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Research Report

Improving learning from animated soccer scenes: Evidence for the expertise reversal effect

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ABSTRACT

In two experiments, we investigated how animation of play (soccer) should be designed in order to avoid the high cognitive load due to the fleeting nature of information. Using static pictures and altering the animation's presentation speed have been proposed as instructional strategies to reduce learners' cognitive load. In the first experiment, we tested the effect of static vs. animated presentations on learning. The results indicated that novices benefited more from the static presentation whereas experts benefited more from the animated presentation. The second experiment investigated the effect of low vs. normal vs. high levels of presentation speed on learning. The results showed that novices profited more from the low presentation speed while experts profited more from the normal and high presentation speeds. Thus both experiments demonstrated the occurrences of the expertise reversal effect. Findings suggest that the effectiveness of instructional strategies depends on levels of soccer players' expertise.

1. Introduction

The ability to learn a complex game pattern is indispensable for successful performance in open skill team sports such as soccer. Visualizations are considered as one of the most fundamental and powerful tools to enable players to learn these game patterns efficiently, because they can deliver the visuospatial information about the game in a direct and parsimonious way, and thereby facilitate reasoning processes grounded in perception (Goldstone & Son, 2005; Schwartz, 1995). In recent years, dynamic visualizations such as animations (e.g., Garsoffky, Schwan, & Hesse, 2002) or videos (e.g., North, Ward, Ericsson, & Williams, 2011), have been extensively employed by soccer coaches and researchers examining soccer. Such visualizations extend the possibilities of traditional instructional media (e.g., sets of static pictures, written/oral explanations) by explicitly representing dynamic characteristics of game patterns (motion, acceleration, and timing). However, learning from dynamic visualizations could be a challenging task, as information is often fleeting (Ayres & Paas, 2007; Moreno & Mayer, 2007). Visual information essential for understanding the game situation may disappear from sight before the learner has time to adequately process it or integrate it with new information. Consequently, players may miss crucial information, and, therefore, fail to accurately understand the content communicated by the coach (Paas, Renkl, & Sweller, 2003).

Several studies have suggested ways to avoid or reduce the high perceptual-cognitive demands imposed by the fleeting nature of animations, such as the use of static pictures instead of animations (Hegarty, Kriz, & Cate, 2003; Mayer, Hegarty, Mayer, & Campbell, 2005) or adjusting animations' presentation speed (De Koning, Tabbers, Rikers, & Paas, 2011; Fischer, Lowe, & Schwan, 2008; Fischer & Schwan, 2010). However, according to the expertise reversal effect (Kalyuga, 2007; Kalyuga, Ayres, Chandler, & Sweller, 2003), levels of learner expertise could modulate the effectiveness of such means for enhancing learning. Therefore, it could be predicted that the effectiveness of using static pictures rather than animations and adjusting animations' presentation speed when instructing players about soccer scenes might depend on the players' levels of expertise in soccer.

In this study, a recall reconstruction-paradigm (Chase & Simon, 1973) and mental effort ratings (Paas, 1992) were used to investigate how well, easy and quickly soccer scenes of play were learned from animations and static pictures (Experiment 1) and from animations with different levels of presentation speed (Experiment 2),

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and to investigate whether the effectiveness of these instructional manipulations would depend on levels of player expertise (both experiments).

1.1. Learning from complex animations

Schnotz and Lowe (2008, p. 304) define an animation as "a pictorial display that changes its structure or other properties over time and which triggers the perception of a continuous change". Intuitively, animations are assumed to be the best media for training in team ball sports, because they portray dynamic or change-related information inherent to scenes of play in a natural and realistic way (Mann, Williams, Ward, & Janelle, 2007). However, several nonsporting studies have failed to confirm this intuitive assumption (e.g. Hegarty et al., 2003; Mayer, DeLeeuw, & Ayres, 2007; Mayer et al., 2005). As Tversky, Bauer-Morrison, and Bétrancourt (2002) indicated, the ineffectiveness of animations could be related to their frequent violation of the "apprehension principle" according to which animations should not be too complex or too fast to be accurately perceived and understood by the learners.

Furthermore, cognitive load theory (Sweller, 2010; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005) argues that instructional animations could be ineffective because they often impose high extraneous (unnecessary) cognitive load due to their fleeting nature (transient information effect; e.g., Sweller, Ayres, & Kalyuga, 2011). Because animations change continuously over time, learners may not be able to process and integrate specific key elements of information that occur within the flow of information (e.g., Rasch & Schnotz, 2009). Such processing and integration of information take place in working memory (WM). It is well known that WM is extremely limited in both duration and capacity when processing novel information (Baddeley, 2003). Working memory can manipulate no more than a few interconnected elements of information simultaneously (Cowan, 2001), and this information is usually lost from WM within a few seconds if it is not intentionally rehearsed (Peterson & Peterson, 1959). These limitations of WM pose a problem when dealing with fleeting information, such as the information presented in an animation. When studying a continuous animation, learners are required to temporally hold information from earlier frames in WM to be able to connect it with information presented on later frames in order to form a coherent internal representation of the shown content (Moreno & Mayer, 2007). The activities needed to deal with fleeting information can overwhelm WM, and as a consequence, hinder the learning process and negatively affect learning outcomes (Ayres & Paas, 2007; Sweller et al., 2011).

Two possible ways to avoid the problems related to the fleeting nature of animation are displaying key states of the system with static pictures (e.g., Bétrancourt, 2005; Bétrancourt, Dillenbourg, & Clavien, 2008; Mayer et al., 2005; Schnotz & Lowe, 2008; Boucheix & Schneider, 2009) and adjusting the animations' playing speed (e.g., De Koning et al., 2011; Fischer & Schwan, 2010). Firstly, displaying the key states of the system simultaneously with static pictures provides learners with a permanent visual representation of the information (Arguel & Jamet, 2009) and, therefore, offers the possibility to revisit and to reinspect parts of the display any required number of times (Hegarty, 2004). This is difficult, or even impossible, when the information is presented in an animation. However, Höffler and Leutner (2007) drew the more optimistic conclusion that learning from animations is more effective than learning from static pictures, particularly, if the content to be communicated is realistic (as opposed to schematic), representational (as opposed to decorational), and involves procedural-motor knowledge. In addition, research studies in Aptitude Treatment Interactions (ATI) have identified some factors that may moderate the effectiveness of visualization formats. These factors include spatial ability (Hays, 1996; Höffler & Leutner, 2011), cognitive style (Höffler, Prechtl, & Nerdel, 2010), need for cognition (Kim, Yoon, Whang, Tversky, & Morrison, 2007) and prior knowledge (Kalyuga, 2008). The last factor (i.e., prior knowledge) will be a focus of the current investigation.

