Chapter 1

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What is perceptual-motor automatization?

In human perceptual-motor performance, the first attempts at mastering a novel skill are in general heavily reliant on attentional resources to guide and monitor performance (Anderson, 1993; Fitts & Posner, 1967). Driving a car for the first time requires the coordination of multiple actions to bring the car even into motion. Attention must be divided between coordinating feet and hands (accelerating, braking, shifting, and steering) as well as picking up essential information from the environment, such as road signs and other vehicles. With extensive practice, coordinating the basics of driving a car requires less and less attentional resources and after years the experienced driver is able to use all limbs in driving, adequately monitor the environment, tune the radio, and have a conversation with passengers. Driving a car can then be regarded as automatized as there is little need left for conscious attention to the mechanics of driving. Without this process of automatization, performing a complex skilled action such as driving a car, performing an action in sports, or even walking would be impossible.

As skill automatization is one of the cornerstones of human behavior, research on the topic has been vast. One generally accepted idea on skill automatization is the ‘stages’ view (Anderson, 1993; Bernstein, 1996; Fitts & Posner, 1967). The common denominator in these theories is that skill acquisition typically passes through different stages of learning that are identifiable from the amount of attention devoted to movement preparation and control. Support for this view comes from experiments that distract attention away from movement execution, as is commonly achieved by adding an irrelevant secondary task to primary task performance. Typically, novice performance is disrupted under such conditions, illustrating the need for novices to attend to movement execution. A novice driver needs to pay all attention to the essentials of driving and cannot even perform a relatively simple cognitive task such as having a conversation. In contrast, a disruption of primary task performance under secondary task loading is not normally reported for expert performers. This is exemplified by the experienced driver who has no problems to engage in conversation while driving.

One of the possible mechanisms behind the decrease in attentional demand over the course of skill acquisition is that the knowledge structures supporting movement execution change over the course of learning. Movement execution during the early development of a skill is characterized by the reliance on declarative or explicit knowledge structures that are consciously accessible by working memory (Anderson, 1993; Gentile, 1998; Masters 1992). Novices typically use verbal instructions, often provided by a coach or teacher and manipulate these in working memory to support movement execution. For instance, driving instructors typically explain to students how to combine clutch and stick shift to
gear up. This information is then manipulated in working memory to be used in movement execution. As learners become more proficient at a task, the underlying knowledge representations gradually transform to procedural or implicit knowledge structures that are inaccessible to conscious awareness (Anderson, 1993; Gentile, 1998; Masters 1992). The experienced driver becomes unaware of his or her driving actions and cannot describe the exact components of his performance, a phenomenon referred to as ‘expertise-induced amnesia’ (Beilock, Wierenga, & Carr, 2002).

One of the earliest documented studies on the topic of movement automatization is the thorough work of Jacques Van der Veldt, a psychologist from Belgium. His work “L’apprentissage du mouvement et l’automatisme” (translated: “The learning and automatization of movements”) was published 1928 and later discussed by Van Parreren (1963). The experimental set-up consisted of a big tablet with twelve randomly placed holes with a light embedded in each hole. The lights corresponded to a visual cues (a three letter syllable without meaning, such as KOF) presented on a screen placed at the far end of the tablet. Participants were required to attend to the visual cue, and correspondingly move the hand to the illuminated light on the tablet. On the basis of subsequent cues the participants learned a sequence consisting of 12 individual movements. Similar to later theories on skill automatization (e.g., Anderson, 1993; Fitts & Posner, 1967) Van der Veldt identified a number of stages in this process. Van der Veldt characterized the first stage as ‘isolated awareness of space’. The action of participants could be clearly divided into isolated processes of cue perception, spatial awareness (where is the corresponding light), and movement (transport of the hand to the target light). Van der Veldt termed the second step in learning the stage of fusion because, within this stage, perception, space awareness and movement fuse together into one action. The visual cues change their meaning and instead of mere locations on the tablet, they come to represent the corresponding movements. The third and final stage is termed automatization. The visual cues automatically bring about the corresponding movements and “over the course of practice the participants couldn’t even remember the visual cue they were presented with” (Van der Veldt in Van Parreren, 1963; translation by Johan Koedijker). The early work of Van der Veldt illustrates the longstanding research interest in the domain of movement and also inspired the experimental set-up reported in Chapter 5.

