

Does cognitive load influence performance in a game-based learning task?



Jessica Witvoet
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SUMMARY	3
INTRODUCTION	4
METHOD	10
<i>PARTICIPANTS</i>	10
<i>GAME-BASED LEARNING TASK</i>	10
<i>BEHAVIORAL MEASURES</i>	11
<i>DESIGN AND PROCEDURE</i>	12
<i>EEG-RECORDING</i>	12
RESULTS	13
<i>PERFORMANCE</i>	13
<i>COGNITIVE LOAD</i>	13
<i>CORRELATIONS</i>	14
<i>BEHAVIORAL MEASURES</i>	14
DISCUSSION	15
REFERENCES	17

Summary

Does cognitive load influence performance in a game-based learning task? Thirty students of the department of behavioural sciences were instructed to play with one of two versions of a game-based learning task, while cognitive load was measured by electroencephalography. One version of the game was tuned to the anticipated skills of the participants (LT), while the other was not (HT). Videogame experience and knowledge of physics were also taken into account. Performance was defined by changes in conceptual knowledge and the number of completed levels within the game-based learning task. This study found no indications that cognitive load influences learning outcomes. Results indicate that there are no significant changes in conceptual knowledge, and that this does not differ between the LT-group and the HT-group. On the other hand, it was found that the number of completed levels does differ significantly between conditions. The number of completed levels was significantly higher in the LT-group than in the HT-group, which would suggest a difference in task-difficulty between the two conditions. Though, statistical analysis found that cognitive load is not significantly higher or lower in one of the conditions, and that both theta power and alpha power do not significantly change over time. Furthermore, no significant correlations were found between cognitive load and performance. Finally, it was found that videogame experience and knowledge of physics do not influence the number of completed levels. Videogame experience does not influence changes in conceptual knowledge, but knowledge of physics does, as can be expected. Both videogame experience and knowledge of physics do not significantly influence cognitive load.

Introduction

PC-based videogames are emerging as an increasingly popular instructional tool in education (Burgos, Tattersall & Koper, 2007). It is easy to understand why, since nowadays, games play a central role in young people's lives outside school, holding a special fascination and provoking a deep sense of engagement in them (Facer, 2006; Kafai, 2001; Kirriemuir & McFarlane, 2004). More and more young people's intrinsic motivation towards games contrasts with their lack of interest in curricular contents (Prensky, 2003). It has even been written that the world of games shapes students' cognitive abilities and expectations about learning, making scholastic content and practices seem tedious and meaningless (Facer, 2006; Prensky, 2003). This creates a dissonance between formal education and the digital, informal learning environments that students experience outside school (Downes, 1999; Mumtaz, 2001; Oblinger, 2004). However, in recent years, the motivation of games is being combined with curricular contents into what Prensky (2003) calls 'Digital Game-Based Learning' (DGBL). Games that encompass educational objectives and subject matter are believed to hold the potential to render learning of academic subjects easier, more learner-centered, more enjoyable, more interesting, and, thus, more effective (Kafai, 2001; Malone, 1980; Prensky, 2001). However, the research on DGBL is not without criticism, with a fair amount of research showing that instructional games do not always lead to the desired motivational properties and instructional gains (Hays, 2005). Given the increasing popularity of using videogames for instructional purposes, research has sought to identify factors that maximize the effectiveness of this instructional medium. Prior research demonstrates that videogame attributes, such as task difficulty, realism, and interactivity, affect learning outcomes in game-based learning environments (Belanich, Sibley & Orvis, 2004; Garris, Ahlers & Driskell, 2002). For instance, this prior work suggests that in order to be most effective, instructional games should present an optimal level of difficulty to learners. This optimal range of difficulty can be thought of along the lines of Vygotsky's zone of proximal development, where training should be difficult to the learner, but not beyond his/her capability (Vygotsky, 1978). Instructional games that are too easy or too difficult can lead to reduced motivation and time on task (Bowman, 1982; Malone, 1980; Malone & Lepper, 1987; Paas, Tuovinen, Van Merriënboer & Darabi, 2005; Provenzo, 1991), which, in turn, may ultimately result in less positive learning outcomes, such as diminished knowledge or skill acquisition and retention (Colquitt, LePine & Noe, 2000; Mathieu, Tannenbaum & Salas, 1992; Tannenbaum & Yukl, 1992).

