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To move or not to move? The effect of active versus passive pre-training on cognitive load and in-game performance in an AR game

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Abstract: A distinct feature of educational games using augmented reality (AR) is that the game is played through physically interacting with the environment, whereas physical interaction is typically rather limited in other digital games. Understanding and performing the interactive game mechanics can be cognitively demanding. Adding pre-training could help students manage cognitive load during in-game performance. However, traditional approaches of pre-training (eg, paper-based or video sequences) might not be sufficient, given the crucial role of physical interactions in educational AR games. In the present study, primary and early secondary school students ($N = 255$) were randomly assigned to an active pre-training, which involved students practising the movements needed in the game or a passive pre-training, where students watched a video explaining the game. The aim was to investigate whether active pre-training reduces students' cognitive load and improves in-game performance. It was also examined whether these effects were dependent on students' visuospatial working memory capacity (WMC). Results showed no significant differences between the conditions regarding students' cognitive load and in-game performance. However, visuospatial WMC predicted students' dropout of the game. This suggests that observing the movements

in the passive pre-training might be similarly effective as enacting the movements. Nevertheless, more research is needed to gain a better understanding of how different levels of WMC impact learning with educational AR games and how students with low visuospatial WMC can be efficiently supported.

KEYWORDS

AR, game-based learning, movement, pre-training, working memory

Practitioner notes

What is already known about this topic

- Working memory capacity influences students' ability to successfully perform complex tasks.
- Not every learning medium is equally effective for students with different levels of working memory capacity.
- Pre-training in educational games can support learning and increases the academic performance of students.
- Educational games with AR can be cognitively demanding, since students need to understand the interactions with the used device in addition to the game content and mechanics.
- It is unclear how to sufficiently support students in AR environments.

What this paper adds

- Both active and passive pre-training are equally effective.
- Students with lower working memory capacity were more likely to drop out during the educational AR game than students with high working memory capacity.

Implications for practice and/or policy

- Both practising and watching movements may be helpful for students to learn the relevant game mechanics to interact with the AR environment.
- There are students who do not optimally benefit when AR games are implemented in education and may need additional support.

INTRODUCTION

Games are widely used in education to enhance student motivation and improve learning outcomes (Arztmann et al., 2023; Lamb et al., 2018; Riopel et al., 2019). Yet, recent research suggests that educational games do not always lead to their intended learning effects (Homer & Plass, 2014; Lawson & Mayer, 2024; Makransky et al., 2019). Playing educational games has often been argued to be a cognitively demanding process due to the complexity of the game environment consisting of both game elements and educational content (Buchner et al., 2021; Makransky & Petersen, 2021; Mayer, 2021). Specifically, game mechanics can be complicated and overwhelm students (Bainbridge et al., 2022), leaving few cognitive resources available for understanding the educational content. The cognitive

demands can be exceptionally high in immersive and interactive educational games, such as those built with newer technologies like augmented reality (AR; Buchner et al., 2021; Radu, 2014). That is, in AR games, students need to learn how to enact specific movements to interact with the digital objects in the AR environment. If students are unfamiliar with or unsure about the movements, they might experience cognitive overload when playing the game since they have to recall and enact the movements while attending to the game elements and the educational content simultaneously. Therefore, cognitive overload may hamper students' in-game performance. Consequently, examining ways to help students manage cognitive overload is important.

Previous research suggested that pre-training (ie, presenting relevant knowledge and skills prior to the task at hand) can help prevent cognitive overload as it introduces students to upcoming tasks (Mayer & Fiorella, 2021). Pre-training has been shown to support students' learning in educational games (Bainbridge et al., 2022; Mayer & Fiorella, 2021; Meyer et al., 2019). Given that educational AR games, as an interactive learning environment, consist of physical movement as an additional modality, passive forms of pre-training, such as watching a video sequence, may not be sufficient to prepare students for playing the educational AR game and improve their in-game performance. Additionally, recent evidence suggests that implementing physical movement (ie, letting students practice the relevant movements) supports learning better than through representation alone (Mavilidi et al., 2015; Schmidt et al., 2019; Sepp et al., 2019). Hence, in educational AR games, students may benefit from active forms of pre-training that allow them to practice the movements necessary to play the game.

Moreover, especially students with low working memory capacity (WMC) may experience cognitive overload when coping with the cognitive demands of an educational game (Jaroslawska et al., 2015; Wiley et al., 2014). Working memory capacity influences students' ability to follow instructions and develop a global understanding of a learning task (Gathercole et al., 2006; Wiley et al., 2014). Therefore, compared with students with higher WMC, students with low WMC may find playing educational games, especially in AR, particularly challenging. Consequently, pre-training that includes physical movement could be particularly helpful for students with low WMC.

The present study investigates whether an *active pre-training*, where students can physically enact actions essential for learning the relevant game mechanics, can help to reduce cognitive load and improve in-game performance in an educational AR game compared with a *passive pre-training* where students only watch a video sequence. In-game performance assessed with log data is increasingly used as an objective measurement of students' learning outcomes and can provide valuable insights into the effectiveness of pre-training (Alonso-Fernández et al., 2019; Norum et al., 2024; Shute et al., 2015). For instance, Norum et al. (2024) showed that in-game performance can explain a significant amount of variance in learning outcomes and that certain in-game metrics (eg, mathematical errors) were positively related to learning outcomes. In the present study, three indicators of in-game performance were assessed with log data: *time-on-task, number of mistakes* and *dropout*. In addition, we examined whether students' WMC influences the effectiveness of active pre-training. Results of the study will contribute to a better understanding of how pre-training can support students in educational games, especially in AR games.