More recently, Bernstein (1996) argued that the process of automatization entails a shift from higher levels to lower levels of motor control. Bernstein distinguished four hierarchical levels of control in motor learning and performance spanning multiple neurophysiologic levels: the level of tone (level A), the level of muscular-articular links or synergies (level B), the level of space (Level C) and the
level of action (level D). In short, the level of tone is the phylogenetic oldest level and concerns the level of muscle activation. The next level of control, that is, the level of muscle synergies, can be described as the formation of single synergies out of separate muscle activation patterns. Levels A and B form the cornerstones of movement execution, as they provide crucial background corrections in action control, but do not have the capability of actually leading movement control. The next level is the level of space and is considered the first level in the hierarchy that is capable of controlling simple, goal-directed movements of the body. Examples of control exerted at or by the level of space are pointing a grasping, but also actions such as walking or jumping. The highest level of control is the level of action. At this level sequences of separate movements are linked to solve a complex motor problem, such as lighting a cigarette or driving a car.

In the early stages of learning a perceptual-motor skill, the leading level of control, that is, the level of action, has to control and correct numerous aspects of performance; movement execution involves extensive foreground corrections. According to Bernstein, automatization involves the delegation of corrections from higher levels of control to lower levels of control, or, put differently, a shift from foreground to background correction mechanisms (see also Beek, 2000). By transferring corrections to the appropriate lower levels of control, attentional resources are freed and available for other relevant information sources. After this ‘distribution of labor’, the last steps in achieving expertise involve the fine tuning of background corrections, which leads to standardization and stabilization of motor performance, the final steps on the long and bumpy road towards expertise.

As automatized performance can be considered a characteristic of expertise, several strategies to optimize the process of automatization have been studied. As attention appears central in this process, numerous experiments explored the role of attention in skill automatization (Beilock, Carr, MacMahon, & Starkes, 2002; Wulf, Höß, & Prinz, 1998; Wulf, Lauerbach, & Toole, 1999; Wulf, McNevin, Fuchs, Ritter, & Toole, 2000; see Wulf & Prinz, 2001 for an overview). Wulf and colleagues have demonstrated repeatedly that direction of attention is an important factor in learning and subsequent performance. In particular, they have found consistent advantages of an external focus of attention (i.e., attention directed to the environment or the implement used, such as a wobble board or golf club) over an internal focus of attention (i.e., attention directed to the body parts involved in the movement, such as, feet in balancing on a wobble board or hands in golf putting) in learning and performing perceptual-motor tasks (Wulf et al., 1999, 1998, 2000). Importantly, learning and performing with an external focus of attention has been reported to lead to lower attentional demands, as evidenced by lower muscle activity (Vance, Wulf, Töllner, McNevin & Mercer, 2004; Zachry, Wulf, Mercer, &
Bezodis, 2005) and shorter secondary task probe reaction times (Wulf, McNevin, & Shea, 2001) compared to internal foci of attention. Wulf argued that deploying an internal focus of attention may constrain the automatic control processes that typically regulate movement execution, whereas an external focus of attention allows the motor system to better deploy automatic control processes.