With traditional learning a similar attribute has been known to alter learning outcomes. The construct of cognitive load has received much attention under the influence of Cognitive Load Theory (CLT; Sweller, Van Merriënboer & Paas, 1998). CLT is concerned with the development of instructional methods that efficiently use people's limited cognitive processing capacity to stimulate their ability to apply acquired knowledge and skills to new situations. Cognitive load can be defined as a multidimensional construct representing the load that performing a particular task imposes on the learner's cognitive system. According to the general model the construct has a causal dimension reflecting the interaction between task and learner characteristics, and an assessment dimension reflecting the measurable concepts of mental load, mental effort, and performance. Mental load is the aspect of cognitive load that originates from the interaction between task and subject characteristics. It provides an indication of the expected cognitive capacity demands and can be considered as an a priori estimate of the cognitive load. Mental effort is the aspect of cognitive load that refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task; thus, it can be considered to reflect the actual cognitive load. Performance can be defined in terms of learner's achievements (Paas, Tuovinen, Tabbers & Van Gerven, 2003).

CLT is based on a cognitive architecture that consists of a working memory that is limited in capacity and time when it comes to holding or processing novel information (Miller 1956; Peterson & Peterson, 1959) and a long-term memory with virtually unlimited capacity (Sweller et al. 1998). Only 7 ± 2 information elements can be held in working memory, and the number decreases when information has to be not only remembered but also processed (Cowan, 2001). Thus, the higher the number of interacting information elements a task contains, the more difficult it is and the higher the intrinsic load it imposes on working memory. However, information that has already been learned, that is, stored in long-term memory in the form of cognitive schemata, reduces working memory load because a schema can be handled in working memory as a single information element. Therefore, having prior knowledge on a task lowers the cognitive load imposed by that task. Moreover, when a task or aspects of a task are repeatedly practiced, cognitive schemata become automated, and no longer require controlled processing (Shiffrin and Schneider, 1977), which further frees up working memory resources. The intrinsic load imposed by a task thus consists of the inherent complexity of the content in relation to the learner's level of expertise. Next to intrinsic load, there is load imposed by instructional design of the task: germane and extraneous load. Germane load is defined as the cognitive resources required to handle intrinsic cognitive load. Germane load occurs when information presentation is designed to encourage assimilation or accommodation of new concepts and appropriately challenge the learner.

Extraneous load, on the other hand, is the unnecessary mental burden that is caused by cognitively inappropriate design and presentation of information; in other words, cognitive processes that induce extraneous load do not contribute to learning (Sweller, 2010).

Since the 1990s this interaction between information structures and cognitive architecture has begun to emerge as an explicit field of study for instructional designers and researchers (Paas, Renkl & Sweller, 2004). In 1998, CLT had been used almost exclusively to study instruction intended to decrease extraneous cognitive load. In contrast, recent work examines instructional methods that affect intrinsic and germane cognitive load rather than extraneous load. With good reason, extraneous cognitive load and intrinsic cognitive load are additive. Whether extraneous cognitive load presents students with a problem depends, in part, on the intrinsic load: if intrinsic load is high, extraneous cognitive load must be lowered; if intrinsic load is low, a high extraneous cognitive load due to an inadequate instructional design may not be harmful because the total cognitive load is within working memory limits (Sweller & Van Merriënboer, 2005). This total cognitive load is highly influential on learning, as total load cannot exceed the working memory resources available if learning is to occur (Paas, Renkl & Sweller, 2003). Many studies have found that tasks that require less total cognitive load predict more efficient learning because they require less training time and less mental effort to attain the same or better learning and transfer performance (Paas et. al., 2003). It is proposed that learners' behavior in a certain learning condition is more efficient if their performance is higher than might be expected on the basis of their invested mental effort, and/or their invested mental effort is lower than might be expected on the basis of their performance. High task performance associated with low effort is called high-instructional efficiency, whereas low task performance with high effort is called low-instructional efficiency (Paas & Van Merriënboer, 1993).

