory (bottom up) processing areas via attentional

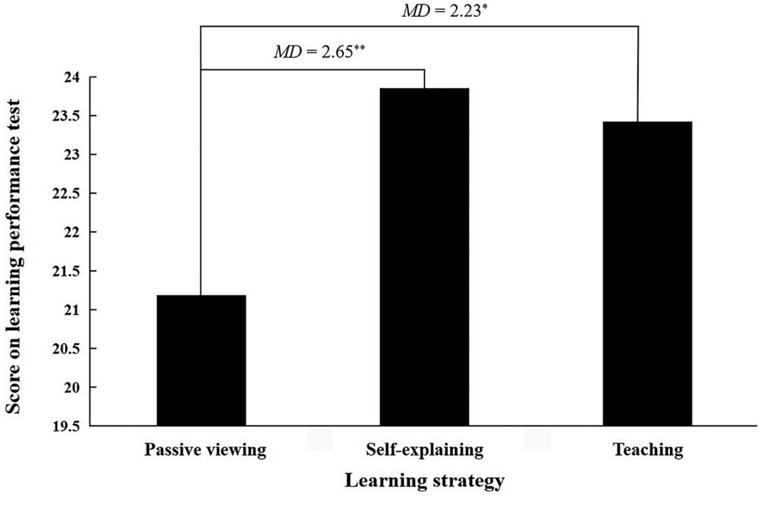

*Figure 7: Differences in learning performance score among the three learning strategies (*p < .05, **p < .01)*

(top-down) control mechanisms (Fink & Benedek, 2014; Wang, Rajagovindan, Han, & Ding, 2016; Wöstmann, Lim, & Obleser, 2017). Specifically, alpha power has been shown to increase during performance of internal attention tasks (eg, creative idea generation, a Sternberg-like task) over the parietal and occipital cortex (Fink & Benedek, 2014; Jensen *et al.*, 2002). Therefore, the inhibition of visual processing areas might be driven by a top-down control mechanism for shielding to-be-maintained information from possibly distracting visual input. Video lectures combine multiple sources of information (eg, text, diagrams and speech) and the information disappears after presentation to be replaced by new information. In order to effectively learn from video lectures, learners must be aware of the learning process so that they pay attention to relevant information (Moreno, 2007). Higher alpha power might allow learners to not just be driven "bottom-up" by the external stimulus in video lectures, but to control their learning process by internal constraints such as expectancy or the current behavioral goal (Fink & Benedek, 2014; Wöstmann *et al.*, 2017).

Both the self-explaining strategy and the teaching strategy elicited significantly greater oscillations in the theta band and alpha band than the passive viewing strategy did, consistent with the self-explanation principle in multimedia learning (Wylie & Chi, 2014) and empirical evidence of peer tutoring effects (Fiorella & Mayer, 2013; Kobayashi, 2019a; Roscoe & Chi, 2008). This suggests that both strategies based on explaining involved working memory and attention processes. However, the EEG data also indicated a significant difference between the self-explaining and teaching strategies. Both theta power and alpha power were higher for participants in the teaching condition than those in the self-explaining condition, suggesting that the learning-by-teaching strategy involves greater engagement of working memory and attention than the self-explaining strategy does, allowing information to be processed at a deeper level (Kobayashi, 2019a). This difference was observed in all brain regions that were tested, namely the frontal, fronto-central, bilateral temporoparietal, parietal and occipital regions. This is the first study to compare these strategies in terms of learners' attention and memory while processing learning material.

It should be noted that we found global effects of the strategies of learning by self-explaining and learning by teaching in brain, suggesting that the active learning strategies involve greater cognitive activities, such as general attentional processing, active working memory maintenance, top-down control and suppression of distracting information flow. First, the higher theta power seen in the learning by self-explaining and learning by teaching conditions compared to the passive strategy condition was observed in the fronto-central, right temporoparietal, parietal and occipital regions. However, the power of theta band has been shown to index different processes in different regions. Frontal and central theta power increases with working memory load during tasks that generally demand attentional processing (Castro-Meneses *et al.*, 2020; Wang *et al.*, 2020) and parietal and temporal theta power increases with successful remembering of previously presented stimuli (Osipova *et al.*, 2006). These results suggest that fronto-central theta is related to the learning processes that demand general attentional processing and active working memory maintenance and posterior theta (ie, right temporoparietal, parietal and occipital regions) is related to the learning processes that promote successful memory encoding.

Second, the higher power of alpha band in the active learning conditions compared to the passive learning condition was also observed in multiple regions, most prominently in frontal, bilateral temporoparietal and occipital regions. However, enhanced alpha oscillations in the frontal region may index different processes than those in the occipital region. Frontal alpha power has been shown to reflect a state of high internal processing demands (Benedek, Bergner, Könen, Fink, & Neubauer, 2011), whereas alpha power in occipital and parietal regions has been shown to reflect suppression of distracting information flow from the visual system (Jensen *et al.*, 2002).

