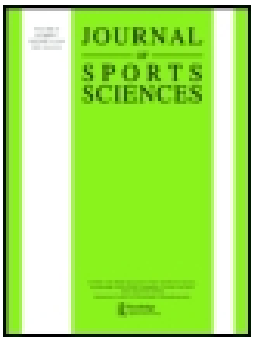

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The key to success in elite athletes? Explicit and implicit motor learning in youth elite and non-elite soccer players

L. Verburgh[a], E. J. A. Scherder[a], P. A. M. van Lange[b] and J. Oosterlaan[a]

[a]Section of Clinical Neuropsychology, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands; [b]Department of Experimental and Applied Psychology, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

ABSTRACT

In sports, fast and accurate execution of movements is required. It has been shown that implicitly learned movements might be less vulnerable than explicitly learned movements to stressful and fast changing circumstances that exist at the elite sports level. The present study provides insight in explicit and implicit motor learning in youth soccer players with different expertise levels. Twenty-seven youth elite soccer players and 25 non-elite soccer players (aged 10–12) performed a serial reaction time task (SRTT). In the SRTT, one of the sequences must be learned explicitly, the other was implicitly learned. No main effect of group was found for implicit and explicit learning on mean reaction time (MRT) and accuracy. However, for MRT, an interaction was found between learning condition, learning phase and group. Analyses showed no group effects for the explicit learning condition, but youth elite soccer players showed better learning in the implicit learning condition. In particular, during implicit motor learning youth elite soccer showed faster MRTs in the early learning phase and earlier reached asymptote performance in terms of MRT. Present findings may be important for sports because children with superior implicit learning abilities in early learning phases may be able to learn more (durable) motor skills in a shorter time period as compared to other children.

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KEYWORDS
Talented athletes; sequential motor learning; skill acquisition; implicit learning; soccer players

Introduction

The main goal of many organisations is to create an environment for young sports talents to optimally develop their performance in a specific sport by providing high level training and coaching and adapted school programmes (Baker, Horton, Robertson-Wilson, & Wall, 2003). This environment is essential for success in sports and is accompanied by high costs and efforts (e.g., Abbott & Collins, 2002; Reilly, Williams, Nevill, & Franks, 2000; Van Hilvoorde, Elling, & Stokvis, 2010). Therefore, effective talent identification and development are a major challenge for national Olympic associations, youth academies, coaches and funding (Abbott & Collins, 2004).

Ample evidence exists on the roles of both genetic factors and training in determining performance of elite athletes and distinguishing elite athletes from less well-performing athletes (Tucker & Collins, 2012). In search of what exactly defines an elite athlete, studies focused on physiological, psychological and neurocognitive factors. It has been shown that physiological characteristics of sports talents (e.g., sprint performance and endurance capacity) distinguish between expertise levels in sports such as soccer, but do not seem to be predictive for future successful performance later in the career (Carling & Collins, 2014). Psychological factors such as motivation, self-confidence and concentration have also been found to discriminate between expertise levels in sports (e.g., Mahoney, Gabriel, & Perkins, 1987), but it is disputable whether psychological factors predict success in sports (see for a meta-analysis, Rowley, Landers, Kyllo, & Etnier, 1995).

During the last decades, there has been an increasing interest in the question whether the brain of elite athletes is different in terms of structure and function (Faubert, 2013). Regarding brain structure, a recent study using diffusion tensor imaging showed alternated white matter microstructure in brain regions that are crucial for voluntary control of movements in karate experts as compared to karate novices (Roberts, Bain, Day, & Husain, 2012). Furthermore, it has been shown that elite athletes have increased cortical thickness in a few areas of the brain and that this increased anatomical volume is correlated with the level of expertise (Wei, Zhang, Jiang, & Luo, 2011). With regard to brain functioning, recent studies focused on neurocognitive performance of athletes in order to investigate whether years of training or innate inter-individual differences in neurocognitive functioning are associated with superior sports performance (see for a review Yarrow, Brown, & Krakauer, 2009). For example, studies report on superior abilities of elite athletes on sport-specific perceptual abilities, visual skills (Savelsbergh, Van der Kamp, Williams, & Ward, 2005) and attention (Mann, Williams, Ward, & Janelle, 2007). However, on nonsport-specific, more basic perceptual skills, visual information processing and reaction time, no differences between expertise levels were found (e.g., Helsen & Starkes, 1999; Kida, Oda, & Matsumura, 2005). Interestingly, it has been shown that elite athletes outperform non-elite

CONTACT L. Verburgh l.verburgh@vu.nl Vrije Universiteit Amsterdam, Department of Clinical Neuropsychology, Van der Boechorststraat 1, Amsterdam, BT 1081, The Netherlands.

athletes on higher order (more complex) nonsport-specific neurocognitive functions (i.e., executive functions) such as inhibition (Alves et al., 2013; Verburgh, Scherder, van Lange, & Oosterlaan, 2014; Vestberg, Gustafson, Maurex, Ingvar, & Petrovic, 2012). In the study of Vestberg and colleagues (2012), it was reported that executive functioning even predicted later performance in soccer in terms of scoring goals and providing assists.