Working memory capacity

Working memory refers to a limited capacity system allowing the temporal storage and manipulation of information (Baddeley, 2000). Working memory is divided into four subcomponents: (1) the phonological loop and (2) the visuospatial sketchpad, responsible for storing verbal and visuospatial information, respectively, (3) an attentional control system

called the central executive and (4) the episodic buffer, which is assumed to connect working memory with long-term memory (Baddeley, 2000, 2006). Working memory capacity refers to an individual's ability to utilize this system and regulates one's ability to follow instructions (Gathercole et al., 2006; Wiley et al., 2014), remember information and develop a global understanding of the task at hand (Unsworth & McMillan, 2013; Wiley et al., 2014). WMC develops steadily across the primary and secondary school years, but there can be a substantial degree of individual differences in WMC within a classroom (Gathercole et al., 2006). Students with low WMC usually have difficulties with tasks involving simultaneous storage and processing of information (Alloway et al., 2006; Gathercole et al., 2006; Kane & McVay, 2012), struggle with remembering lengthy instructions (Gathercole et al., 2006) and are subsequently less successful when working on complex tasks as compared with students with high WMC.

Recent research suggested that not every learning medium is equally effective for students with different levels of WMC. Lawson and Mayer (2024) reported that students with higher WMC performed better after a virtual reality lesson compared with students with lower WMC. In contrast, such differences were not observed in the slideshow condition. Educational games, in general, are typically complex and rich in multimedia representations, as students have to process dynamic visual information (ie, through moving avatars and game objects) (Hegarty, 2005; Makransky & Petersen, 2021; Mayer, 2021). Homer and Plass (2014) demonstrated that students with low WMC performed poorer than those with high WMC when playing a simulation game with high levels of complexity in the environment. Their results indicate that WMC could be an important factor to consider when examining students' in-game performance. While prior research suggests that students with lower WMC may have more difficulties when playing educational AR games, to our knowledge, only one study (Homer & Plass, 2014) has examined how students' WMC affects their performance in an educational game.

Given the rich dynamic visualizations and physical interactions in educational AR games, WMC, specifically visuospatial WMC, may play an influential role. Visuospatial WMC influences how well students can process the information of dynamic visualizations (Chikha et al., 2021; Hegarty, 2005; Höffler, 2010) and play an important role in managing planned movements (what to do and when), especially for newly learned tasks (Fournier et al., 2014). Moreover, research in traditional learning environments showed that students with lower visuospatial WMC have difficulties with single modality designs (eg, receiving only written information) and irrelevant learning content, whereas students with higher visuospatial WMC are able to learn from dynamic multimedia environments no matter how the information is presented (Brucker et al., 2015; Greenberg et al., 2020; Höffler, 2010). Besides the rich dynamic visualizations and physical interactions of educational AR games, games typically contain distracting elements that are unnecessary for learning and place high demands on students' WMC (Buchner et al., 2021; Makransky & Petersen, 2021). Therefore, students with low visuospatial WMC may benefit from some form of support to cope with the high cognitive demands of educational AR games.

Cognitive load and the pre-training principle

Cognitive load theory (CLT, Sweller et al., 2019) states that learners have a limited WMC. When the cognitive demands of a task exceed a learner's WMC, overload is experienced, which hampers learning. CLT distinguishes between two types of cognitive load: (1) intrinsic cognitive load, which is associated with the intrinsic nature of the learning material, such as its inherent difficulty, and (2) extraneous cognitive load, which is associated with the presentation of the learning material. Intrinsic and extraneous cognitive load are additive (Mayer, 2021), suggesting that students can experience cognitive overload even with low

levels of intrinsic cognitive load if extraneous cognitive load is high, and vice versa. In an educational game, intrinsic cognitive load is associated with the learning content, while extraneous cognitive load is associated with how the game is designed (ie, game mechanics) and the medium chosen to present the information (Meyer et al., 2019). Complicated game mechanics may overwhelm students (Bainbridge et al., 2022) and cause overload, leaving less cognitive resources available for understanding the educational content. When students experience cognitive overload, they may have poorer performance in the game where they take more time to complete the game (ie, higher time-on-task), make more mistakes and are more likely to drop out of the educational game. Prior research (Arztmann et al., in press) shows that one of the main reasons for dropout is that students are unable to successfully perform actions needed in the game which could be due to cognitive overload.

The pre-training principle of CLT states that pre-training can reduce cognitive load and enhance learning in multimedia environments (Mayer, 2021). Pre-training provides learners with prior knowledge that reduces the amount of processing needed to understand the educational content during training (Mayer & Fiorella, 2021). Accordingly, learning will be more effective with pre-training that familiarizes students with the key components of the game, such as the game characteristics and concepts addressed in the game (Mayer & Fiorella, 2021). Indeed, previous research on the effects of pre-training in educational games has shown that pre-training supports learning and increases the academic performance of students (Bainbridge et al., 2022; Mayer & Fiorella, 2021; Meyer et al., 2019). The problem of overload might be even more prevalent in educational games with AR compared with those without, since students are required to understand the interactions with the used device in addition to the game content and mechanics. Therefore, it is important to investigate the type of pre-training support needed to reduce cognitive load in educational AR games.