An important part of CLT has been to find ways to measure cognitive load. This is not easy because of its multidimensional character. Two classes of techniques for assessing cognitive load can be identified; namely, techniques that use subjective indices (rating scales) and techniques that use physiological indices (e.g., pupil diameter and heart-rate variability). In adopting subjective measures, two assumptions are made. Firstly, it is assumed that learners are able to reflect on their cognitive processes and assess the amount of mental effort used during learning tasks. Considerable evidence has supported this assumption as subjective measures have been found to be highly reliable, unobtrusive and more sensitive than physiological methods (Paas, 1992; Paas & Van Merriënboer, 1994). Secondly, it is assumed that there is a direct relation between the subjective measures and actual cognitive load. However, finding evidence for this assumption is problematic. It is

unclear how this mental effort relates to actual cognitive load. Physiological measures, such as heart rate and pupil dilation only have an indirect causal link to cognitive load. For example, high cognitive load may lead to high stress in an individual, which may lead to changes in heart rate, as may the individual's emotional response to the learning materials. A promising direct method of measuring load, however, is the use of neuroimaging techniques (Brünken, Plass & Leutner, 2003).

Within the spectrum of neuroimaging techniques one effective method to measure cognitive load is electroencephalography (EEG). EEG can noninvasively measure brain activity via electrodes that are placed on the scalp, unlike other techniques, which require subjects to lie in restricted positions, or to ingest hazardous materials. The measured brain activity varies predictably in response to changing levels of cognitive stimuli (Anderson & Bratman, 2008; Klimesch, 1999). The raw EEG signal is composed of voltage fluctuations in various frequencies, which are assumed to reflect information representation and transfer within and across neuronal assemblies (Klimesch, Schack & Sauseng, 2005). Several researchers have repeatedly observed that the activity of two powerbands of the raw EEG, alpha and theta, are related to task difficulty or cognitive load in a variety of task demands. These studies have found that frontal theta EEG activity increased and posterior alpha activity decreased with increasing cognitive load (Gevins, Smith, McEvoy & Yu, 1997; Gevins et al., 1998; Stipacek, Grabner, Neuper, Fink & Neubauer, 2003). An amusing, yet interesting, description of alpha blocking was provided in an early study by Penfield and Jasper (1954) for Einstein who showed continuous alpha rhythm while conducting complex but for him fairly automatic, mathematical operations. Suddenly, Einstein's alpha waves dropped out. He reported that he had found a mistake in the calculation he had made the day before. Sterman, Mann, Kaiser and Suyenobu (1994) analyzed EEG data obtained from 15 Air Force pilots during air refueling and landing exercises performed in an advanced technology aircraft simulator and found a progressive suppression of alpha with increasing amounts of cognitive load. Gevins et al. (1997) examined changes in cortical activity during spatial and verbal working memory tasks in eight participants and observed lower alpha activity in the difficult as compared with the easy task version. In addition, theta activity increased in magnitude with higher task difficulty. These results suggest that alpha and theta oscillations are differentially related to task difficulty. As task difficulty increases, alpha activity decreases (desynchronize), whereas theta activity increases (synchronize). According to Klimesch, Sauseng and Hanslmayr (2007) the desynchronization of alpha reflects the gradual release of inhibition associated with the emergence of complex spreading activation processes. In contrast, the frontal theta rhythm has been noted to increase in strength as tasks require more focused attention (Gevins et al., 1979 a,b,c;

Miyata, Tanaka & Hono, 1990; Yamamoto & Matsuoka, 1990; Gundel & Wilson, 1992).