In addition, it may be suggested that another important neurocognitive function in sports is the ability to acquire complex movements (Di Cagno et al., 2014; Doyon & Benali, 2005; Yarrow et al., 2009). A recent study investigated motor learning in elite and sub-elite gymnasts and found that learning rate on sport-specific motor skills predicted competition ranking in later years (Di Cagno et al., 2014). Furthermore, a study by Faubert (2013) showed that elite adult athletes showed more rapid learning of nonsport-specific complex visual scenes, as compared to lower level athletes and novices. It might thus be that motor learning capacity is a key determinant of the potential that an individual athlete has, and that the rate of learning is crucial in the development of an athlete (Di Cagno et al., 2014; Faubert, 2013).

In 1993, Ericsson and colleagues proposed the theory of "deliberate practice", which is described as intensive practicing and repetition of motor skills (Ericsson, Krampe, & Tesch-Römer, 1993). Studies have shown that learning movements follow a pattern of stages in which a phase of fast learning is followed by a phase of consolidation, which is completed by a phase of optimisation of the movements in terms of precision and timing. This final stage is also called the automatisation phase and requires less attention compared to earlier learning stages (Brashers-Krug, Shadmehr, & Bizzi, 1996; Penhune & Steele, 2012).

These phases of learning, consolidation and automatisation are strongly linked to different conceptualisations of learning. In particular, skill acquisition can be reached by explicit or implicit learning. Explicit learning is the learning of new skills using explicit instructions and rules, resulting in declarative knowledge and the ability to articulate how to perform the skill (Liao & Masters, 2001). In contrast, implicit learning is learning unconsciously, without instruction and rules, leading to few declarative knowledge (Reber, 1989; Rendell, Farrow, Masters, & Plummer, 2011). A review of Reber (2013) summarised existing literature on neural substrates of implicit and explicit motor learning and reported that implicit motor learning reflects general plasticity of neuronal circuits. Interestingly, studies showed that experts in sports and music show enhanced structural and functional plasticity in neuronal networks as compared to novices (Chang, 2014; Nakata, Yoshie, Miura, & Kudo, 2010; Wei & Luo, 2010).

Implicit learning has several advantages over explicit learning. First, execution of implicitly learned motor skills is more stable in terms of intra-individual variability than explicitly learned skills (Gabbett & Masters, 2011; Poolton, Masters, & Maxwell, 2007). Second, it is not related to the intelligence of the learner (Maybery, Taylor, & O'Brien-Malone, 1995). Third, a study by Liao and Masters (2001) showed that elite table tennis players who learned a new skill implicitly, performed better than a group that explicitly learned a skill when a secondary task was added. Fourth, implicitly obtained skills are less vulnerable to choking under pressure (Lam, Maxwell, & Masters, 2009; Masters, Poolton, & Maxwell, 2008). Choking under pressure is a well-known phenomenon in sports, which describes a decrease in performance with increasing stress put on an athlete (Hill, Hanton, Matthews, & Fleming, 2010). Choking under pressure is one of the key concepts of the reinvestment theory (see Masters et al., 2008 for a review). This theory describes decreases in performance due to reinvestment during execution of a learned movement under acute stress. Results of numerous studies suggest that implicitly learned movements are less prone to reinvestment because an athlete does not have explicit, declarative knowledge about the skill (e.g., Lam et al., 2009; Masters et al., 2008) and therefore cannot "think" about execution of the skill. However, an interesting recent study on reinvestment in athletes proposed that reinvestment is not always negative. Sometimes, learned movements must be changed or verbalised to be improved (Malhotra, Poolton, Wilson, Omuro, & Masters, 2015). In addition, explicit knowledge through reinvestment may be advantageous in some situations, for instance when declarative knowledge is required for transfer of knowledge to new skills or during teaching (Sun, Merrill, & Peterson, 2001).

Surprisingly, very little is known about skill acquisition and motor learning in young talented athletes. However, learning rate, preferred learning style or reinvestment characteristics during learning in talented youth may not only be a key factor in the development of an athlete, but may also provide valuable information for coaching (Gabbett & Masters, 2011).