Pre-training in educational AR games

Traditionally, pre-training uses paper-based approaches or video sequences. These forms of pre-training have been shown to be effective in digital learning environments (Mayer & Fiorella, 2021; Meyer et al., 2019). However, these approaches might not be sufficient for immersive learning environments like AR. AR environments display virtual content in the physical environment, which is a distinct difference from other digital learning environments (Radu, 2014). When used in an educational game setting, AR can allow students to explore the game environment and change their perspective, for example through using one's hand to rotate the virtual object (Radu & Antle, 2017). Another distinctive feature of immersive technologies like AR is that the game is played through physically interacting with the environment (eg, scanning the environment and moving the device closer to interact with the game objects), whereas movement is rather limited in more traditional games. Since movements are essential for educational AR games, understanding and performing interactive game mechanics can be cognitively demanding.

However, little is known about the effects of pre-training in educational AR games. A recent review highlighted that thus far, no study has investigated pre-training in an AR environment and more research is needed (Çeken & Taşkın, 2022). This lack of research can be problematic since previous research in digital learning environments indicated that pre-training might not be effective under all conditions (Kester et al., 2004; Tsai et al., 2022; Experiment 2 of Pilegard & Mayer, 2016). Given that implementing physical movement into learning tasks has been shown to support the acquisition of information better than simple presentation (Agostinho et al., 2015; Hu et al., 2015; Mavilidi et al., 2015; Schmidt et al., 2019), it might be that adding movements in pre-training for educational AR games might be particularly beneficial. That is, familiarizing students with the actual actions needed to interact with the

game environment prior to playing the educational AR game (ie, active pre-training) may help to reduce the cognitive load during the gameplay and improve in-game performance more than solely observing relevant game mechanics from videos (ie, passive pre-training). Moreover, pre-training involving physical movement might be particularly helpful for students with lower WMC.

The present study

Educational AR games are complex learning environments with rich dynamic visualizations and high interactivity between the digital and physical worlds (Hegarty, 2005; Makransky & Petersen, 2021; Mayer, 2021). This study focuses on acquainting players with the game mechanics prior to gameplay, using an educational AR game on chemistry. Therefore, the present study aimed to examine whether active pre-training results in lower cognitive load and better in-game performance compared with passive pre-training. To address the cognitive demands of playing educational games in AR (which requires physical interaction with the virtual environment), we propose that pre-training that allows students to physically enact actions that are essential for learning the game concepts (active pre-training) will be more effective than pre-training with only watching a video sequence (passive pre-training). Therefore, we propose the following hypothesis **H1:** *Active pre-training leads to reduced cognitive load and increased in-game performance (shorter time-on-task, fewer mistakes, less dropout) compared with passive pre-training*.

Given that the cognitive demands of an educational AR game are quite high, students with lower WMC may be more likely to experience cognitive overload than those with higher WMC. Based on the pre-training principle and given that movement can serve as a general support mechanism for working memory (Sepp et al., 2019), active pre-training might therefore be especially beneficial for students with lower visuospatial WMC. By allowing students to practice the movements required in the educational AR game before gameplay, the cognitive demands will be lower during gameplay, freeing up cognitive resources for understanding the educational content. Thus, the present study additionally examined whether the effects of active versus passive pre-training depend on students' WMC and therefore we propose the additional hypothesis **H2:** *The effect of active pre-training on cognitive load and in-game performance is stronger for students with lower WMC compared with students with higher WMC*.

METHOD

Design

This study employed a randomized control design where students within different classrooms were randomly assigned to one of two conditions (active or passive pre-training).

Participants

In total, 10 classes with 255 students in their last year of primary school as well as Years 1 and 2 of Dutch secondary schools participated in this study during one of their science lessons ($M_{age} = 12.6$, $SD = 0.8$). The Dutch educational system differentiates secondary schools into six adjacent tracks: (1) practical training, (2) basic pre-vocational secondary education, (3) middle pre-vocational secondary education, (4) theoretical pre-vocational education,

(5) senior general secondary education and (6) pre-university education. Primary schools do not have different tracks. The present sample included students from senior general secondary education (20.3%), a combined track for senior general secondary education and pre-university education (19.1%), and pre-university education (49.6%). Eleven per cent attended the last year of primary school.

The a-priori power analysis for MANCOVA through G*Power (Version 3.1.9.7) suggested a sample size of 120 participants (power > 0.9, effect size $f_2 = 0.10$, α-level = 0.05). Additionally, the power analysis for a binary logistic regression for two groups suggested a sample size of 156 participants (power > 0.9, effect size $f_2 = 0.10$, α-level = 0.05). Given that the dropout rates of students for Marie's ChemLab are around 17% (see Arztmann at el., 2022), oversampling was chosen to enhance the accuracy of the dropout variable. In this study, two students were excluded due to an error in the data collection (ie, changing a tablet and being assigned to a new game condition). Moreover, only the data of students who completed the game and answered the post-test were considered for all outcome variables except dropout. As such, the final sample for the analyses on these outcome variables consisted of 189 students. For the other variable, dropout during the game, all 253 students were included.