Secondly, decreasing the animations' presentation speed may provide learners with more time to perform the necessary processing in WM, thus reducing the probability that key information is missed (De Koning et al., 2011). In addition, decreasing the speed of presentation alters the perceptibility profile of the presented information, so that changes that occur at the micro level of the animated system or procedure become more perceivable and accessible, thereby making its apprehension more likely (Meyer, Rasch, & Schnotz, 2010; Schnotz & Lowe, 2008).

1.2. The expertise reversal effect

A number of studies have shown that designs and techniques that are effective for learners with lower levels of prior knowledge (novices), might not be effective for learners with higher levels of prior knowledge (experts), and vice versa. The reversal in the relative effectiveness of instructional methods as levels of learner knowledge in a domain change has been referred to as the expertise reversal effect (Kalyuga, 2007; Kalyuga et al., 2003). This effect represents a clear example of ATI (Cronbach & Snow, 1977). It has been suggested that when the presented information needs to be integrated in working memory with already available knowledge structures of learners, this integration process may impose an additional cognitive overload resulting in the expertise reversal effect. For example, presenting detailed instructional explanations to knowledgeable learners (especially if they cannot ignore or otherwise avoid processing these explanations) may trigger their cognitive activities that support construction of knowledge that they already have thus interfering with rapid retrieval and fluent application of available knowledge structures in Long-Term Memory (LTM). Such redundant activities may overload working memory resulting in reduced learning outcomes. The expertise reversal effect has been identified in many studies with a wide range of instructional techniques (procedures) and learners, and has been reported either as a complete reversal (i.e., disordinal, crossover interaction) with significant differences for both novices and experts or, as a partial reversal (i.e., ordinal, non-crossover interaction) with non-significant differences for novices or experts, but with a significant interaction (Kalyuga & Renkl, 2010). The major implication of these studies is the necessity to tailor the learning material as learners acquire more expertise in a specific domain.

Kalyuga (2008) provided evidence for an expertise reversal effect using animated or static diagrams demonstrating transformations of simple linear and quadratic functions in high school mathematics. The results indicated a significant interaction between levels of learner expertise and learning materials. Novice learners profited more from a set of equivalent static pictures depicting the major stages of the procedure. However, animations were more beneficial for expert learners who have already developed a sufficient knowledge base (already stored in LTM) for dealing with the fleeting nature of the animation.

This result stands in contrast to the assumption of Höffler (2010) stating that learners with low prior knowledge might benefit from learning with animations, while learners with high prior knowledge might not. Animations might act as a "cognitive prosthetic" (Hegarty & Kriz, 2008) for learners with low prior knowledge since the visualization provides an external representation system/procedure that helps them to build an adequate mental model. Oppositely, high prior knowledge learners might not profit from animation as they are able to perform mental (internal) animation by themselves, and the external support could be redundant.

1.3. Attaining expert performance

Findings regarding the expertise reversal effect suggest the importance of taking learners' level of expertise into consideration when designing instruction. Hence, understanding the cognitive characteristics of experts, factors that influence the achievement of expertise, and perceptual-cognitive processes underlying expert performance is important.

The attainment of expertise occurs as a result of extensive learning and practice in a specific domain. Chase and Simon (1973) and Ericsson and Lehmann (1996) suggested that a minimum of 10 years or more than 10,000 h of preparation are necessary to attain an expert level. In many sporting domains including swimming (Kalinowski, 1985), tennis (Monsaas, 1985), and soccer (Helsen, Starkes, & Van Winckel, 1998) such a large amount of practice is indeed necessary for the development of expertise. However, as Ericsson and Polson (1988) found, the amount of practice itself does not guarantee the attainment of an expert level, but rather the amount of engagement in relevant practice. Lehmann and Ericsson (1999) introduced the term deliberate practice, comprising those practice activities that are the most effective for improving performance through sustained repetition, continuous correction, and maximal informative feedback to the learners. These activities are effortful and not enjoyable; they need full concentration (attention), and do not lead to immediate social and monetary rewards (Lehmann & Ericsson, 1999).

Deliberate and prolonged practice enables developing of a special form of working memory that has been called long-term working memory (LT-WM, Ericsson & Delaney, 1999; Ericsson & Kintsch, 1995). In situations within their domain of expertise, experts can use relevant knowledge structures in their LTM as retrieval structures that are processed as single units of information in WM, which allows them to significantly expand effective capacity of WM (Guida, Tardieu, & Nicolas, 2009). These retrieval structures (or cognitive schemas) are abstract, hierarchical knowledge representations, where encoded information is associated with retrieval cues. It is proposed that these retrieval structures allow expert players to rapidly encode information in LTM and efficiently access it when required. In game sports, the use of LT-WM structures enable experts to quickly construct a coherent mental representation of a pattern of play, allowing them to memorize complex patterns in a relatively short time.

In a classic sporting study, Allard, Graham, and Paarsalu (1980) replicated de Groot's (1945/1965) findings on chess and demonstrated that after viewing either slides (static presentation) or filmed stimuli (dynamic presentation) for brief periods of time, skilled players were able to more accurately recall players' positions than less-skilled players. However, when participants had to recall unstructured situation (i.e., players randomly positioned on the field of play), few patterns were recognizable, and the superiority of expert players virtually disappeared. This effect was initially demonstrated in basketball, and subsequently reported in volleyball (Bourgeaud & Abernethy, 1987) and soccer (Williams & Davids, 1995). These results suggest that expert players acquire and store in LTM enormous amounts of chunks (retrieval structures or schemas) that correspond to familiar and prototypical patterns of play commonly found in real games. As a result, these cognitive structures (acquired through experience) enable players' rapid categorization and recognition of a specific pattern, thus facilitating recall of the elements' location in the field (i.e., position of the players and the ball). In contrast, novice players may find it difficult to encode and recognize correctly specific patterns in the play because of the restricted capacity of WM and a lack of background knowledge (see also, Gobet & Simon, 1996; Gobet & Simon, 1998, for similar findings in chess).

1.4. Aims – Hypothesis

The aim of the current study was to investigate the effect of different forms of visualizing a soccer scene on learners' cognitive load and learning outcomes. The main objective of this study was to ascertain whether the efficiency of these visualizations is affected by levels of players' expertise (expertise reversal effect). Most of the available evidence for the expertise reversal effect is based on learning from abstract diagrams used to illustrate/visualize complex natural processes, mechanical systems, and problem solving methods. Yet to date, no studies have explored whether this phenomenon could occur using naturalistic scene stimuli (e.g., sport scenes). Naturalistic scenes possess a degree of complexity and semantic coherence far greater than diagrams. Scenes are collection of various visual features, such as background elements, surfaces, structures, textures and colors (e.g., Brockmole & Henderson, 2005), and therefore, may afford viewing conditions quite dissimilar to those provided by diagrams. Thus, this study addresses the question of whether the same mechanisms underlying learning from diagrams also operate under naturalistic viewing conditions.