To the best of our knowledge, the present study is the first to address sequential explicit and implicit motor learning in youth talented athletes by comparing youth elite soccer players (playing at a premier league soccer club's youth academy) to non-elite soccer players (playing at a regular amateur soccer club). Explicit and implicit motor learning will be measured using the serial reaction time task (SRTT), which is developed in by Nissen and Bullemer (1987) to investigate the influence of adding a secondary task on learning. In the SRTT, participants are required to learn a sequence of stimuli, which should be automatised after intensive practice of the sequence (for a review, see Robertson, 2007). The SRTT has been shown a valid instrument for measuring motor learning in a broad range of age-groups, healthy populations and clinical populations such as attention-hyperactivity deficit patients, Parkinson's disease, Alzheimer's disease and dyslexia (Barnes, Howard, Howard, Kenealy, & Vaidya, 2010; De Kleine & Verwey, 2009; Van Tilborg & Hulstijn, 2010; Vicari, Marotta, Menghini, Molinari, & Petrosini, 2003). Perceptual processing plays an important role in the SRTT (Robertson, 2007), but as has been shown in previous research, nonsport-specific stimulus perception and visual information processing do not differ between athletes with different expertise levels (e.g., Helsen & Starkes, 1999). Therefore, the SRTT is expected to be useful for investigating rate of motor learning in athletes differencing in expertise levels. Furthermore, because the soccer players in the present study are not familiar with learning skills with their hands, the elite soccer players could not benefit from experience in terms of soccer training or expertise on this task, and results may therefore provide new insights about a possible underlying capacity that facilitates highly talented athletes in learning new motor skills. Explicit and implicit motor learning will be investigated parallel in the present study in order to investigate whether youth elite soccer players faster learn explicit or implicit motor sequences as compared to non-elite youth players (see Song, Marks, Howard, & Howard, 2009; Willingham & Goedert-Eschmann, 1999).

Methods

Participants

Fifty-two soccer players participated in the present study. Twenty-seven elite soccer players (mean age 12.3 years, SD .63, all male) were recruited from two youth academies of a Dutch Premier League soccer club. Twenty-five participants played at an amateur soccer club in Amsterdam (mean age 11.5 years, SD 1.2, 9 females) and were recruited from teams in the same age-category as the elite soccer players. The elite soccer players all played in the highest competition level for their age, and on average four levels higher than the amateur soccer players (see for more details on the Dutch soccer system Verburgh et al., 2014). Participants were free of known behavioural, learning and medical conditions that might impact performance on the motor learning task and were excluded when they had an IQ < 70, measured by a short form of the Wechsler Intelligence Scale for Children III (Wechsler, 1997). Furthermore, because some evidence suggest an association between playing a music instrument and motor skills (Romano Bergstrom, Howard, & Howard, 2012), we asked whether participants played an instrument and if so, which instrument they play, since when, and if the participant attended lessons. We also assessed gaming and computer time (Barnett, Hinkley, Okely, Hesketh, & Salmon, 2012; Hammond, Jones, Hill, Green, & Male, 2014; Rosenthal et al., 2011), by a self-report questionnaire (TNO, 2007). Total minutes per week spent on gaming (game console such as Nintendo® or PlayStation®) and total minutes per week spent on the computer (personal computer, laptop or tablet) were included as dependent measures. Demographics of both groups are displayed in Table 1. The study was approved by the local ethical committee of the Institutional Review Board of the Vrije Universiteit Amsterdam. All participants and parents and/or legal guardians were informed about the procedures of the study before giving their written informed consent prior to participation.

Materials

SRTT

A modified version of the SRTT (Robertson, 2007) was used to measure explicit and implicit motor learning in parallel. Four squares were horizontally presented on a computer screen with a black background (Figure 1). The squares were 2.5 × 2.5 cm and corresponded to keys on the keyboard. The most left square corresponded to the V key, the second square to the B key, the third to the N key and the most right square to the M key. The participants were required to lay the fingers of their dominant hand on top of the keys (with the index finger on the V etc., or the little finger on the V for left-handed participants).

Table 1. Participant characteristics.

	Elite soccer players (N = 22) Mean (s)	Non-elite soccer players (N = 22) Mean (s)	Statistics
Demographics			
Age	12.3 (.63)	11.5 (1.2)	$p = .006$[a]
Soccer experience (years)	7.9 (2.7)	5.1 (2.3)	$p = .001$[a]
Total time spent in soccer (h/week)	7.33 (1.4)	4.57 (1.7)	$p = .001$[a]
Estimated full-scale IQ	100 (14.7)	105 (14.2)	$p = .26$[a]
% right-handed	89	88	$p = .60$[b]
Plays music instrument (N)	4	5	$p = .40$[b]
Gaming (min/week)	171.1 (217)	184.4 (293.2)	$p = .85$[a]
Computer time (min/week)	495 (539.7)	490.8 (415.4)	$p = .98$[a]
Questionnaire			
Recall explicit sequence	25.9%[c]	23.3%[c]	$p = .43$[b]
Recognition explicit sequence	52%[c]	66%[c]	$p = .10$[b]
Recall implicit sequence	8.9%[c]	4.6%[c]	$p = .70$[b]
Recognition implicit sequence	23.5%[c]	10%[c]	$p = .44$[b]

IQ: Estimated full-scale intelligent quotient. [a]Univariate analysis of variance; [b]Fisher's exact test; [c]Percentage correctly recalled and recognised of the participants who reported to suspect an order in the implicit sequence.