Materials

The game: Marie's ChemLab

Marie's ChemLab is a mobile augmented reality (MAR) game designed for young adolescents. It provides a virtual environment to learn the basic concepts of acid–base using examples of daily life chemistry. To help students proceed in the levels, they are guided by Marie, the intelligent agent of Marie's ChemLab, who provides hints and instructions throughout the game. The flow of the game is procedural, which means that a player needs to follow certain steps to advance within a level or to the next level. The objects within the game need to be combined (eg, the fruits need to be smashed with the hammer), and in case of a wrong interaction, the player receives audio feedback signalling a mistake. In this game, students are supposed to rank objects based on their acidity, measure them and get introduced to different indicators (such as pH strips or blueberry juice).

Active and passive pre-training

The pre-training consisted of four tutorial videos (Figure 1) that were implemented in the game environment and were shown at the start of the game. The tutorial videos were developed and tested with students during the piloting phase of the game (Author) and covered the relevant game mechanics of Marie's ChemLab. The four video sequences covered the following four movements:

1. scanning the environment to place the game content;
2. moving close to objects in order to interact with them;
3. picking up a game object and dropping it using the ‘grab’; and
4. using game objects to carry out an action (eg, adding fruits to the blender).

The detailed instructions that were provided to students in the video sequences can be found in Table A1 in the Appendix. The two pre-training conditions differed in the set-up (see Figure 2): Students in the active pre-training condition were asked to practice the movement

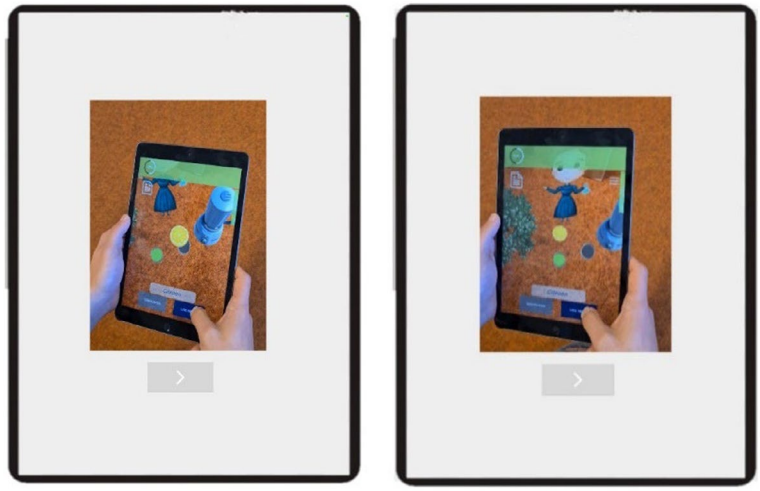

FIGURE 1 Screenshots of a video sequence used for the pre-training.

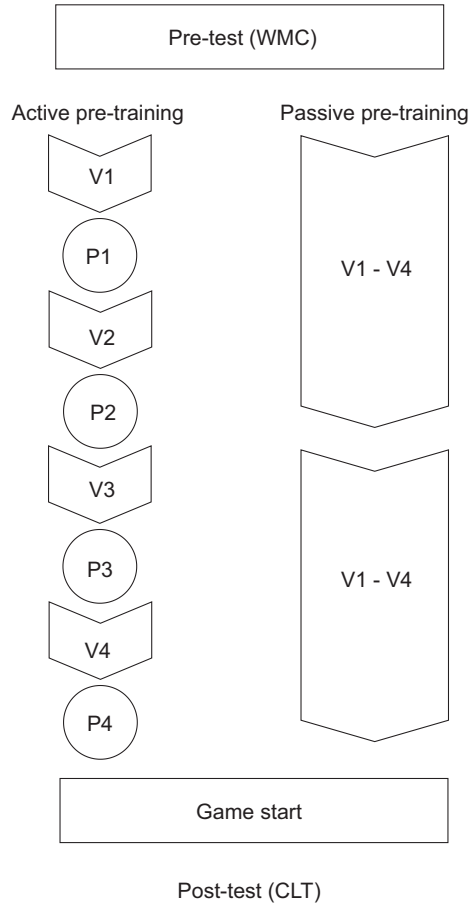

FIGURE 2 Study design for both conditions. V = video, P = practice.

they observed after each video, while the students in the passive pre-training condition watched each video sequence twice. Thereby, each condition had a similar duration.

Measurements

Working memory capacity

To assess students' WMC, the Corsi Block-Tapping task (Corsi, 1972) was used and administered through Inquisit Web's software for mobile testing (https://www.millisecond.com/), prior to the game intervention. Previous research indicated that this task is a valid and reliable measure of visuospatial WMC (Kessels et al., 2000; Williams et al., 2005) and has been normed for use with children (Farrell Pagulayan et al., 2006). Following the set-up of Kessels et al. (2000), the students saw nine blocks that light up in a sequence on the tablet. The students were asked to remember the sequence in the same order. The sequence length ranged from two to nine, if a student entered the sequence correctly, the next higher sequence was presented. The minimum score a student could obtain was 2 and the maximum was 9.