It is clear that cognitive load can influence learning outcomes tremendously with traditional learning methods (Salomon, 1983; Paas et. al., 2005), which makes it interesting to investigate whether the same effect can be observed with the instructional method of DGBL. However, much of the existing body of research on cognitive load focuses on materials that are either text based or a combination of text and images (e.g. Brunken, Plass, & Leutner, 2004; Carlson, Chandler & Sweller, 2003), while much less is known about cognitive load in DGBL or even more broadly, cognitive load in multimedia learning. In an article by Greitzer, Kuchar and Huston (2007) it is stated that “ experiential/discovery-based approaches to computer-based training (which includes DGBL) impose a higher cognitive load on the learner”, though they fail to explain why. According to Kiili (2005) the main problem of multimedia learning materials is that the working memory capacity of learners is often overloaded due to inappropriate ways of presentation, because the rich multimedia elements create unnecessary extraneous cognitive load. Unfortunately empirical evidence to support the statement is lacking. This study will aim to investigate whether cognitive load influences learning outcomes in a game-based learning task by researching the relationship between performance and the amount of cognitive load demanded by the task. Videogame experience and knowledge of physics will also be taken into account. Cognitive load will be measured by EEG, promoting the direct, objective measurement of cognitive load in a complex learning process.

The game-based learning task used in this study is an educational game, called Space Challenge, designed by Hoevenaar and Koops (2012). The game was developed to form a basis for the conceptual change of knowledge regarding Newtonian mechanics by offering an alternative experience. Two versions of the game were designed, a Loose Timing version (LT) and a Hard Timing version (HT). The degree of difficulty of the LT-version is tuned to the anticipated skills of the participants whereas the degree of difficulty of the HT-version is higher than the anticipated skills of the participants. It is thus expected that cognitive load will be higher in the HT-version than in the LT-version. Performance is defined by measuring changes in conceptual knowledge and by assessing the number of completed levels within the game.

In line with prior research, it is expected that as cognitive load increases, performance will decrease. More specifically, it is expected that an increase in theta EEG activity and a decrease in alpha activity, which indicates an increased cognitive load, is related to a decrease in performance. It is expected that alpha power synchronization is positively

correlated with performance, whereas the opposite holds true for the theta band. At the beginning of the task, it is expected that alpha power will decrease while theta power increases. Furthermore it is expected that cognitive load will be higher in the HT-version of the game, than in the LT-version and that performance will be lower in the HT-version. Finally, it is expected that videogame experience and knowledge of physics will facilitate learning by decreasing cognitive load and thus increasing performance.

Method

Participants

The experiment was conducted with 30 participants, 10 males and 20 females. Participants were students of the department of behavioural sciences who received course-credits for their participation. At the beginning of the experiment all participants gave their informed consent. Their age ranged between 18 and 32 years with a mean age of 22 (SD=3.63). No special requirements for participation had to be met.

Game-based learning task

The game-based learning task used in this experiment is an educational game, called Space Challenge, designed by Hoevenaar and Koops (2012). The game was developed to form a basis for the conceptual change of knowledge regarding Newtonian mechanics by offering an alternative experience. The game is about a spaceship in a frictionless environment and allows players to explore the concepts of Newtonian mechanics in a powerful way, offering a contrast to everyday experiences (Hoevenaar & Koops, 2012). In the game participants maneuver a spaceship through a 2D maze. The mission is to collect all diamonds in each level. Each level can be finished by hovering completely still over a stop sign. Walls, mines, and debris, which are present in some of the levels, have to be avoided.