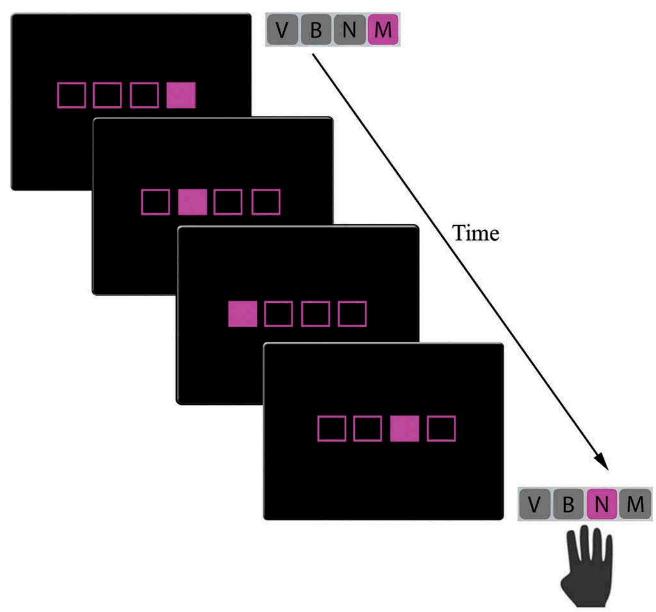

Figure 1. Schematic representation of the first four windows of the explicit sequence of the serial reaction time task (SRTT). The most left square corresponded to the V key, the second square to the B key, the third to the N key and the most right square to the M key. Participants were required to lay the fingers of their dominant hand on top of the keys (with the index finger on the V etc., or the little finger on the V for left-handed participants). One of the squares filled in solid yellow for the implicit sequence, or fuchsia for the explicit sequence. When a participant responds by correctly pressing the corresponding key (V, B, N or M), the next square filled in solid yellow or fuchsia after a fixed interval of 120 ms.

There were two learning conditions in this paradigm. In the explicit learning condition, the sequence that participants were required to learn consisted of a sequence of targets with a fuchsia border that filled in solid fuchsia in the following order: MBVNBMNV. In the implicit learning condition, the sequence consisted of targets with a yellow border that filled in solid yellow. The reversed order (VNMBNVBM) of the explicit condition was used in order to control for complexity of the sequence. A sequence started with a 500 ms interval after one of the squares filled in solid fuchsia or yellow to which the participant was required to respond as fast as possible by pressing the corresponding key on the keyboard. The task started with one block of 10 practice trials with a standardised sequence of four fuchsia squares: VBNM. With this simplified example of the explicit condition, participants were instructed about seeing and learning an order of fuchsia (explicit) stimuli in an explicit way. Following the practice trials, participants were instructed to learn the eight targets of the fuchsia sequence (like in the practice trials). Nothing was told about yellow stimuli. Five test blocks were administered, each containing 25 explicit and 25 implicit learning condition trials, presented in a randomised order, but identical for each participant. In total, both learning conditions were performed 125 times by a participant. All four target squares remained on the screen during a trial. The target square remained filled in fuchsia or yellow until the participant responded correctly. The inter-stimulus interval was 120 ms, the inter-trial interval 500 ms, and there was a short break between blocks. At the end of each block, the participants received feedback about their mean reaction time (MRT) and accuracy of the preceding block. The MRT and accuracy of each test block (learning phase) and of both learning conditions were used as dependent variables.

After completion of the SRTT, participants immediately filled in a short questionnaire about the task that first asked them to recall the explicit learning condition and then to identify the explicit sequence from a four-choice question (recognition test). Next, it was asked if the participant had anything to report about the yellow stimuli and if the participant said that he or she suspected a sequence in the yellow stimuli, the recall and recognition questions were examined for the implicit learning condition as well. Aim of the questionnaire was to ensure that participants indeed gained declarative knowledge of the explicit learning condition, but not of the implicit learning condition. Recall scores were considered correct when at least five consecutive items of the 8-key sequence were correctly recalled, following procedures of Willingham and Goedert-Eschmann (1999) and Robertson, Pascual-Leone, and Press (2004) by using five items as cut-off score for having achieved explicit knowledge about a sequence.

Full-scale IQ estimation

Full-scale IQ was estimated by the Wechsler Intelligence Scale for Children III (Wechsler, 1997). Two subtests (Vocabulary and Block Design) were administered and subtest scores were converted into a composite score that was used to calculate an estimated, which each correlate >.90 with full-scale IQ (Groth-Marnat, 1997).

Procedure

The elite youth soccer players performed the test in a quiet room at their soccer academy, prior to their soccer training. Non-elite soccer players were tested in a quiet room at the VU University Amsterdam, also prior to training hours. Participants were tested individually and assessed by trained assessors using standardised task and debriefing instructions. First, Full-scale IQ was estimated by the Wechsler Intelligence Scale for Children III. Next, the Serial Reaction Time test was administered, followed by the questionnaire examining awareness of the learned motor sequences.

Statistical analyses

SPSS version 22.0 was used for all statistical analyses. A total of eight participants (five elite soccer players and three non-elite soccer players) were excluded from further analyses due to trying to influence task performance by switching fingers on the keyboard or making more than 20% errors, suggesting poor compliance with the task instructions.