Experiment 1 compared animated soccer scenes with static pictures representing the key steps of the soccer scenes with novice and expert soccer players. Even though the general approach was similar to the study reported by Kalyuga (2008), this experiment was novel in a number of ways (in addition to the above noted difference in materials and viewing conditions). Firstly, the previous study was methodologically restricted by the range of prior knowledge of participants. Most of them were neither complete novices nor full experts in the domain, and using a median split of a random sample of university students to discriminate expert-novice differences does not represent an efficient technique. Secondly, there is a problem (frequently found in studies comparing the effects of animated and static pictures) associated with the picture size that could critically affect learning (e.g., Spittle, Kremer, & Hamilton, 2010; Tan, Gergle, Scupelli, & Pausch, 2006). This factor was not controlled in the previous study. Indeed, when learning from static visualization learners were confronted with a set of several static pictures projected simultaneously on the screen of the same size as the animation. Some details in those scaled-down pictures could be unperceivable, while when learning from the animated visualization, learners could perceive the details on a large screen format. This experiment attempted to overcome all these confines. In line with the findings of Kalyuga (2008) (due to the above methodological restrictions, they need to be regarded as preliminary results), an expertise reversal effect was expected: Novice participants would benefit more from static presentation than from animated presentation, while expert participants would benefit more from animated rather than static presentation.

Experiment 2 investigated whether the adjustment of the animations' presentation speed would affect the learning process and learning outcomes of novice and expert soccer players. Fischer et al. (2008) and Fischer and Schwan (2010) provided some evidence that manipulating the animations' presentation speed influenced learning. However, those studies were conducted to investigate how to make micro and macro information more perceivable, and were not intended to reduce extraneous cognitive load generated by the transience of information. Experiment 2 aims at investigating precisely this issue and examining (for the first time, to the best of our knowledge) potential interactions between levels of expertise and different modes of animations' presentation speed. It was predicted that animations with a decreased speed would be more beneficial for novice players, whereas experts who had already acquired sufficient domain-specific knowledge to deal with extraneous cognitive load induced by fleeting animation (Kalyuga, 2008; Spanjers, Wouters, Van Gog, & Van Merriënboer, 2011) would not be influenced by the manipulation of presentation speed.

2. Experiment 1

2.1. Method

2.1.1. Participants

Eighteen expert and eighteen novice male soccer players participated in the experiment. The expert participants (M_{age} = 25.2, SD = 1.7) were semi-professional players engaged with teams from the third division of the French football league. They had been playing soccer for an average of 12.7 years (SD = 1.9) and trained or played for an average of 12.3 h (SD = 3.6) per week. The novice participants (M_{age} = 24.9, SD = 2.5) were all French university students. They knew the rules of the game, but they had never played a team sport in a club. Participants reported normal or corrected to normal levels of visual function. The experiment was approved by the local ethics committee.

2.1.2. Apparatus and materials

The experiment was conducted using a HP Pavilion dv6 computer. The stimuli were presented on a 250 cm × 200 cm screen from a video projection system (Sony VPL EX120 XGA) placed at a distance of 3 m. The display on the screen was 200 cm x 160 cm, with a 45° viewing angle. Two different animated soccer scenes (presented at a rate of 12 frames per second) were designed on SimulFoot 3D-software[1] together with three expert soccer coaches (with over 10 years' experience). Before the construction of the animations, coaches were asked to create counterattack scenes that involved six players who should carry out a tactical combination composed of five passes towards the opponent's court before a shot on goal was taken. During each pass, each player should move in relation to the ball and the teammates' positions in order to offer an appropriate solution to the ball carrier. Each pass corresponded to a new stage made up of multiple offensive actions carried out by the players. Each animation was captured as if it was recorded by a sideline camera in an elevated position (25°). This camera position enabled the entire field of play to be viewed.

Subsequently, a static scene was generated from each animation that included five still frames representing the five main stages of the play, as defined by the same three coaches (i.e., who developed the scenes of play). These frames were displayed simultaneously in the same picture (see Fig. 1). The duration of all scenes of play was 32 s.

2.1.3. Procedure

Participants were tested individually in sessions with duration of approximately 90 min. Each participant was assigned to the two experimental conditions. The order of exposure to experimental conditions was counterbalanced among participants to control for order effects across conditions. After having watched either a static or animated presentation in each of the two study phases players were asked to rate the mental effort invested in studying the scene of play and perform a recall reconstruction test (i.e., there were two test phases).

2.1.3.1. Study phase. Each participant viewed successively the two presentation formats. The task was to memorize the soccer scenes as accurately and as rapidly as possible. For each presentation, the projection of the scene began as soon as the learner clicked on the "*Ready*!" button. Participants could not stop the display, but when it was over, they could see it again as many times as desired by clicking on the "*Repeat*" button (the number of repetitions was registered by the system). When the subjects felt they had learned the scene of play, they had to click on the "*End*" button. The duration of the static scene was equivalent to the duration of the animated scene (i.e., 32 s).

2.1.3.2. Test phase. After the study phase of each version, the participant was asked to perform two successive tasks. (i) Evaluate the mental effort invested in studying the learning material on a 9-point subjective rating scale, ranging from (1) very, very low mental effort to (9) very, very high mental effort (Paas, 1992; Paas, Tuovinen, Tabbers, & Van Gerven, 2003). (ii) Reconstruct the scene of play by drawing it on a paper that contains an empty soccer field, with the same viewing angle as in the experimental conditions. The soccer field was divided into five parts. For each part, players were instructed to reconstruct as accurately as possible the position of the six players in relation to the ball already placed in its correct location. In each stage of play, they had to reproduce the position of (a) the ball carrier, (b) players located in front of the ball (at the left, the middle or the right), and (c) players located behind the ball (at the left, the middle or the right). Participants were instructed to employ conventional arrows, usually used in soccer to illustrate the pattern of play. Hence, solid arrows were used to describe the movement of the ball from one stage to another, whereas dashed arrows were used to describe the movement of the players from one stage to another. To assure the unbiased processes of scoring, the scorer was a person blind to the hypotheses of the project. One point was awarded for each correct placement of a player in the field; zero points were awarded for each incorrect placement of a player in the field. The scores could, therefore, range from 0 to 30.