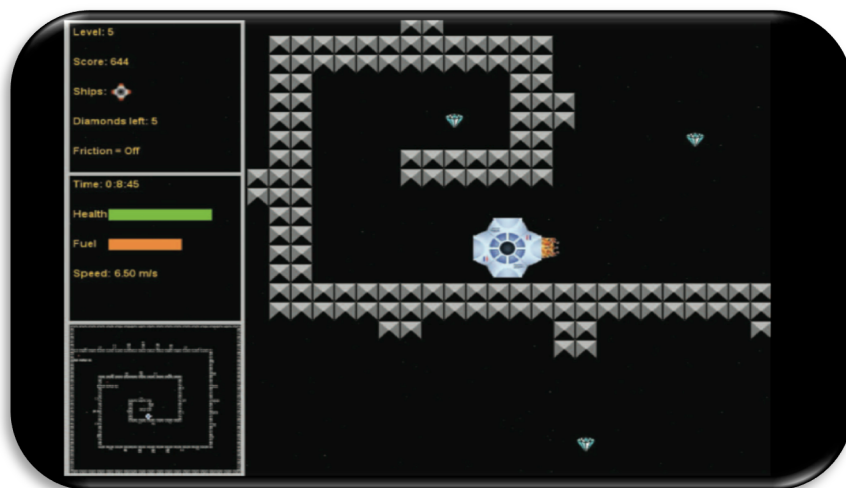


Figure 1: Screenshot Space Challenge

The levels in the game increase in difficulty. In Levels 1 and 2, the participants must accelerate and stop along a straight line, both with and without friction. Levels 3 and 4 involve maneuvering the spaceship along a curved path, both with and without friction.

Levels 5 and 6 incorporate more complex maneuvers and narrow pathways. Level 7 combines these basic movements in a more complex environment with an increasing number of obstacles. The increase in difficulty is maintained throughout consecutive levels.

Two versions of the game were designed, a Loose Timing version (LT) and a hard timing version (HT). The degree of difficulty of the LT-version is tuned to the anticipated skills of the participants whereas the degree of difficulty of the HT-version is higher than the anticipated skills of the participants. The two versions only differ in the amount of time, fuel and health given to the player. The game-design and all other game elements are similar.

Behavioral measures

Performance was defined by measuring changes in conceptual knowledge and by assessing the number of completed levels within the game. To assess changes in conceptual knowledge the Force Concept Inventory was used. The Force Concept Inventory is a 30-item multiple-choice test, designed to measure conceptual knowledge regarding Newtonian mechanics. It forces participants to choose between correct scientific answers and many common intuitive alternatives. For a review of validity and reliability see Hestenes, Wells and Swackhamer (1992). The test was administered before and after the game-based learning task. Furthermore participants were asked to fill in a short questionnaire to establish age, gaming experience and self-reported knowledge of Newtonian mechanics.

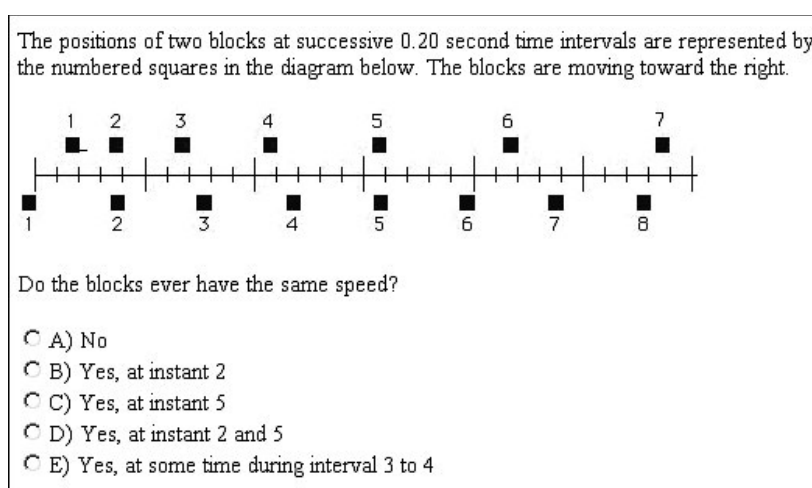


Figure 2: A question of the Force Concept Inventory

Design and procedure

This study has a between-subjects design. First participants were asked to finish the questionnaire and the Force Concept Inventory. After which an electrode cap was placed on the participant's scalp. Participants were then randomly assigned to either the LT- or the HT-version of the game-based learning task and were asked to play with the game for 30 minutes while EEG-recordings were made. Afterwards subjects were once again asked to fill in the Force Concept Inventory.