Possible group differences in age, IQ, gaming and computer time were tested using univariate analyses of variance (ANOVA) and Pearson correlations within each group were performed to determine the possible relationship between those variables and SRTT measurements. Analyses were performed without participants who recalled the sequence of the implicit learning condition to limit possible effects of declarative knowledge about the performance (Kathmann, Rupertseder, Hauke, & Zaudig, 2005; Knopman & Nissen, 1991). Next, to examine the results of the task manipulation and possible group differences, MRTs and accuracy of both explicit and implicit learning conditions derived from the SRTT were subjected to separate two-way repeated measures ANOVA with two within-group factors: MRT or accuracy of learning phase (five levels: block 1–5), learning condition (two levels: explicit and implicit) and group (two levels: elite soccer players and non-elite soccer players) as between-participant factor. Polynomial contrast analyses were performed to examine linear, quadratic or cubic trends as previous research has shown asymptotic learning curves on the SRTT (Poldrack et al., 2005; Stickgold, 2005). Furthermore, the potential confounding effects of several covariates were tested and sensitivity analyses were performed for age, IQ, gaming, computer time, gender, handedness and playing an instrument, and if required, included as covariates in the final two-way repeated measures ANOVA's on MRT and accuracy and subsequent polynomial contrast analyses. Greenhouse–Geisser corrections were applied when the sphericity assumption of the F test was violated. Effect sizes were calculated in terms of ηp^2 with values .01, .06 and .14 referring to small, moderate and large effects (Cohen, 2013). Effect sizes of larger than .01 are generally interpreted as practically relevant (Winter, Abt, & Nevill, 2014), although they should be interpreted with caution because a negative relationship with sample size has been shown, indicating that small sample sizes may result in overestimation of effect sizes (Kühberger, Scherndl, & Fritz, 2013). Descriptive analysis included means ± SD and 95% confidence intervals (CIs) for dependent variables. Alpha was set at .05.

Results

Participants

Group characteristics are presented in Table 1. Two elite soccer players and one non-elite soccer player (all male) correctly recalled the at least five items of implicit sequence, and these three participants were excluded from further analyses to minimise the influence of explicit knowledge on reaction times in the implicit sequence (Kathmann et al., 2005; Knopman & Nissen, 1991). Age was significantly related to MRTs of both the explicit and implicit learning condition only for the first block (r = −.48, p < .001 and r = −.51, p < .001 for the explicit and implicit sequence, respectively), indicating that older children were faster in the first block of both learning conditions. Therefore, age was included as covariate in further analyses. Significant Pearson correlations were also found between IQ and the MRTs (−.05 > rs < −.45, .002 > ps < .05), indicating that a higher IQ is associated with faster MRTs. However, because groups did not differ on IQ, IQ was not included as covariate. Gaming and computer time were not associated with MRTs of both sequences (.02 > rs < .26, .09 > ps < .94).

SRTT

The two-level repeated measure analysis with MRTs of both learning conditions as dependent variables, age as covariate and group as between-participant factor revealed a linear effect of learning condition (F(1,38) = 5.5, p < .05, ηp^2 = .01), indicating faster MRTs in the explicit learning condition . Furthermore, a linear effect of learning phase was found (F(1,38) = 17.6, p < .001, ηp^2 = .31), indicating faster MRTs in later blocks. The quadratic effect of learning phase was also significant (F(1,38) = 13.9, p = .001, ηp^2 = .26), indicating that MRTs approached an asymptote in later blocks. There was no significant interaction effect between learning phase and learning condition (F(4,35) = .67, p = .62, ηp^2 = .01), indicating that the decreases in MRT during the task were not different for the learning condition. Furthermore, no significant main effect of age (F(1,38) = .61, p = .55, ηp^2 = .00) and no significant interaction between learning condition and age (F(1,38) = .91, p = .35, ηp^2 = .03) was found. However, an interaction effect was found between learning phase and age (F(4,35) = 3.4, p < .05, ηp^2 = .27). *Post hoc* pair-wise comparisons between blocks indicated that older participants showed faster MRTs than younger participants, but only in the first block of the explicit sequence (F(1,38) = 2.0, p < .05, ηp^2 = .09).

Moreover, no statistical significant main effect of group (F(1,38) = .61, p = .44, ηp^2 = .02), no significant interaction between learning phase and group (F(4,35) = .56, p = .70, ηp^2 = .01) and no significant interaction between learning condition and group were found (F(1,38) = .13, p = .72, ηp^2 = .003). However, a significant linear effect between learning phase, learning condition and group was found (F(4,35) = 4.4, p < .05, ηp^2 = .21), indicating that the interaction between learning phase and group was different for the individual learning conditions (Table 2 and Figure 2).