On completion of the immediate test phase, there was about 25-min break during which participants were instructed to perform a set of interfering tasks: (a) complete a practice history questionnaire, (b) count backwards by 3 from 999 (Peterson & Peterson, 1959), (c) complete a short version of the paper folding test (Ekstrom, French, Harman, & Dermen, 1976). These tasks were executed to reduce the possibility that recall performances could occur on the basis of short-term memory. The order of tasks was counterbalanced. Immediately after performing the interfering tasks, the participants were required to complete a delayed recall test by reconstructing the same soccer scenes that had been presented previously in the study phase. The recall time (sec.) for the immediate and delayed tests was recorded for each participant.

2.1.4. Analyses

After verifying that the assumptions for parametric tests – homoscedasticity using Levene's test and normality of distributions using Kolmogorov–Smirnov test – were met, the data were analyzed using mixed design ANOVAs, in which Presentation Format (static, animated) was a within-subjects factor, and Expertise (expert vs. novice) was a between-subjects factor. The dependent variables were immediate recall performance (0–30), time on immediate recall test (sec.), number of repetitions needed to memorize the scene (unlimited), mental effort invested in studying the scene (1–9), instructional efficiency (score), delayed recall performance (0–30), and time on delayed recall test (sec.).

Instructional efficiency was computed based on Kalyuga and Sweller's (2005) approach: Efficiency = Performance/Mental Effort (the likelihood model, according to Hoffman & Schraw, 2010), however, with a third variable, the number of repetitions, added to the formula. As an alternative to the deviation model of instructional efficiency based on the difference between standardized

[1] SimulFoot was developed by researchers from the SimGraph team of the Information Science and Systems Laboratory (LSIS) at Aix-Marseille University.

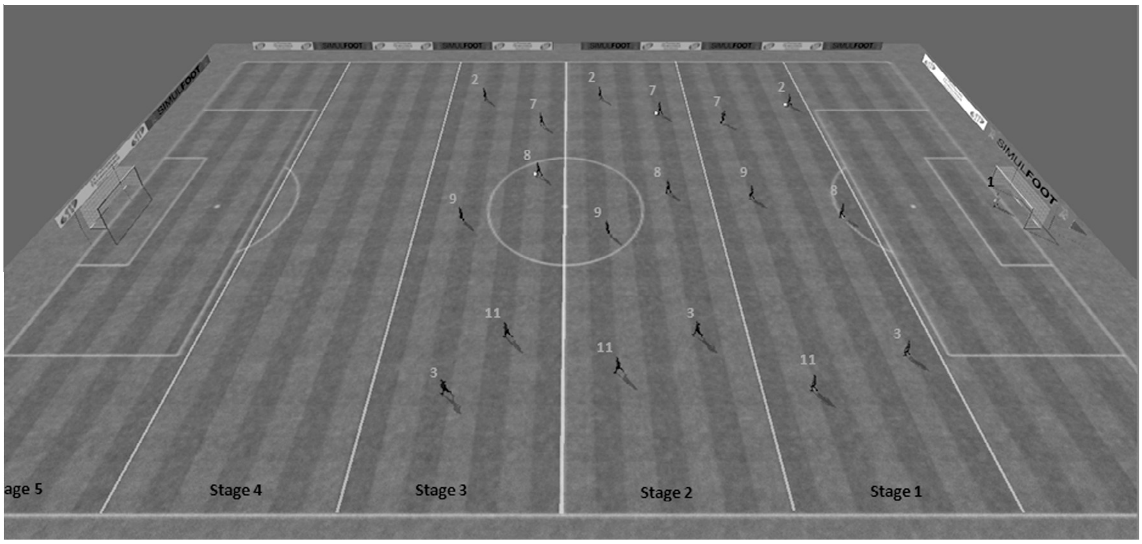

Fig. 1. Static picture representing three key stages of the soccer animation.

scores (Paas & van Merriënboer, 1993), the likelihood model is simple to calculate, and it is easily modifiable to take into account additional measures related to the mental cost of performance. The number of repetitions during the learning stage is such a measure: a greater number of repetitions required for achieving the same level of performance indicate a lower instructional efficiency. Thus, the new modified formula for calculating instructional efficiency used in the current study was: Efficiency = Performance/(Mental Effort $\times$ Number of Repetitions).

2.2. Results

Descriptive statistics for recall accuracy, time on immediate recall test, mental effort, number of repetitions, efficiency, delayed recall accuracy, and time on delayed recall test for expert and novice participants for each format are presented in Table 1.

2.2.1. Recall accuracy

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 71.91$, $p < .001$, $\eta_p^2 = .68$, a significant effect of format, $F(1,34) = 10.18$, $p = .003$, $\eta_p^2 = .23$, and a significant interaction between these two factors, $F(1,34) = 18.36$, $p < .001$, $\eta_p^2 = .35$. The post hoc analysis for the experts revealed a significant difference between the two formats, $p < .001$. It appeared that the expert participants performed better with the animated than with the static format. However, the post hoc analysis for the novice group showed no difference between the two formats, $p = .369$. Thus, the novice participants performed at the same level regardless of the format. Further analyses revealed that the expert participants had significantly better recall performance than the novice participants with both formats, static, $p = .001$, and animated, $p < .001$.

Table 1
Means and standard deviations for immediate recall, time on immediate recall, mental effort, number of repetitions, efficiency, delayed recall, and time on delayed recall for the experts and novices for each format in Experiment 1.

	Static	Animated
Expert		
Immediate recall	24.28 (1.99)	26.56 (1.46)
Time on immediate recall	95.00 (9.11)	97.28 (10.60)
Mental effort	4.44 (0.62)	3.28 (1.07)
Number of repetitions	5.22 (0.65)	4.17 (0.71)
Efficiency	1.08 (0.21)	2.23 (0.91)
Delayed recall	23.56 (1.76)	26.00 (1.50)
Time on delayed recall	102.33 (8.64)	106.22 (10.90)
Novice		
Immediate recall	22.22 (1.40)	21.89 (0.96)
Time on immediate Recall	122.28 (5.75)	137.00 (6.51)
Mental effort	4.83 (0.71)	6.00 (1.03)
Number of repetitions	6.00 (0.84)	7.44 (0.92)
Efficiency	0.80 (0.18)	0.51 (0.11)
Delayed recall	20.94 (1.26)	18.89 (1.13)
Time on delayed recall	139.83(11.37)	152.78 (6.86)

2.2.2. Time on immediate recall test

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 293.18$, $p < .001$, $\eta_p^2 = .90$, a significant effect of format, $F(1,34) = 19.56$, $p < .001$, $\eta_p^2 = .37$, and a significant interaction between expertise and format, $F(1,34) = 10.48$, $p = .003$, $\eta_p^2 = .24$. The post hoc analysis for the experts revealed no significant effect, $p = .513$. So, expert participants needed about the same time on the immediate recall test, regardless of the presentation format. However, the post hoc analysis for the novices showed a significant difference, $p < .001$. Novices needed less time on the immediate recall test following the static format than the animated format. Further analyses revealed that the expert participants needed significantly less time on the immediate recall test than the novice participants with both formats, static, $p < .001$, and animated, $p < .001$.