EEG-recording

The electrode montage consisted of 61 Ag/AgCl electrodes located in an electrode cap according to the international 10–10 system. Two Ag/AgCl electrodes were placed 2 cm above and 2 cm below the left eye to record vertical electrooculogram (EOG) and two electrodes were positioned at 1 cm external to the outer canthus of each eye for horizontal EOG recording. A ground electrode was placed on the forehead. Electrode impedances were kept below 20 k Ω . Signals were recorded digitally at a sampling frequency of 500 Hz. Fast Fourier Transforms were made offline. The distinguished powerbands were: theta (4-7 Hz) and alpha (8-12 Hz). Artifacts were corrected by using the built in algorithms of the software program Vision Analyzer 2.0 by Brainproducts. For each measurement, the spectral content was computed for epochs of 5.12 seconds of the EEG, bad intervals were skipped. The spectral power values of subjects 1, 5, 9 and 30 were left out of statistical analysis because the EEG recordings contained too many artifacts.

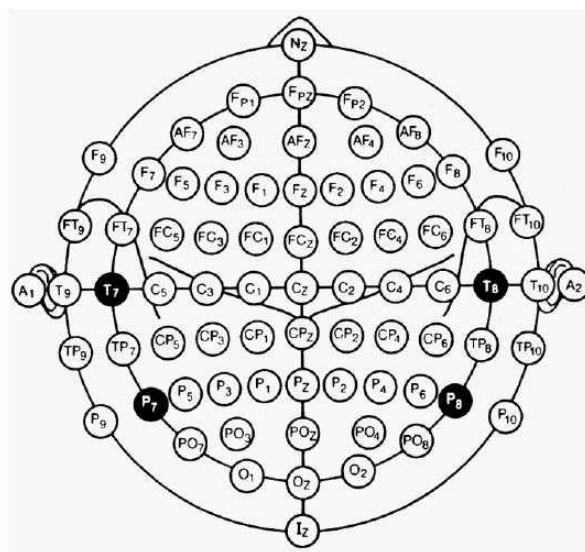


Figure 3: International 10-10 System of EEG Electrode Placement

Results

Performance

A repeated-measures analysis of variance was performed in SPSS to assess changes in conceptual knowledge and the effects of condition on this change. Results indicate that there are no significant changes in conceptual knowledge, $F(1,28)= 0.69$; $p>0.05$, and that this does not differ between the LT-group and the HT-group $F(1,28)= 0.69$; $p>0.05$. On the other hand, an analysis of variance showed that the number of completed levels does differ significantly between conditions, $F(1,24)=19.01$; $p<0.01$. The number of completed levels was significantly higher in the LT-group ($M=8.36$; $SD=0.41$) than in the HT-group ($M=5.75$; $SD=0.44$), which might mean that there is a difference in task-difficulty between the two conditions.

Cognitive Load

To investigate whether cognitive load influences performance, firstly, it was assessed at which recording sites alpha and theta power was most prominent. Mean theta power was most prominent at: Fpz ($M=0.27$; $SD=0.21$), AF7($M=0.30$; $SD=0.28$), FP1 ($M=0.29$; $SD=0.27$) and F7 ($M=0.22$; $SD=0.21$). For alpha, mean activity was highest at: PO8 ($M=0.13$; $SD=0.08$), O1 ($M=0.10$; $SD=0.05$), Oz ($M=0.10$; $SD=0.05$) and O2 ($M=0.11$; $SD=0.06$). These electrodes were used in further statistical analysis.