To further investigate the three-way interaction, *post hoc* repeated contrast analyses were performed which showed no significant group differences or interactions between group and learning phase for the explicit motor sequence (all contrasts ps > .05). However, for the implicit learning condition, interaction effects were found between learning phase and blocks 2 and 3 (F(1,38) = 6.7, p < .05, ηp^2 = .15) and blocks 3 and 4 (F(1,38) = 4.6, p < .05, ηp^2 = .11). No significant interactions were found between learning phase and group for blocks 1 and 2, and 4 and 5 (F(1,38) = 1.1, p = .29, ηp^2 = .03 and F(1,38) = .23, p = .63, ηp^2 = .006, respectively). This indicates that the groups started and ended at similar MRTs, but that in the third block of the implicit learning condition, the MRTs of the elite soccer players already approached an asymptote, whereas the MRTs of the non-elite soccer players continued learning between the third and fourth block.

Table 2. Mean reaction time and confidence interval's for both groups per learning phase.

	Elite soccer players Mean (s)	Non-elite soccer players Mean (s)
Explicit sequence		
Block 1		
Mean (s)	557.7 (153.8)	547.5 (134.11)
95% CI	496.5–618.3	484.5–611.9
Block 2		
Mean (s)	445.2 (113)	459.14 (99.5)
95% CI	389.2–491.1	412.1–505.2
Block 3		
Mean (s)	379.53 (96.4)	418.66 (100.6)
95% CI	337.1–422	375.2–462.1
Block 4		
Mean (s)	346.0 (82.1)	370.3 (95.5)
95% CI	308.3–383.7	328.6–417.3
Block 5		
Mean (s)	341.5 (87.3)	360.4 (87.3)
95% CI	304.9–378.7	321.9–399.8
Implicit Sequence		
Block 1		
Mean (s)	558.2 (134.8)	551.5 (139.2)
95% CI	499.2–616.2	491.2–611.9
Block 2		
Mean (s)	448.8 (95.6)	487.6 (100.6)
95% CI	499.2–616.2	441.6–533.6
Block 3		
Mean (s)	337.6 (77.2)	426.3 (93.4)
95% CI	301.7–473.4	388.6–464.0
Block 4		
Mean (s)	332.9(76.4)	364.0 (88.4)
95% CI	297.4–386.5	328.6–417.3
Block 5		
Mean (s)	331.2 (81.1)	354.0 (89.3)
95% CI	308.3–382.1	336.2–410.7

CI: Confidence interval.

The two-level repeated measure analysis with accuracy of both learning conditions as dependent variables revealed no significant main effect of group and no significant interactions between group, learning phase or learning condition were found on accuracy (all Fs < 1.0, ps > .16). Additionally, the main effects of age and interactions involving age on accuracy were not significant (all Fs < 1.5, ps > .22). Moreover, Pearson correlations showed that accuracy was not significantly related to MRT (.18 > rs <−.18, .93 > ps < .21), indicating that there was no speed-accuracy trade-off.

Rerunning the two-way repeated measure ANOVA's with IQ, gaming computer time as covariates showed that results remained unchanged. Furthermore, separate analyses were rerun without participants playing an instrument, females and left-handed participants, which also did not influence the results.