2.2.3. Mental effort

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 73.84$, $p < .001$, $\eta_p^2 = .68$, a non-significant effect of format, $F(1,34) = .00$, $p = 1.000$, $\eta_p^2 = .00$, and a significant interaction between expertise and format, $F(1,34) = 25.63$, $p < .001$, $\eta_p^2 = .43$. The post hoc analysis for the experts showed that the mental effort invested with the two formats differed significantly, $p = .002$. The experts had to invest less mental effort with the animated than with the static format. The post hoc analysis for the novices also revealed a significant difference in the mental effort invested with the two formats, $p = .003$. The novices had to invest less mental effort with the static format than with the animated format. Further analyses revealed that the experts had to invest less mental effort than the novices with the animated format, $p < .001$. For the static format, the mental effort invested by the experts did not differ significantly from the mental effort invested by the novices, $p = .087$.

2.2.4. Number of repetitions

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 129.98$, $p < .001$, $\eta_p^2 = .79$, a non-significant effect of format, $F(1,34) = 1.02$, $p = .320$, $\eta_p^2 = .03$, and a significant interaction between expertise and format, $F(1,34) = 42.14$, $p < .001$, $\eta_p^2 = .55$. The post hoc analysis for the expert group revealed a significant difference between the two formats, $p < .001$. It was found that expert participants needed a lower number of repetitions with the animated format than with the static format. The post hoc analysis for the novice group also showed a significant difference between the two formats, $p < .001$. Novice participants needed a lower number of repetitions with the static format than with the animated format. It appeared from the further analyses that with both formats the expert participants needed a significantly lower number of repetitions than the novice participants, static, $p < .005$, and animated, $p < .001$.

2.2.5. Efficiency

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 86.04$, $p < .001$, $\eta_p^2 = .72$, a significant effect of format, $F(1,34) = 13.56$, $p < .001$, $\eta_p^2 = .29$, and a significant interaction between expertise and format, $F(1,34) = 37.52$, $p < .001$, $\eta_p^2 = .52$. The post hoc analysis for the experts revealed a significant difference between the two formats, $p < .001$. For the experts, learning was more efficient with the animated format than with the static format. The post hoc analysis for the novices showed a significant difference between the two formats as well, $p < .001$. For novices learning with the static format was more efficient than learning with the animated format. Further analyses revealed that learning was more efficient for the expert participants than for the novice participants with both formats, static, $p < .001$, and animated, $p < .001$.

2.2.6. Delayed recall accuracy

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 181.97$, $p < .001$, $\eta_p^2 = .84$, a non-significant effect of format, $F(1,34) = 0.39$, $p = .54$, $\eta_p^2 = .01$, and a significant interaction between expertise and format, $F(1,34) = 51.90$, $p < .001$, $\eta_p^2 = .60$. The post hoc analysis for the experts revealed a significant difference between the two formats, $p < .001$. Experts had higher delayed recall accuracy after studying the animated format than the static format. The post hoc analysis for the novices also showed a significant difference between the two formats, $p < .001$. Novices had higher delayed recall accuracy after studying the static format than the animated format. Further analyses revealed that the expert participants had significantly better recall performance than the novice participants with both formats, static, $p < .001$, and animated, $p < .001$.

2.2.7. Time on delayed recall test

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 252.73$, $p < .001$, $\eta_p^2 = .88$, a significant effect of format, $F(1,34) = 21.58$, $p < .001$, $\eta_p^2 = .39$, and a significant interaction between expertise and format, $F(1,34) = 6.24$, $p = .017$, $\eta_p^2 = .16$. The post hoc analysis for the experts revealed no significant difference, $p = .138$. So, expert participants needed about the same time on the delayed recall test, regardless of the format. However, the post hoc analysis for the novices showed a significant difference, $p < .001$. Novices needed less time on the delayed recall test with the static format than with the animated format. Further analyses revealed that the expert participants needed significantly less time on the delayed recall test than the novice participants with both formats, static, $p < .001$, and animated, $p < .001$.

2.3. Discussion of Experiment 1

The aim of the first experiment was to examine the effects of learner expertise and static vs. animated presentation of soccer scenes on the learning process and learning outcomes. The results supported the expected interaction between presentation formats and levels of player expertise. In line with the predictions based on cognitive load theory, novice players benefited more from studying a static presentation than from studying an animated presentation. By presenting the information in a static format, the high perceptual-cognitive demands associated with the fleeting nature of dynamic information were avoided. Consequently, the novice players could process and integrate each element of information in the static condition without time constraints (Hegarty, 2004).

In contrast, expert players benefited more from studying an animated presentation than from a static presentation. As a result of deliberate practice and extended experience within their domain of expertise, experts may have acquired well-attuned knowledge structures and were able to engage the mechanism of LT-WM that enabled them to fluently process the fleeting dynamic information without a cognitive overload. When learning a complex animation of play, expert players can construct and continuously update a mental representation of the dynamic information in WM by retrieving associated components of their knowledge base from LTM. Due to the effective associations with appropriate LTM structures (schemas), it is durable enough to withstand to the temporal constraints imposed by the transient nature of animation. Consequently, these players could benefit from the animation depicting the motion information and temporal relationships between elements of play. Furthermore, the results are consistent with Mann et al.'s (2007) meta-analysis demonstrating that the possibility of finding an expert advantage is larger when players are asked to perform in a dynamic environment (i.e., video) rather than in a static environment (i.e. static slides). These authors argued that the more natural and realistic (i.e., dynamic) the visual presentation mode is, the greater are the performance differences between expert and nonexpert participants.

In sum, the results suggest that the choice of the presentation format to communicate how systems of play work should be based on players' level of expertise. Whereas animations are more suitable in promoting learning for expert players, well-designed series of static pictures are more beneficial for novice players.

3. Experiment 2

In Experiment 1, novice players were found to have difficulties in dealing with the fleeting nature of animations, contrary to expert players. The questions that arise from those results are (i) whether decreasing the animations' presentation speed may reduce the negative effect of their fleeting nature and, therefore, support novices in understanding the scene of play, and (ii) whether experts can maintain their level of performance, despite an increase in the animations' presentation speed. To answer these questions we conducted Experiment 2 which tested the effects of different speed levels of animated soccer scenes of play (low, normal, high) on the learning process and learning outcomes of experts and novices.