Cognitive load

At the end of the game, students answered a commonly used single-item question reflecting self-reported cognitive load (Anmarkrud et al., 2019). The question was based on the item used by Leahy and Sweller (2016) with the term 'task' replaced with 'game' to fit the context (ie, *Rate how easy/difficult you found this game to understand*). Thus, the students were asked to rate how difficult they experienced the game environment. The item was ranked on a Likert scale ranging from 1 (ie, very easy) to 7 (ie, very difficult).

In-game performance

Three indicators of in-game performance were distinguished: *time-on-task*, *number of mistakes* and *dropout*, which were assessed with the available log data of Level 1. *Time-on-task* was measured with the total time it took to complete the level. A shorter time-on-task indicated that a student was more efficient in playing the game. *Mistakes* were measured with the number of wrong interactions. For *dropout*, the post-test (ie, cognitive load measure) was used to determine whether the participant completed the study. The absence of post-test data indicated that the participant did not finish the game and was coded as a dropout.

Procedure

Prior to data collection, approval by the institutional ethics committee was obtained, and both parents and teachers were asked for consent. To ensure anonymity, the researchers assigned random ID numbers to the students, which were used to connect their questionnaire answers with the log data. Data collection took place during a regular science lesson. The students started with the working memory task. After completion of the task, the game started automatically. At the end of the game, students' cognitive load was assessed. The game was played on iOS tablets provided by the researchers, including matching headphones. To ensure randomization of conditions, one half of the tablets had the game version with active pre-training installed, and the other half had the other game version. The tablets

were randomly assigned to the students and had no indication of which version was installed on them. Prior to playing the game, the students were instructed to test a newly developed game about science and that they should try to play by themselves and not talk to each other. In total, the students had 30 minutes to play the game, after which the game automatically moved them to the end. Students who finished early received riddles that they could solve until their classmates were done.

Data-analyses

First, the data distribution was checked for normality and potential outliers (Buchanan, 2020). For easier interpretation, a *z*-score for the variable *time-on-task* was created. After that, correlations between all variables were calculated. We performed one MANCOVA with the pre-training condition as the independent variable and the in-game performance measures, *time-on-task* and *number of mistakes*, as well as students' cognitive load as dependent variables. Based on the Mahalanobis distance test, two multivariate outliers were present and were removed for the final analysis, resulting in a final sample of 187 students. The assumptions of linearity, homogeneity (Levene's $ps > 0.001$), homoscedasticity, and normality were all met.

To examine whether WMC moderated the effects of pre-training on the outcome variables, we added students' WMC as a predictor to the existing model and checked for a possible interaction effect of WMC and condition on the outcome variables, which would suggest that WMC had a differential effect according to the pre-training condition that the students played. For the dichotomous outcome variable *dropout*, we performed a binary logistic regression using the same model as in the MANCOVA. All analyses were conducted in R and the car package (Fox & Weisberg, 2019) was used for calculating the MANCOVA.

RESULTS

In Table 1, the descriptive statistics of all the dependent variables and the moderator variable of both conditions are presented. The in-game performance indicators *time-on-task* and *number of mistakes* were significantly correlated ($r = 0.44$, $p < 0.001$), whereas cognitive load was not correlated with time-on-task ($r = 0.08$, $p = 0.266$) and number of mistakes ($r = 0.09$, $p = 0.207$). Correlations between WMC and the dependent variables were not significant ($p > 0.05$).

TABLE 1 Mean and standard deviation for the variables per condition.

	Active pre-training			Passive pre-training		
	n	***M***	***SD***	***n***	***M***	***SD***
Dependent variables						
Cognitive load	98	3.89	1.49	89	3.57	1.64
Time-on-task	98	−0.11	0.99	89	0.15	0.99
Number of mistakes	98	23.09	22.44	89	24.17	19.54
Dropout	26	–	–	31	–	–
Moderator variable						
WMC	98	5.18	0.89	89	5.36	1.22

To examine the overall effect of pre-training condition and the moderating role of students' WMC, a MANCOVA was performed with condition, WMC and the interaction between condition and WMC as predictors, and *cognitive load, time-on-task* and *number of mistakes* as dependent variables. We found no significant effect of condition on cognitive load and performance, $F(3, 181) = 1.19$, $p = 0.314$, *Wilk's* $\Lambda = 0.98$, $\eta_p^2 = 0.02$, indicating that the students in the active pre-training condition did not report lower cognitive load nor performed better than the students in the passive pre-training condition. Moreover, we found no significant interaction effect between WMC and condition on cognitive load and performance, $F(3, 181) = 0.93$, $p = 0.427$, *Wilk's* $\Lambda = 0.98$, $\eta_p^2 = 0.02$, suggesting that the effects of pre-training condition did not depend on students' WMC.

For the in-game performance indicator *dropout*, the overall model of the binary logistic regression was significant: $\chi^2(3) = 10.22$, $p = 0.017$, Nagelkerke's $R^2 = 0.06$. Looking at the results displayed in Table 2, the higher the WMC the more likely it is that a student finishes the game ($B = 0.40$, $p = 0.034$) irrespective of pre-training condition. The pre-training condition alone did not predict dropout.