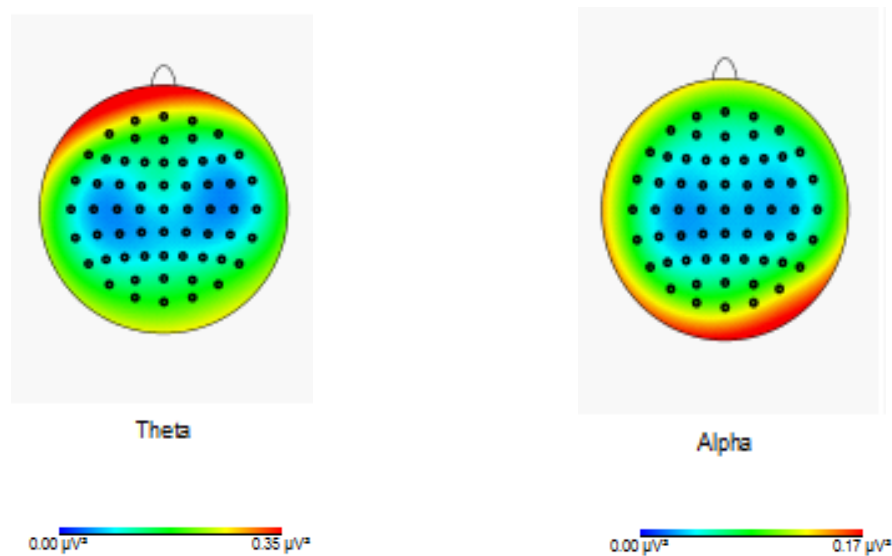


Figure 4: Topographical Mapping of Mean Theta and Alpha power

A test of variance was conducted to see if cognitive load would differ between the conditions. Results show that both theta power, $F(1,24)=0.04$; $p>0.05$, and alpha power, $F(1,24)=3.17$; $p>0.05$, do not significantly differ between the HT- and LT-version. Thus, cognitive load is not significantly higher or lower in one of the conditions. To explore whether cognitive load changes during the course of the task eight segments of the EEG were analysed. Epochs 1, 50, 100, 150, 200, 250, 300, and 350 were analysed. A repeated-measures analysis of variance showed that both theta power, $F(7,17)=1.31$; $p>0.05$, and alpha power, $F(7,17)=1.01$; $p>0.05$, did not significantly change over time. Finally, a test of variance showed that cognitive load does not significantly alter performance; cognitive load does not influence changes in conceptual knowledge, $F(18,4)=0.59$; $p>0.05$, nor the number of completed levels, $F(12,4)=0.57$; $p>0.05$.

Correlations

To further examine the relationship between cognitive load and performance correlations were computed, using Pearson's Correlation Coefficient. Results merely show that alpha and theta power are highly correlated, $r=0.52$; $p<0.01$, as can be expected considering their proximity in frequency. None of the other correlations were found to be significant.

Behavioral measures

To test the hypothesis that videogame experience and knowledge of physics would facilitate learning, by decreasing cognitive load and thus increasing performance, an analysis of variance was performed. Results show that both videogame experience, $F(8,15)=0.80$; $p>0.05$, and knowledge of physics, $F(1,15)=1.36$; $p>0.05$, do not significantly influence the number of levels completed. Furthermore, results show that videogame experience does not significantly influence conceptual knowledge, $F(8,15)=0.98$; $p>0.05$, while knowledge of physics does, $F(1,15)=5.55$; $p<0.05$. Pairwise comparisons using Bonferroni show that conceptual knowledge is higher when participants have knowledge of physics ($MD=5.65$; $SD=2.49$). To test whether cognitive load would be influenced by videogame experience and knowledge of physics another test of variance was conducted. Results show that both videogame experience, $F(16,30)=0.89$; $p>0.05$, and knowledge of physics, $F(2,14)=0.03$; $p>0.05$, do not significantly influence cognitive load.