Therefore, frontal alpha power may exert top-down control over posterior regions, a process that might be mediated by functional coupling between these brain regions (Klimesch, Sauseng, & Hanslmayr, 2007; Sauseng *et al*., 2005). The increased alpha power in frontal, bilateral temporoparietal and occipital regions suggests that efficient internal processing, top-down control and suppression of distracting information flow are essential—but certainly not the only—characteristics of self-explaining and teaching strategies when learning from video lectures.

Although we found support for the hypothesis that the teaching group would show more activation in EEG frequency bands associated with working memory and attention than the self-explaining group, we did not find support for our hypotheses regarding the traditional measures of self-reported learning experience (motivation and engagement) or learning performance scores. This pattern suggests that even when strategy groups do not differ on traditional strategy-related outcome scores, EEG data still provide information on the processes that underlie the strategies themselves. Results based on traditional outcome measures have also been inconsistent across studies on learning from video lectures. First, whereas we saw no differences in the self-reported learning experience in the self-explaining and teaching conditions, other studies have found greater motivation and engagement after explaining versus not explaining to a peer (Chase *et al*., 2009; Rienovita, Taniguchi, Kawahara, Hayashi, & Takeuchi, 2018). This inconsistency across studies may have resulted from differences in measurement. In previous studies, participants' motivation and engagement were measured by self-efficacy and the amount of time they spent engaged in learning activities (Chase *et al*., 2009; Rienovita *et al*., 2018), whereas in the present study, participants' motivation was measured by their self-reported enjoyment, willingness, understanding, interest, perception that the videos were useful and motivation; their engagement was measured by their perception of the difficulty of the learning material and mental effort.

The use of self-efficacy and time spent engaging in learning tasks as indicators of motivation and engagement (Chase *et al*., 2009; Rienovita *et al*., 2018) may be especially helpful in distinguishing the effects of self-explaining from the effects of learning by teaching. Self-efficacy refers to judgment of one's ability to complete or succeed at a task (Rienovita *et al*., 2018) and a learner's self-efficacy is thought to be enhanced by experiences of success (Bandura, 1982). When learning by teaching, learners get some feedback from the peer they are instructing face to face, such as smiles and head nods. This feedback in turn may promote self-efficacy and as a result, greater motivation. By contrast, the measure of motivation used in the current study focused on learners' feelings, such as enjoyment and the desire to learn more about the content. To some extent these items reflect the learner's level of comfort with the task. In fact, learners have default learning strategies and preferred learning materials and these may or may not match the assigned tasks. Discomfort should affect a participant's ratings of engagement across conditions, reducing the possibility of finding between-condition effects. Furthermore, in our study participants gave especially high ratings on the questionnaire item regarding how much mental effort they put into the task (around 6 points on average on a 7-point scale), suggesting the possible influence of social desirability bias (Pi, Hong, & Yang, 2017). In contrast, time engaged in learning activities is an objective measure of engagement that is less likely to be influenced by social desirability bias and is, therefore, preferable to the self-report measure used in the current study.

Learning performance after the video lectures also did not differ significantly between the self-explaining condition and the teaching condition. This finding was inconsistent with previous studies that found teaching to be superior to self-explaining in terms of the effects on learning (Coleman, Brown, & Rivkin, 1997; Rittle-Johnson, Saylor, & Swygert, 2008). This inconsistency might have to do with differences across studies in terms of the extent of teaching. In the present study, we limited participants in both groups to generating one sentence for each vocabulary word, whereas in previous studies participants generated as many explanations as possible (Coleman *et al.*, 1997; Rittle-Johnson *et al.*, 2008). This limitation might have mitigated evidence of the expected benefits of teaching relative to self-explaining. For example, in one study participants in the teaching condition tended to provide more explanations than those in the self-explaining condition; furthermore, the more often participants provided explanations, the better their learning performance was (Rittle-Johnson *et al.*, 2008).

The measure of learning performance might also have contributed to the inconsistency between the findings in our study and those in other studies. Participants' learning performance in previous studies was assessed by tests of recall and transfer, with the results indicating that learning by teaching leads to higher transfer scores (but not recall scores) than learning by self-explaining (Coleman *et al.*, 1997; Rittle-Johnson *et al.*, 2008). In the current study participants' learning performance was assessed by a recall test (not a transfer test) in which learners chose one word from four choices to complete a sentence, a task similar to generating sentences that included the vocabulary word after watching video lectures.

The mixed results across studies suggest that a wider range of measures should be used to test the effects of different learning strategies. For example, in our own study, EEG results regarding attention and motivation differed from results based on self-reported motivation and engagement. Other measures (such as performance on tests requiring the application of knowledge in new settings, behavioral observation) might clarify whether self-explaining or teaching is the more helpful learning strategy in terms of learning outcomes.