3.1. Method

3.1.1. Participants

Eighteen expert and eighteen novice male soccer players participated in this experiment. The expert participants ($M_{age} = 26.2$, $SD = 2.4$) were semi-professional players engaged with club organizations from the third division of the French football league. They had played soccer for an average of 12.75 years ($SD = 2.3$) and trained or played for an average of 11.5 h ($SD = 2.7$) per week. The novices players ($M_{age} = 25.3$, $SD = 3.6$) were all French university students. They knew the rules of the game but they had never played a team sport in a club. Participants reported normal or corrected to normal levels of visual function. The experiment was approved by the local ethics committee.

3.1.2. Materials

Three animations with the same features as the animations used in Experiment 1 (e.g., number of players, number of steps, viewing angle) were designed together with three soccer coaches (with over 10 years of experience) using SimulFoot 3-D software. The normal presentation speed of the animations was 12 frames per second (fps). This speed was based on the standard speed of the software. Besides this normal presentation speed, we generated the same animations with a low presentation speed (6 fps) and a high presentation speed (18 fps).

3.1.3. Procedure

The tasks and procedure were identical to the tasks and procedure used in Experiment 1. All participants were presented with all three experimental conditions. The order of exposure to experimental conditions was counterbalanced among participants to minimize any affects due to the order of presenting the experimental conditions.

3.1.4. Design

The data were analyzed using mixed design ANOVAs, in which animations' presentation speed (low vs. normal vs. high) was a within-subjects factor and expertise (expert vs. novice) was a between-subjects factor. The dependent variables were again immediate recall performance (0–30), time on immediate recall test (sec.), number of repetitions needed to memorize the scene (unlimited), mental effort invested in studying the scene (1–9), instructional efficiency (score), delayed recall performance (0–30), and time on delayed recall test (sec.). Degrees of freedom were corrected using Greenhouse–Geisser statistics when Mauchly's test of sphericity indicated that the sphericity assumption has been violated. The *p*-values reflect these changes. The significance-level for the three sets of post hoc analyses, used for determining the source of significant interaction effects, was 0.0167, because each set consisted of three tests.

3.2. Results

Descriptive statistics for recall accuracy, time on immediate recall test, mental effort, number of repetitions, efficiency, delayed recall accuracy and time on delayed recall test for expert and novice participants for each speed level are presented in Table 2.

Table 2
Means and standard deviations for immediate recall, time on immediate recall, mental effort, number of repetitions, efficiency, delayed recall and time on delayed recall for the experts and novices for each speed level in Experiment 2.

	Low	Normal	High
Expert			
Immediate recall	27.17 (1.15)	26.83 (1.25)	27.11 (1.41)
Time on immediate recall	94.72 (10.50)	91.22 (9.64)	88.67 (9.39)
Mental effort	4.61 (0.61)	3.00 (0.69)	2.83 (0.62)
Number of repetitions	4.33 (0.91)	4.17 (0.62)	4.22 (0.65)
Efficiency	1.44 (0.35)	2.32 (0.68)	2.42 (0.66)
Delayed recall	26.56 (1.34)	26.22 (1.56)	26.72 (1.60)
Time on delayed recall	102.83 (8.44)	98.11 (11.59)	92.56 (10.37)
Novice			
Immediate recall	24.44 (1.76)	22.50 (1.38)	21.89 (1.60)
Time on immediate recall	119.67 (6.52)	135.67 (7.07)	137.72 (7.04)
Mental effort	4.78 (0.55)	5.89 (0.76)	7.22 (0.65)
Number of repetitions	5.67 (0.77)	6.94 (0.73)	7.94 (0.64)
efficiency	0.94 (0.22)	0.56 (0.10)	0.39 (0.06)
Delayed recall	23.44 (1.79)	19.78 (2.18)	18.78 (1.80)
Time on delayed recall	135.06 (9.76)	152.44 (6.36)	150.72 (6.98)

3.2.1. Recall accuracy

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 175.87$, $p < .001$, $\eta_p^2 = .84$, a significant effect of speed level, $F(1.50,50.87) = 9.96$, $p < .001$, $\eta_p^2 = .23$, and a significant interaction between these two factors, $F(1.50,50.87) = 7.92$, $p = .003$, $\eta_p^2 = .19$. Post hoc analyses for the experts revealed no significant differences between the three speed levels: low/normal, $p = .345$; low/high, $p = .912$, and normal/high, $p = .439$. This implies that the experts performed equally regardless of the presentation speed of the animations. Post hoc analyses for the novice group showed significant differences between the low presentation speed and the other two presentation speed, low/normal, $p < .001$ and low/high, $p < .001$, but a non-significant difference between normal/high, $p = .119$. So, it was found that novice players had better recall scores with low presentation speed than with normal and high presentation speed. Further analyses revealed that the expert participants had significantly better recall performance than the novice participants with all three speed levels, low, $p < .001$; normal, $p < .001$; high, $p < .001$.

3.2.2. Time on immediate recall test

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 394.31$, $p < .001$, $\eta_p^2 = .92$, a significant effect of speed level, $F(1.02,34.58) = 8.20$, $p = .007$, $\eta_p^2 = .19$, and a significant interaction between expertise and speed level, $F(1.02,34.58) = 26.81$, $p < .001$, $\eta_p^2 = .44$. Post hoc analyses for the experts revealed no significant differences between the low speed level and the other two speed levels, low/normal, $p = .373$; low/high, $p = .132$. However, a significant difference was found between the low and high speed level, $p < .001$. This implies that experts needed less time on the immediate recall test with the high speed level than with the low speed level. Post hoc analyses for the novice group showed significant differences between the three speed levels: low/normal, $p < .001$; low/high $p < .001$; normal/high $p < .001$. This result implies that novices needed less time with the low speed level than with the normal and high speed levels, and less time with the low speed level than with the normal speed level. Further analyses revealed that the expert participants needed significantly less time on the recall test than the novice participants with all three speed levels, low, $p < .001$; normal, $p < .001$; high, $p < .001$.

3.2.3. Mental effort

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 383.48$, $p < .001$, $\eta_p^2 = .92$, a significant effect of speed level, $F(1.92,65.28) = 7.48$, $p = .001$, $\eta_p^2 = .18$, and a significant interaction between expertise and speed level, $F(1.92,65.28) = 100.00$, $p < .001$, $\eta_p^2 = .75$. Post hoc analyses for the experts showed significant differences in the mental load invested between the low presentation speed and the other two presentation speeds, low/normal, $p < .001$; low/high; $p < .001$, but a non-significant difference between normal/high, $p = .381$. The experts had to invest less mental effort with the normal and high presentation speed than with the low presentation level. Post hoc analyses for the novices revealed significant differences in the mental effort invested between the three speed levels, low/normal, $p < .001$; low/high, $p < .001$; normal/high, $p < .001$. The novices had to invest less mental effort with the low presentation speed than with normal and high presentation speed, and less mental effort with the low presentation speed level than with the normal presentation speed level. Further analyses revealed that the experts also had to invest less mental effort than the novices with the normal presentation speed, $p < .001$, and high presentation speed, $p < .001$. For the low presentation speed, the mental effort invested by the experts was not different from the mental effort invested by the novices, $p = .394$.