DISCUSSION

Students may need additional support in complex learning environments, such as in an educational AR game, as it may cause cognitive overload and, therefore, hamper their performance. This may especially be the case for students with a low WMC. Therefore, the aim of this study was to investigate whether active pre-training for learning the relevant game mechanics in an educational AR game would lower students' cognitive load during gameplay and increase their in-game performance compared with passive pre-training, and whether the effects of active pre-training would be most beneficial for students with low WMC. Given that educational AR games require students to perform certain movements to interact with the game environment, we expected that active pre-training, where participants could familiarize themselves with these movements, would lower their cognitive load and achieve better in-game performance compared with passive pre-training (H1). Contrary to our expectations, the findings showed no significant differences in cognitive load and in-game performance between active and passive pre-training conditions. Hence, the findings suggest that the active pre-training condition was not more effective than the passive pre-training condition. We also hypothesized that students with lower WMC would benefit more from active pre-training compared with students with higher WMC (H2), but in contrast to our expectations, the results did not support this hypothesis either. Nevertheless, the findings indicated that students with lower WMC were more likely to drop out during the game, irrespective of pre-training conditions. While this finding confirms that WMC is an important factor for students playing educational AR games, providing active pre-training does not seem to support

TABLE 2 Binary logistic regression with pre-training condition and working memory capacity (WMC) predicting the in-game performance indicator dropout.

	Est	*SE*	*p*	*OR*	95% CI
Intercept	−0.97	0.97	0.320		
Active pre-training	0.28	1.38	0.839	1.32	0.09, 19.72
WMC	0.40	0.19	0.034*	1.50	1.03, 2.18
Active pre-training * WMC	0.004	0.27	0.987	1.00	0.59, 1.71

Note: Reference category non-dropouts versus dropouts, $n = 253$.

those students better than passive pre-training. Below, these findings are discussed in more detail.

Effects of active pre-training on cognitive load and in-game performance

Based on CLT, we expected that adding movement to the pre-training condition would reduce students' cognitive load and increase their in-game performance compared with the passive pre-training condition. Despite the additional modality in the active pre-training condition, where students could practice the required movements, their cognitive load was not significantly lower, nor did they have significantly higher in-game performance than those in the passive pre-training condition who watched a video sequence of the movements. One reason for not finding statistically significant differences could be that the two pre-training conditions in this study were not different enough to yield an effect of adding movements into pre-training and both conditions similarly enforced the learning of the game mechanics. That is, performing (ie, active) and observing (ie, passive) movements during pre-training seem similarly beneficial. In the passive pre-training, students observed the movements with visible hands in the videos. Prior research showed that observing movements when learning procedural tasks, such as knot-tying and paper-folding, yielded better learning outcomes than static images (Ayres et al., 2009; Wong et al., 2009). Therefore, given the presence of visible hands in the videos, students could have equally benefitted from observing the hand movements in the passive pre-training or performing the movements in the active pre-training condition.

Based on the pre-training principle of CLT, acquainting students with the relevant concepts (ie, game mechanics) leads to reduced cognitive load and higher performance (Mayer, 2021; Mayer & Fiorella, 2021). However, the pre-training principle is based on the assumption that the learning environment and the learning content impose high cognitive load. The descriptive statistics suggested that the cognitive load students experienced in both conditions of the present study was not exceedingly high. It could therefore also be that the cognitive demands of the educational AR game might not have exceeded students' WMC. This could be another reason why the expected pre-training effect was not found. Similar findings have been reported in previous studies investigating the effects of pre-training (Hu, 2023; Kester et al., 2004).

Another reason based on CLT could be related to the type of information presented in the pre-training and the timing of the presentation. It could be that presenting the relevant concepts before the gameplay is not effective. For instance, previous studies reported that presenting relevant information during learning tasks is more effective than before (Hu, 2023; Kester et al., 2004; Pilegard & Mayer, 2016). In addition, the effectiveness of pre-training could be dependent on the type of information. Kester et al. (2004) found that presenting conceptual information during practice and procedural information before practice was unexpectedly more efficient where students achieved higher test performance and invested lower mental effort on the transfer task than presenting conceptual information before and procedural information during practice. The authors explained that presenting conceptual information during practice provides a meaningful context for students to apply the information needed to carry out the task. In the current study, the movements can be considered as conceptual (ie, information on how to move the object) and not procedural (ie, information on when a certain object needs to be moved). In both pre-training conditions, conceptual information was presented before gameplay. Thus, it might be that presenting such information during gameplay could be more effective. On the contrary, Hu (2023) recently compared whether timing of game-specific information influences performance and did not find any differences. Here, it is important to emphasize that

Hu (2023) used screenshots to provide step-by-step guidance on how to play the first game level, which can be considered procedural information. Thus, future studies could investigate whether presenting supportive game-specific information during gameplay could be more effective than presenting them as pre-training before gameplay.

Moreover, it is also possible that the intervention time was too short to fully familiarize students with the movements needed to play the game, and potentially, students may have needed more practice to benefit from the active pre-training (see Yamada et al., 2019). Future studies could investigate whether adding additional practice time could support students better.