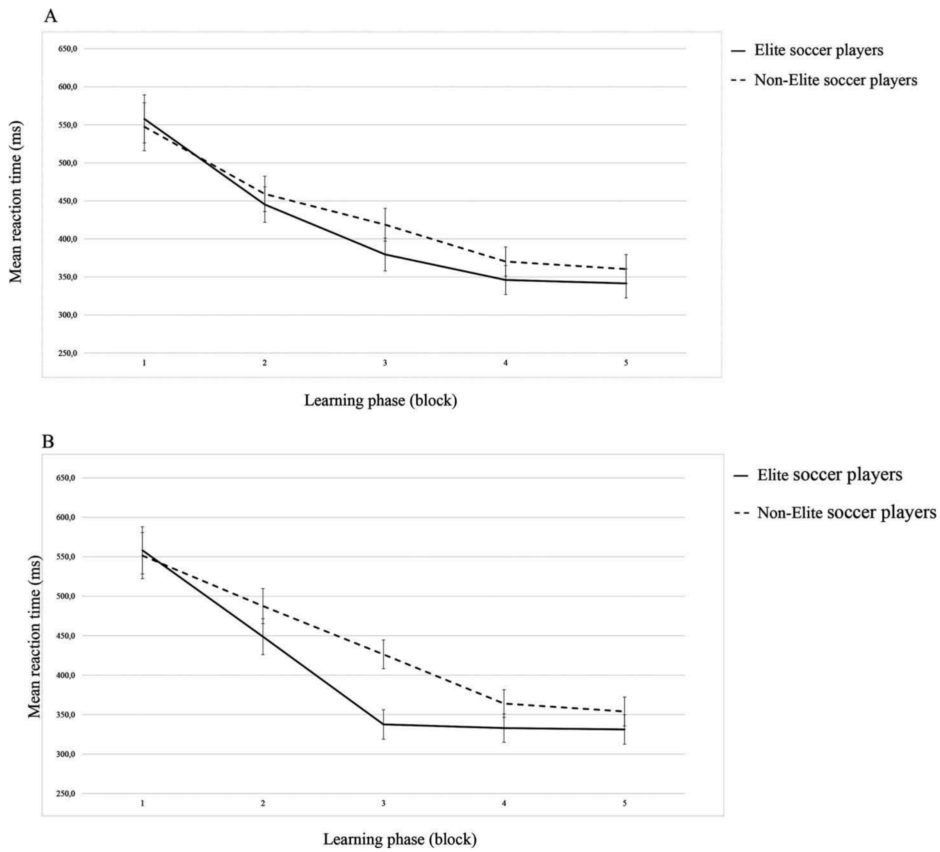

Figure 2. Learning curves for both groups. (A) Mean reaction times (MRTs) per block for the explicit learning condition; (B) MRTs per block for the implicit learning condition. Vertical bars show standard errors of the mean.

Recall and recognition questionnaire

Free-recall and recognition of the learning conditions were analysed to assess the effectiveness of the sequence manipulation. It was shown that 24.6% of the participants correctly recalled the complete explicit sequence, and 59% correctly recognised that sequence (from a four alternatives forced-choice question). For the implicit sequence, 64% of the participants did suspect an order in the stimuli. Only 9% of these participants who suspected an order in the stimuli correctly recalled five or more items of the implicit sequence, indicating that only 4.9% of all participants recalled the sequence. Twenty-six per cent of the 64% that suspected an order correctly recognised the sequence, which means that only 17% of all participants correctly recognised the sequence. As there are no commonly used cut-off values to define awareness of learned sequences, we followed procedures of Willingham and Goedert-Eschmann (1999) and Robertson et al. (2004) by using five items as cut-off score for having achieved explicit knowledge about a sequence. Our results compare favourably with those of a study using a 10-key sequence to measure implicit motor learning in children aged 6–10, which showed 60–80% recognition and 30–40% recall scores in these age groups (Savion-Lemieux, Bailey, & Penhune, 2009). There were no group differences in recall and recognition for both sequences. Group results are shown in Table 1.

Discussion

The present study investigated implicit and explicit motor learning in young talented athletes by comparing elite soccer players and non-elite soccer players in terms of speed of motor learning using the SRTT.

Results show a steep learning curve as measured by MRTs of both learning conditions: During the first three blocks, a rapid decrease in MRTs was found for both the explicit and implicit learning condition with performance approaching asymptote performance in the last blocks. This result is in line with the learning phases described by Penhune and Steele (2012). It was shown that MRTs of the explicit learning condition were somewhat faster than MRTs of the implicit sequence, which is also in line with previous literature (Curran & Keele, 1993; Maxwell, Masters, & Eves, 2000). In the study of Maxwell and colleagues, it was found that performance on a skill was poorer in the early learning phase when a skill was learned implicitly, as compared to the explicitly learned skill. In our study, the on average slightly slower MRTs of the implicitly sequence seem to be due to the less steep learning curve of the implicit learning condition of the non-elite soccer players as compared to the elite soccer players.

Results of the explicit learning condition suggest that when participants were explicitly instructed on learning the sequence, both soccer-player groups showed similar performance with equal learning curves with a similar decrease in reaction times during the course of the task.

Importantly, the elite soccer players learned more rapidly on the implicit learning condition, reaching asymptote performance after the third block with fast and stable execution of the motor sequence, whereas the non-elite soccer players continued learning during the fourth block. Effect sizes of .15 and .11 were found for the differences between groups between the second and third, and third and fourth block, indicating a moderate to large effect. These results provide preliminary evidence that when nothing is told about what should be learned, or even that something should be learned, the elite soccer players learn faster than the non-elite soccer players. In other words, it may be suggested that elite soccer players are superior during the early learning phase. The rapid first stage improvement in performance is attributed to the cortico-cerebellar and cortico-striatal networks and it has been shown that the lateral cerebellum plays a crucial role in early implicit motor learning (Penhune & Doyon, 2005; Tzvi, Münte, & Krämer, 2014). Moreover, a recent study showed that white matter integrity of the dentato-thalamo-cortical tract, connecting the lateral cerebellum to motor and prefrontal areas, is associated with motor sequence learning (Schulz Wessel, Zimerman, Timmermann, Gerloff, & Hummel, 2015). In addition, it has been shown that white matter integrity of these circuits predicts performance during implicit motor learning (Bennett, Madden, Vaidya, Howard, & Howard, 2011), which may lead to the suggestion that youth elite soccer players have better connectivity in these circuits. Our results are in line with studies on brain structure and functioning in experts on sports and music (Chang, 2014; Nakata et al., 2010; Roberts et al., 2012; Wei & Luo, 2010), supporting the relationship between general brain plasticity, motor learning skills and expertise. However, as also stated in a review on plasticity and learning by Zatorre, Fields, and Johansen-Berg (2012), it could be questioned whether learning results increased white matter integrity or whether enhanced white matter integrity is a key characteristic of fast learning capacities. Scholz and colleagues (2009) investigated the effects of experience on white matter integrity and showed that 6 weeks of juggling training resulted in increased white matter integrity in healthy adults, suggesting that learning results in increased white matter integrity. Nevertheless, despite recent findings on experience induced brain structure adaptations (see for reviews, Dayan & Cohen, 2011; Zatorre et al., 2012), it is possible that some children have an innate higher brain plasticity and are (therefore) more likely to participate in high level sports training and/or become an elite athlete. In short, causality and the direction of possible causality remain unknown and in view of talent identification and development of future elite athletes and musicians, future longitudinal studies on motor learning and white matter integrity are required. Specifically, studies on the youngest soccer players that are selected for a professional youth academy or talent development programme are required, because only in this way, conclusions could be drawn about the possibility of enhanced cognitive functions and/or brain structure and functioning as a result of soccer training and experience. Either way, assessing white matter and cognitive functions in youth talented soccer players, might have a large impact on talent identification and development, since a growing body of research showed the importance of excellent cognitive functioning for performance and success on the field at the elite sports level (e.g., Cona Cavazzana, Paoli, Marcolin, Grainer, & Bisiacchi, 2015; Romeas & Faubert, 2015; Vestberg et al., 2012).