Limitations and future directions

This study has limitations that can be addressed in future studies. First, the sentences that participants created and read out loud were not analyzed in terms of their content. This limitation occurred because the learners' explanations were presented orally and it was not always possible to understand some learners' regional accents and non-standard English. It can be assumed that the quality and quantity of explanations would moderate the effectiveness of learning by self-explaining and teaching. Indeed, prior research indicated that learners who generate higher quality self-explanations and a greater number of explanations show better learning performance (Roelle & Renkl, 2020; Ruiz-Primo, Li, Tsai, & Schneider, 2010). Further work is needed to understand how the quantity and quality of explanations interact to influence the effects learning by explaining after video lectures.

Second, our design did not allow us to separate the effects of the experimental manipulation and effects due to simple peer presence. According to the concept of social facilitation/inhibition effects, individuals do better on simple tasks but worse on complex tasks when in the presence of peers (Geen, 1983). Therefore, the effects of learning by explaining to a peer face-to-face should vary depending on the difficulty of the task. However, we could not test this possibility directly because although pilot study participants said they believed the vocabulary words in the three strategy conditions were of similar difficulty, we did not strictly control for the difficulty of the three word lists. Future research should test the interactive effects of the difficulty of learning tasks and the strategies learners use to learn from video lectures.

Furthermore, effect of peer presence might explain differences between self-explaining and teaching. It would be useful to further isolate whether the benefits of teaching seen in EEG oscillations can be attributed to teaching a peer or merely peer presence while learners watch video lectures and generate self-explanations. Several studies have shown that the mere presence of others without teaching goals positively influences both learners' behavioral performance (eg, motivation, generative activities, attention allocation and learning performance) and neural oscillations (Chib, Adachi, & O'Doherty, 2018; Sulaiman & Njansiu, 2018). For example, a recent study indicated that others' presence improved both secondary teachers and students' classroom performance (eg, presentation, class management and control and students' activities; Sulaiman & Njansiu, 2018). Future work should test the peer presence effect in learning by explaining after video lectures, by comparing different types of generative learning strategies (self-explaining, self-explanation in the presence of a peer and teaching via explaining to a peer face-to-face).

In sum, compared with learning by passive viewing, learning by self-explaining and learning by teaching are effective learning strategies when learning from video lectures. Future research should continue to explore the unique benefits and boundaries of learning by self-explaining and learning by teaching.

Contributions and implications

The present study advances our understanding of the various effects of two types of generative learning strategies when learning from a video lecture. Previous studies on video lectures have predominantly focused on design principles and learning strategies are just beginning to gain attention (Fiorella & Mayer, 2018; Hoogerheide, Visee, Lachner, & van Gog, 2019). In the present study, we compared three learning strategies, namely passive viewing, self-explaining and teaching via explaining. We confirmed the benefits of learning by self-explaining and teaching relative to learning by passive viewing, based on both behavioral and neural evidence.

Our findings about learning strategies have implications for using video lectures in educational settings. First, teaching is an effective strategy for learning from video lectures. Compared with learners who passively view the video, learners who use the strategy of teaching appear to engage more working memory and use more top-down attentional processing, resulting in higher learning performance. Therefore, learners are encouraged to generate explanations and teach a peer face-to-face during pauses in video lectures or after viewing them. Second, learners are also encouraged to learn by self-explaining when they are not in the company of peers, as this strategy can also improve their learning performance relative to passive viewing.

To our knowledge, this is the first study to test the neural effects of learning from video lectures when using either self-explaining or teaching as a learning strategy. Specifically, EEG oscillations, which have not been examined in other research on this topic (Fiorella *et al.*, 2020), showed higher theta and alpha power in the teaching condition than in the self-explaining condition, indicating successful memory encoding or retrieval and greater internal attention (Castro-Meneses *et al.*, 2020; Fink & Benedek, 2014; Herweg *et al.*, 2020; Wang *et al.*, 2016). The results suggest that learners who were told they would teach a peer face-to-face after the video lecture were socially motivated to learn and were more engaged in selecting the most relevant incoming information, organizing the selected information into a coherent mental representation in working memory and integrating the new representation constructed in working memory with relevant knowledge structures stored in long-term memory. The neural evidence extends previous behavioral studies (Coleman *et al.*, 1997; Rittle-Johnson *et al.*, 2008) by providing information about the neural processes involved in different learning strategies based on explaining.

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Statements on open data, ethics and conflict of interest

Our data are not yet available online in any institutional database. However, we will send the whole data package by request. The request should be sent to Professor Jiumin Yang: yjm@mail.ccnu.edu.cn.

This research was approved by the Ethics Committee of the School of Educational Information Technology at Central China Normal University. The participants were volunteers who provided written informed consent. They were informed that they had the right to withdraw from the study at any time without penalty. Confidentiality was ensured by using numbers instead of names in the research data base. Data were only used for research purposes.

There is no conflict of interest, as we conducted this study only as part of our research program.

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