Finally, correlations were computed between knowledge of physics, videogame experience, performance, and cognitive load. As expected, only the correlation between knowledge of physics and conceptual knowledge was significant, $r=-0.55$; $p<0.01$.

Discussion

The aim of this study was to investigate whether cognitive load would influence performance in a game-based learning task and, more broadly, to establish whether cognitive load should be considered as a variable in maximizing the effectiveness of game-based learning outcomes. This study found no indications that cognitive load influences learning outcomes in a game-based learning task. However, cognitive load was not successfully manipulated. It was expected that cognitive load would be higher in the HT-version of the game than in the LT-version of the game, but statistical analysis found that cognitive load was not significantly higher or lower in one of the conditions. Furthermore, the electrode impedances of the EEG-recordings were fairly high ($< 20 \Omega$). Thus, the measurement of cognitive load was not as reliable as it could have been. On the construct of performance, results indicate that there are no significant changes in conceptual knowledge. This might have something to do with the effectiveness of the game-based learning task. The effectiveness of the game-based learning task, designed by Hoevenaar and Koops (2012), has not been sufficiently validated. Though in the research by Hoevenaar and Koops 'Space Challenge' proved to be an effective tool in teaching newtonian mechanics, their participants played the game as part of their physics classes, with additional instructions on newtonian mechanics from their teacher. Furthermore, the Force Concept Inventory was used to measure changes in conceptual knowledge, by administering the test before and after the game-based learning task. However, results of the second administration may have been influenced by fatigue and lack of motivation, since the test is quite long and demands a fair amount of focused attention.

All in all this study has not succeeded in establishing whether cognitive load influences learning outcomes in a game-based learning task. Though, by making a step towards a broader application of CLT, by researching it's influence in DGBL, this study will hopefully inspire more research on how cognitive load influences learning in DGBL, as there are many gaps to be filled. For instance, research is needed on the origin of cognitive load in game-based tasks. As discussed earlier some researchers state that the main problem of multimedia learning materials is that the working memory capacity of learners is often overloaded due to inappropriate ways of presentation, whilst the rich multimedia elements create unnecessary extraneous cognitive load (Kiili, 2005). If this is the case designing strategies need to be made, with educational theories in mind. Some steps in this direction have already been made. To overcome the limited capacity problem Mayer (2001) presented a cognitive theory of multimedia learning that assumes that working memory includes limited channels for both visual and auditory (verbal) processing. Mayer has primarily examined

different presentation formats in order to reduce the extraneous cognitive load of learning materials. Although this modality effect, assuming that working memory capacity may be increased by the use of visual, auditory and haptic information processing channels simultaneously, might be valuable, it is important to notice that while graphics and sounds may attract the player the gameplay keeps the player engaged. Thus, a challenging task of educational game design is to find a balance between attractive elements and educational objectives in order to optimize the possibility of players experiencing flow while learning the relevant skills and information provided by the game.

However, the reduction of the extraneous cognitive load by an ideal instructional format does not guarantee that all free cognitive resources will be allocated to a deeper knowledge construction process (Bannert, 2002). Unused working memory capacity should be used by optimizing the germane cognitive load, by stimulating the player to process the problems provided more deeply. According to Kirschner (2002) the approach of encouraging learners to engage in appropriate cognitive processing can only work if the total cognitive load of instructional design is within working memory limits. If a learner's cognitive system is overloaded, it might impact negatively on learning.

In summary, research is needed to establish whether controlling cognitive load can maximize the effectiveness of DGBL. Is so, cognitive load, be it intrinsic, extraneous or germane, should be optimized, perhaps by cutting down irrelevant multimedia elements or by applying the modality effect, ultimately providing usable user interfaces and challenges that support knowledge construction.

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