Importantly, a study by Rendell et al. (2011) showed that implicit learning was effective in improving already learned sport-specific techniques also in expert performers (professional netball players). Gabbett and Masters (2011) described several possible effective strategies for improving implicit learning such as the use of errorless learning (learning without mistakes through step-by-step introducing of parts of a new skill), random practice (flexible working on skills, instead of a logical structure during training) or using dual-tasks to avoid step-by-step learning of a specific skill. However, because implementing such strategies in already highly skilled athletes is difficult, Maxwell, Masters, and Poolton (2006) suggested to make use of an external focus of attention during skill execution, which also prevents reinvestment in high-pressure situations. Related to this, it has been shown that low reinvesters perform better during early learning phases as compared to high reinvesters (e.g., Maxwell et al., 2000), although a study by Malhotra and colleagues (2015) suggested that reinvestment in the early learning phase might be sometimes beneficial, because it generates explicit knowledge about a to be learned skill. This in turn might be necessary to adapt technical execution of the skill. To be able to draw conclusions about the possible necessity of reinvestment in early learning and the relationship with performance under pressure, future research should study implicit motor learning in talented athletes and assess reinvestment using the Movement-Specific Reinvestment Scale (Masters, Eves, & Maxwell, 2005).

We should also acknowledge some limitations of the present study. A first limitation is that the assessment of implicit motor learning may have been affected by some explicit thought processes in which participants verbalised the sequence. It is not clear how this may have influenced the key findings of the present research. However, this is a well-known problem when aiming to measure implicit motor learning, and in our study we directly manipulated awareness about the implicit sequence by measuring explicit motor learning in parallel. As a result, participants focused on the explicit sequence (Robertson, 2007). Second, the current study does not allow drawing conclusions about possible differences in robustness of both types of motor learning. This is an important issue because in elite sports, motor skills should be fully automatised in order to benefit performance (Beilock & Carr, 2001). Inclusion of a delayed retention task would allow examining robustness in performance of both types of motor learning (Stickgold, 2005) and an offline learning period (e.g., sleeping) could be included in order to investigate consolidation of both types of motor learning (Robertson et al., 2004). Moreover, it would be interesting to translate the SRTT to gross motor skills with direct relevance for soccer to increase generalisability on achieving soccer-specific motor skills. Translation to soccer-specific motor skills is relevant because the results suggest that talented athletes specifically outperform non-elite peers in the early phase of implicit learning, and in view of the theory of reinvestment during early learning, it would be interesting to investigate whether in soccer-specific skills, the highly talented players are also superior in the early phases, which may lead to the practical implication of implicit instructions during the learning of sport-specific skills. A third limitation is that, although controlled for in the analyses, and despite all participants playing in similar age-classified teams, the elite soccer players were significantly older than the non-elite players (ηp^2 = .12). This could be explained by the relative age effect: Athletes born closest to the cut-off age used for admittance to a particular age group are overrepresented in a talented group because they are often more matured as compared to their younger peers. This effect is commonly seen in elite sports (Hancock, Adler, & Côté, 2013). The elite soccer players also reported more years of experience in soccer (they started at a younger age, ηp^2 = .08). For future research, it is suggested to compare soccer players with similar years of experience and trainings hours to be able to conclude more about possible underlying mechanisms of a higher rate of implicit learning in talented athletes.

In conclusion, the present study showed that with explicit learning instructions, youth elite soccer players did not learn faster as compared to youth non-elite soccer players, but when learning was implicit (unintentionally), elite soccer players outperformed the non-elite soccer players in rate of learning. Results should be replicated and include a delayed retention task to draw conclusion about robustness of our findings and whether individual differences in the efficiency of implicit motor learning could be predictors for future levels of performance.

Disclosure statement

No potential conflict of interest was reported by the authors.

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