Finally, given the lack of pre-training research using immersive technologies like AR, other factors, such as motivation, could explain the results of the present study. First, both educational games and immersive environments are effective in increasing students' motivation (Arztmann et al., 2023; Lamb et al., 2018; Makransky & Petersen, 2021), and it seems possible that high levels of motivation could reduce cognitive load (Evans et al., 2024). Additionally, the results could be due to the affordances of AR as an immersive environment, since 3D representations have been shown to be less cognitively demanding compared with 2D when used in AR (for a review, see Buchner et al., 2021). Hence, in educational AR games, students may be less reliant on their WMC and report lower cognitive load compared with other learning environments.

The role of WMC

Previous studies (Homer & Plass, 2014; Jaroslawska et al., 2015; Lawson & Mayer, 2024) have shown that students with higher WMC perform better in complex learning environments than students with lower WMC. Thus, students with lower WMC may be more likely to experience cognitive overload compared with students with higher WMC and might therefore benefit from additional support, such as active pre-training. However, the results did not support the second hypothesis stating that the effect of active pre-training on cognitive load and in-game performance would be stronger for students with lower WMC compared with students with higher WMC. This finding could indicate that both types of pre-training are equally effective for students with low WMC. Our study did not include a condition without pre-training; however, it might be that both active and passive pre-training are more effective for students with low WMC compared with students with higher WMC.

Although WMC did not moderate the effects of pre-training on cognitive load and in-game performance, we did find a main effect of WMC on one of the in-game performance indicators, that is, dropout, irrespective of pre-training conditions. As such, students with lower WMC were more likely to drop out. This result confirms that students with lower WMC have more difficulty performing complex learning tasks (Alloway et al., 2006; Gathercole et al., 2006; Greenberg et al., 2020; Homer & Plass, 2014). Moreover, this result aligns with the results of Lawson and Mayer (2024), who found that students with higher WMC learned better in a VR environment compared with students with lower WMC. Both attention and processing speed have been shown to influence WMC in children (Barrouillet et al., 2011; Cowan et al., 2005; Gordon et al., 2020). Therefore, it could be that students who were distracted or took longer to understand the presented information were more likely to forget where they left certain game objects or the next steps that were explained by the intelligent agent of the game. Hence, this may explain why students with lower WMC may have had more difficulties playing the game. Future research could further investigate the in-game behaviour of students with lower WMC to gain insights into whether this might have been the case. To support students with lower WMC in AR games, game designers could consider splitting information into smaller chunks to support students who take longer to process

information. Also, practitioners may consider adding additional breaks to increase students' ability to focus.

Moreover, in this study, we specifically measured the visuospatial WMC of students. WMC may have affected students' dropout, because the AR game relied heavily on students visuospatial WMC. Visuospatial WMC is important for orientation and remembering the locations of objects (Castillo Escamilla et al., 2023; Weisberg & Newcombe, 2016). The AR game in this study did not limit the space in the AR environment that the students could play in. Thus, it was possible that the students might have left game objects at locations that were very distant from the main game area and had difficulties remembering the locations and finding the objects again. Similarly, previous research has found that children might struggle more with AR due to differences in their spatial understanding (Radu, 2014). This might be particularly relevant for children with lower visuospatial WMC. Thus, to make gameplay easier for students, it might be worthwhile to consider limiting the space in an AR environment.

Alternatively, the association between WMC and dropout may also be explained by self-efficacy. Prior research has found that students with lower self-efficacy are more likely to drop out of an educational AR game, while WMC was not related to the other performance indicators time-on-task or the number of mistakes students made (Arztmann et al., in press). Hence, students with lower WMC may not actually be less successful in playing the game, but are still more inclined to drop out. This could perhaps be attributed to their self-efficacy. If students with lower WMC feel unable to succeed, they may subsequently be more likely to give up, even when their overall performance does not differ from students with higher WMC. Future studies could further investigate how students' WMC may be associated with their self-efficacy and in turn relate to dropout.

Even though CLT assumes that WMC is predictive of cognitive load, we did not find a correlation between the two measures. Most traditional CLT studies do not include a measure of WMC, even when they mention WMC (for a review, see Anmarkrud et al., 2019). Additionally, the studies often lack a clear conceptualization of WMC. As such these studies are unable to test the underlying assumptions of CLT. Hence, to better understand how learners' WMC affects the cognitive load during learning tasks, studies on cognitive load need clear conceptualizations of WMC and include WMC measures. Since WMC consists of different components, it is important to understand which aspect of WMC is relevant for specific types of learning tasks. For instance, previous research indicated that verbal WMC was not predictive of performance in an educational AR game (Arztmann et al., in press), whereas the present study indicates that visuospatial WMC is related to the in-game performance indicator dropout. It may be that visuospatial WMC, but not verbal WMC, plays an important role in educational AR games. Visuospatial WMC pertains to managing planned movements, especially for newly learned tasks (Fournier et al., 2014), whereas verbal WMC is more strongly related to remembering instructions (Jaroslawska et al., 2015). This could imply that educational AR games draw more strongly on abilities that require visuospatial WMC.