3.2.4. Number of repetitions

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 260.58$, $p < .001$, $\eta_p^2 = .88$, a significant effect of speed level, $F(1.91,64.77) = 24.37$, $p < .001$, $\eta_p^2 = .42$, and a significant interaction between expertise and speed level, $F(1.91,64.77) = 30.05$, $p < .001$, $\eta_p^2 = .47$. Post hoc analyses for the expert group revealed non-significant differences between the three speed levels, low/normal, $p = .528$; low/high, $p = .668$, normal/high, $p = .805$. So, experts repeated the animations an equal number of times with the three presentation speed levels. However, post hoc analyses for the novice group showed significant differences between the three speed levels, low/normal, $p < .001$; low/high, $p < .001$; normal/high, $p < .001$. Novice participants needed a lower number of repetitions with the low presentation speed than with the normal and high presentation speed, and a lower number of repetitions with the low presentation speed than with the normal presentation speed. It appeared from the further analyses that with all speed levels, the experts participants needed a significantly lower number of repetitions than the novice participants, low, $p < .001$, normal, $p < .001$, and high, $p < .001$.

3.2.5. Efficiency

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 322.34$, $p < .001$, $\eta_p^2 = .90$, a significant effect of speed level, $F(1.94,66.10) = 3.66$, $p = .03$, $\eta_p^2 = .10$, and a significant interaction between expertise and speed level, $F(1.94,66.10) = 32.24$, $p < .001$, $\eta_p^2 = .49$. Post hoc analyses for the expert group revealed significant differences between the low speed level and the two other speed levels, low/normal $p < .001$ and low/high $p < .001$, but not between the normal and high speed levels, $p = .615$. This implies that for the experts, learning was more efficient with the normal and high speed levels than with the low speed level. Post hoc analyses for the novice group revealed significant differences between the three speed levels, low/normal $p < .001$, low/high $p < .001$ and normal/high $p < .001$. This implies that learning for the novices was more efficient with the low speed level than with the normal or high speed level, and that learning with the normal speed level was more efficient than learning with the high speed level. Further analyses revealed that learning was more efficient for the expert participants than for the novice participants with all three speed levels, low, $p < .001$, normal, $p < .001$, and high, $p < .001$.

3.2.6. Delayed recall

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 252.94$, $p < .001$, $\eta_p^2 = .88$, a significant effect of speed level, $F(1.92,65.42) = 20.42$, $p < .001$, $\eta_p^2 = .38$, and a significant interaction between expertise and speed level, $F(1.92,65.42) = 20.54$, $p = <.001$, $\eta_p^2 = .38$. Post hoc analyses for the expert group revealed non-significant differences between the three speed levels, low/normal, $p = .430$, low/high, $p = .746$ and normal/high, $p = .376$. So, experts had similar delayed recall scores regardless of the presentation speed of the animation. Post hoc analyses for the novice group, however, showed significant differences between the low speed level and the other two speed levels, low/normal $p < .001$ and low/high $p < .001$. No significant difference was found between the normal and high speed levels, $p = .126$. This implies that novices had better delayed recall scores with the low speed level than with the normal and high speed levels. Further analyses revealed that the expert participants had significantly better delayed recall scores than the novice participants with all three speed levels, low, $p < .001$, normal, $p < .001$, and high, $p < .001$.

3.2.7. Time on delayed recall test

The mixed design ANOVA showed a significant effect of expertise, $F(1,34) = 654.14$, $p < .001$, $\eta_p^2 = .95$, a significant effect of speed level, $F(1.60,54.29) = 4.76$, $p = .018$, $\eta_p^2 = .12$, and a significant interaction between expertise and speed level, $F(1.60,54.29) = 23.11$, $p < .001$, $\eta_p^2 = .40$. Post hoc analyses for the expert group revealed significant differences between the high speed level and the two other speed levels, low /high $p = .008$ and normal/high $p = .003$, but not between the low/normal speed, $p = .217$. So, experts needed less time on the delayed recall test with the high speed level than with the other two speed levels. Post hoc analyses for the novice group showed significant differences between the low speed level and the other two speed levels, low/normal $p < .001$ and low/high $p < .001$, but not a significant difference between the normal and high speed levels, $p = .493$. So, novices needed less time on the delayed recall test with the low speed level than with the other two speed levels. Further analyses revealed that the expert participants needed significantly less time than the novice participants with all three speed levels, low, $p < .001$, normal, $p < .001$, and high, $p < .001$.

3.3. Discussion of Experiment 2

The aim of the second experiment was to investigate the effects of altering animations' presentation speed on the learning process and learning outcomes. The results showed the occurrence of an expertise reversal effect: Novice players achieved higher recall scores, needed a lower number of repetitions and had to invest less mental effort when the animations were played at a low speed than when they were played at a normal or high speed. Additionally, when the animations were presented at a normal speed they needed a lower number of repetitions and had to invest less mental effort to achieve a similar level of performance than when the animations were presented at a high speed. In contrast, expert players had to invest less mental effort to achieve the same level of recall performance with the same number of repetitions, when the animations were presented at a normal or high speed than when they were presented at a low speed.

As mentioned in the introduction, there are two possible explanations for the effectiveness of decreasing animations' presentation speed for novice players. First, it provides them with additional time to process and integrate the presented information, which reduces the probability that key information is missed (De Koning et al., 2011). In the high speed presentation condition, novice players were forced to process and integrate the fleeting information rapidly, because the same amount of information was presented in less time. As a consequence, the players may have missed some information because it was displayed very briefly (e.g., Schnotz & Lowe, 2008) and/or forgot some information because it was 'overwritten' in WM by the information presented subsequently (Lowe, 1999; Wouters, Paas, & van Merriënboer, 2008). Second, the low speed animation may have highlighted micro-events by making the fine-grained information that occurs within the soccer scene more perceivable (Lowe, 2006; Meyer et al., 2010). For instance, the macro-event "progression of the team bloc" from one stage to another consisted of a set of micro-events such as *overleaping*, *crossing*, and *rotating*. These micro-events often took place simultaneously and players could find it difficult to build a mental model that accurately represented these complex patterns of play. Accordingly, reducing the animation speed may increase the probability that these micro-level events could be correctly perceived, processed and integrated in LTM structures. These findings are opposite to those reported by Fischer et al. (2008) and Fischer and Schwan (2010) demonstrating that the increase of the animation' speed can enhance the participants' understanding if the original events are unfolding rather slowly (i.e., observing the mechanics of a clock). However, those studies did not manipulate the animation's speed in order to handle the fleeting information, but instead advocated accelerating rather slow events. This suggests that decreasing the speed of animation in order to counteract the fleeting nature of dynamic visualizations and to decrease extraneous load is just important for animations depicting events that unfold rather quickly.