In all, the hypotheses H1 and H2 derived from CLT were not supported by the findings of the present study. In the case of AR, other frameworks may potentially be more useful for understanding the complex processes involved in immersive learning. One example could be the Cognitive Affective Model of Immersive Learning (CAMIL; Makransky & Petersen, 2021). This model provides a research-based theoretical framework for understanding learning in immersive environments. Whereas the CLT mainly focuses on factors related to working memory, the CAMIL model takes into account additional factors that are particularly relevant for immersive learning environments (eg, self-efficacy, motivation and embodiment). Future research could explore whether this framework can help to better understand the complex interplay of cognitive and affective processes in immersive learning environments.

LIMITATIONS

In this study, cognitive load was assessed by a single-item measure from Leahy and Sweller (2016). Even though this measure is commonly used, it uses a slightly different wording (ie, difficulty) compared with other commonly used measures of cognitive load (ie, mental effort; see Anmarkrud et al., 2019). We chose this measure since it is typically used in similar age groups as the wording is more suitable for our target group of the present study compared with other measures. Nevertheless, it could be that this measure may not be able to represent the different aspects of cognitive load (ie, intrinsic and extraneous cognitive load). Moreover, since subjective measures may show higher sensitivity to response bias compared with objective measures (Brenner & DeLamater, 2016), combining different measures might be more suitable. Future studies could examine alternative ways to assess cognitive load among young adolescents.

Another limitation of this study is the fact that we did not assess test performance after gameplay. While students' in-game performance did not differ between the two pre-training conditions, it is unclear if an effect would be found on students' learning gains. Even though previous research emphasized that in-game performance can inform learning outcomes (Alonso-Fernández et al., 2019; Norum et al., 2024; Shute et al., 2015), future studies could assess test performance apart from in-game performance to gain a more complete understanding of the potential pre-training effects.

Moreover, the sample consisted mainly of students attending higher school tracks, which could have resulted in a smaller range of WMC among students. The small range in WMC among the sample could make it hard to detect differential active pre-training effects for students with higher and lower WMC. A broader range of WMC could help examine whether active pre-training might be particularly beneficial for students with very low WMC compared with those with very high WMC.

Finally, to avoid classroom effects, we randomized the two conditions within classrooms, with half the students in each class being randomly assigned to the active pre-training and the other half to the passive pre-training. Since the study took place in classrooms, students from different conditions could be seated next to each other. Students were instructed to play the game by themselves and not talk with each other; however, a spill-over effect, even though highly unlikely, can therefore not entirely be excluded.

CONCLUSION

Overall, the results of the present study showed that there were no differences between active and passive pre-training in an educational AR game regarding students' cognitive load and in-game performance, indicating that both types of pre-training are equally effective. Hence, the assumptions based on CLT could not be supported, and it might be that the theoretical model of CLT cannot fully explain the cognitive mechanisms at play when an immersive technology is used as a learning medium. Moreover, students with lower visuospatial WMC were more likely to drop out during the game than students with high visuospatial WMC. These results may have important implications for practice, as it seems apparent that not all students benefit equally from educational games, and students with lower visuospatial WMC would especially need additional support to succeed in a game environment using AR. More research is needed to gain a better understanding of how students with lower visuospatial WMC can best be supported in these types of complex game environments.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared due to privacy and ethical restrictions.

ETHICS STATEMENT

This research has received ethics approval by the Ethics Review Board of the Faculty of Behavioral and Social Sciences (FERB) of Utrecht University under the number 22–016 to ensure that the research complies to the GDPR, is in line with the university's research data handling framework, and the national guidelines for science practice. Prior to data collection, both teachers and parents were informed about the study and asked for consent, whereas students were informed that they can stop participation at any time. To minimize the effort for the students, the data collection was limited to one school hour and took place during a regular science lesson. To reduce disruptions to the school curriculum to a minimum, the data collection took place towards the end of the school term. To ensure anonymity and compliance to the GDPR guidelines, random ID numbers were assigned and personal data were not collected.

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APPENDIX

TABLE A1 Transcript of the video instructions for both conditions.

	Active pre-training	Passive pre-training
Sequence 1	Move the tablet around to scan your background. When you see the level shape appearing, click in the middle	Move the tablet around to scan your background. When you see the level shape appearing, click in the middle
After Sequence 1	Now it is your turn!	–
Sequence 2	To grab something, you have to move closer until you see the orange outline. Click the right button to lift it. If you want to place it somewhere, you have to move closer until you see the orange outline again. Now, you need to press the orange button to place it. Otherwise, it will not work	To grab something, you have to move closer until you see the orange outline. Click the right button to lift it. If you want to place it somewhere, you have to move closer until you see the orange outline again. Now, you need to press the orange button to place it. Otherwise, it will not work
After Sequence 2	Now it is your turn!	–
Sequence 3	With the right button, you can lift something. If you press the right button again, you can drop it	With the right button, you can lift something. If you press the right button again, you can drop it
After Sequence 3	Now it is your turn!	–
Sequence 4	You can also lift something and add it somewhere. For that, get close and press the orange button. You can now see that some things can change. You can also look around. Sometimes, new things will appear on the left or right side	You can also lift something and add it somewhere. For that, get close and press the orange button. You can now see that some things can change. You can also look around. Sometimes, new things will appear on the left or right side
After Sequence 4	Now it is your turn!	–

Note: The students received the instructions in Dutch.