On the other hand, experts develop the essential prior knowledge structures to adequately deal with the fleeting information in a normal-paced or even in a high-paced condition. However, these players may need to invest relatively more mental effort in studying unnecessary for them details of the soccer scene in the low presentation speed condition. Indeed, it is conceivable that in this condition, expert players may have been forced to attend to detailed information for a longer time (than in the normal and high speed conditions), which may have consumed their cognitive resources that otherwise could be devoted to processing higher-level play patterns, thus effectively imposing an additional unnecessary (extraneous) cognitive load in comparison with expert players studying higher-paced presentations (Ayres & Paas, 2007). Processing details that were unnecessary for them could also potentially frustrate these learners thus adding a possible affective explanatory factor.

Altering animations' presentation speed has been considered as an important strategy to improve understanding and learning of complex animations. However, previous studies have focused only on aligning the animations' presentation speed with cognitive resources of novice learners, without recognizing the role of learner levels of expertise as a significant moderating factor of learning. This experiment provided an initial attempt to investigate this issue.

4. General discussion

This study was conducted to test the effectiveness of two ways to alleviate the extraneous cognitive load caused by the fleeting nature of animations and consequently, positively influence the learning process and learning outcomes. Experiment 1 investigated the learning effects of replacing animations representing the dynamics of a soccer scene with equivalent static pictures for novice and expert players. The findings indicated a significant interaction between levels of expertise and instructional formats. The static presentation was more beneficial for novice players whereas the animated presentation was more beneficial for expert players. In Experiment 2, we compared the effect of three levels of animations' presentation speed: low (6 fps), normal (12 fps) and high (18 fps). The results again demonstrated the occurrence of an expertise reversal effect. Novices benefited more from the low speed presentation than from the normal and high speed presentation formats, whereas experts benefited more from the normal and high speed presentation formats. Note that as in most previous studies of expertise reversal, the experts' performance reported in the two experiments did not actually deteriorate in comparison with novices. The experts still performed better than novices regardless of the instructional format used to portray the soccer scene, which replicates and extends the growing literature on expertise in general, and sport in particular (see Gegenfurtner, Lehtinen, & Säljö, 2011 and Mann et al., 2007 for meta-analyses; Allard et al., 1980 and Abernethy, Baker, & Côté, 2005 for experimental studies). What is essential for an expertise reversal effect, the relative effectiveness of the formats reversed – i.e., if format A was better than format B for novices then format B was better than format A for experts – however, even with format A, experts still performed better than novices.

Even though the expertise reversal effect seems to be very robust in technical and academic domains with instances of the effect found in a wide variety of instructional contexts in mathematics, science, engineering, programming, accountancy, language and literature, management and other fields (e.g., Kalyuga, 2007), there hardly have been any direct studies of the effect in the sport-related fields. One exception that needs to be mentioned is the explicit monitoring effect which has been recently discussed in relation to the expertise reversal effect (Kalyuga, Rikers, & Paas, 2012). According to this effect, explicit attention to fine details of movements could be productive for their execution by novices and counterproductive for experts (e.g., Beilock, Bertenthal, McCoy, & Carr, 2004). For example, some research have demonstrated that experienced players operating in familiar sporting contexts (e.g., such as golf putting, soccer dribbling, and baseball batting) benefit more from conditions that limit attention to execution (e.g., performing a secondary auditory monitoring task) than conditions that prompt step-by-step control (e.g., focusing on a specific aspect), while inexperienced players show the opposite pattern (Beilock, Bertenthal, Hoerger, & Carr, 2008).

Even though the current study did not investigate the effects of different presentation formats on actual execution of observed movements, the general patterns of results are the same, thus providing an additional support to the findings and indicating the need to include actual skill execution measures in learning outcomes in future studies. Also, participants in most of previous studies of expertise reversal effect were students ranging from primary school to university levels. The number of studies involving actual experts in corresponding domains is very limited and definitely needs to be extended. This paper adds one more study to this number.

Visual representations are omnipresent in coaching team-sport activities, especially during debriefing sessions. These representations, trying to simulate different situations of play, are usually used by coaches in two forms: on the one hand, in a static way – via blackboard – to depict the relative movements of players in the field, and on the other hand, in a dynamic way – via animation/video – to illustrate the functioning of a playing system and/or disclose the playing system of the opponent team. This study demonstrated that such types of representation (i.e., static or dynamic) captured the essence of expertise and indicated that proficient players developed a higher perceptual sensitivity than novice counterparts to static and dynamic visualizations. However, even though such visual representations are extensively employed to train and improve perceptual skills, they are low in ecological validity as they involve conditions rather dissimilar to those experienced in real game settings (i.e., in natural conditions). Simulated visualizations lack the functional relationship between perception and natural movements, which are important to capture if the goal is to reveal knowledge about the nature and function of perception (Gibson, 1979).

Besides, it is important to emphasize that in the present studies, the animations were not accompanied by oral commentaries that would be a supportive tool to guide players' attention to specific information in the scenes. The occurrences of the effects with such more comprehensive instructional tools need to be investigated in future studies. Moreover, future studies need to replicate these findings with a number of animations that are more complex (i.e., involving more than 6 players) and unfold at several speed levels (e.g., 25 fps), or with participants at intermediate levels of expertise playing in a soccer team for 1–5 years. There is some evidence indicating that the quantity of the schemas acquired during years of practice could influence differently the learning processes of expert, intermediate and novice players' (e.g., Abernethy, Neal, & Koning, 1994; Helsen & Starkes, 1999). Finally, learning materials used in this study were limited to specific soccer game scenes. Animations are widely used in many instructional settings. Further studies are required to replicate these findings with other materials – including materials with different shares of cognitive and motor components involved – and other instructional non-sport-specific domains such as mathematics and engineering.

From a practical point of view, this study showed that the level of players' expertise should be taken into consideration by coaches when designing learning material depicting a soccer tactic of play. For novice players, it is better to use static presentations (i.e., a series of static pictures) or animations played at a low speed. When the learner becomes an expert in the domain, animations displayed at normal or high speed should be used to further improve and extend acquired skills. In conclusion, the studies suggest the necessity of adjusting the instructional design of learning materials as learners acquire more domain-specific knowledge.

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