Not only instructions or manipulations to guide attention towards the movement effect are thought to speed up automatization processes, it has also been proposed that avoiding explicit knowledge about movement execution during learning would enhance automatization (Masters, 1992). Typically, novices accrue and use explicit knowledge about how to perform a given task during the early stage of skill acquisition (declarative phase; Anderson, 1993). When approaching expertise, performers are no longer reliant on explicit knowledge and use implicit knowledge to guide movement execution. However, Masters (1992) suggested that motor learning does not need to progress through an early, working memory dependent, declarative stage of movement control before becoming automatic and argued that advantages may be associated with learning in this way. Implicit motor learning techniques have been designed, which reduce attention to movement control and encourage the development of procedural or implicit knowledge rather than declarative or explicit knowledge. For example, Masters (1992) sidetracked the attention of novice golfers with a secondary task that required their constant attention during the entire learning phase. The consequence of diverting attention away from movement control was that participants reported very low amounts of declarative knowledge about their putting movements, implying that they had learned implicitly. Implicit motor learning has been demonstrated over relatively short practice periods (50 to 450 practice trials), suggesting that it targets the early, working memory dependent stage of learning (e.g., Maxwell, Masters, Kerr, & Weedon, 2001; Poolton, Masters, & Maxwell, 2006). One important advantage of implicit learning is that it leads to a lower attentional load during subsequent performance compared to the more traditional explicit learning as several experiments demonstrated robust performance of implicitly learned skill over explicitly learned skills under secondary task loading after short practice periods (Liao & Masters, 2001; Maxwell et al., 2001; Poolton et al., 2006). In sum, experimental manipulations that reduce the amount of attention devoted to movement preparation and control, either by guiding attention away towards the action effects or by withholding movement related knowledge, enhance performance automatization and therefore appear beneficial in skill acquisition.
What is deautomatization?
Based on the stages view of skill acquisition, skill automatization can be considered as a reduction in attentional resources needed to plan, execute, and control perceptual-motor performance (Anderson, 1993; Bernstein, 1996, Fitts & Posner, 1967). Whereas automatization received abundant attention in the motor learning literature, the theoretically and practically important reverse process of deautomatization has been left relatively unaddressed (cf. Beek, 2000). According to Bernstein (1996) deautomatization is “the destruction of an already developed automation of a skill” and “a major and dangerous enemy of motor skill” (Bernstein, 1996, p. 199). As an explanation Bernstein argued that “deautomatization influences are observed when a movement is being switched to another, unusual level of control” (Bernstein, 1996, p. 199). As deautomatization can, by definition, only occur in well-learned, automatized skills, it means that deautomatization is caused by conscious attention to one of the background mechanism, thereby switching control from an unconscious background level to a conscious level of control. Within the perceptual-motor performance domain both anecdotal and empirical evidence suggests that deautomatization might be observable under a number of conditions, such as skill-focused attention (Beilock et al., 2002, Gray, 2004), performing under high performance pressure (Beilock & Carr, 2001; Masters, 1992: Masters & Maxwell, 2004) and under extended movement preparation periods (Beilock, Bertenthal, McCoy, & Carr, 2004). These examples will be detailed in the following paragraphs.

Skill-focus instructions
One of the oldest sport psychology tricks in the book involves asking your opponent what he does to his tennis forehand that makes it as good as it is (Gallwey, 1976). By forcing attention towards automatized skill execution, it is argued that skill-focused attention interferes with the control processes that normally run without conscious interference. Beilock et al. (2002) and Gray (2004) investigated the effects on performance of paying explicit attention to movement execution and demonstrated in golf putting, soccer dribbling, and baseball batting alike that such an internal focus of attention harms expert performance. Beilock et al. (2004) argued that directing attention to the control of the movement may be disruptive for an expert but not for a novice. They showed that experts performed more accurately on a golf-putting task when dual-tasking (monitoring for and audibly reporting a specific tone) than when skill-focused (monitoring to keep the club head straight during the swing and verbalizing the word straight at ball contact), whereas novices were to perform more accurately under skill-focused instructions compared to dual-task conditions. All in all, it appears that the performance of relatively automated
movements can be disrupted in situations in which a performer consciously directs attention to movement execution.

**Choking under pressure**

Similarly, it has also been suggested that increased performance pressure might lead to performance deautomatization, a phenomenon also known as ‘choking under pressure’ (Baumeister, 1984; Masters, 1992). In general, in the course of skill acquisition, instructions amass to a pool of explicit knowledge. Once a skill is well-learned, explicit rules accumulated during acquisition may again be processed (reinvested) in working memory to interfere with proceduralized movement execution under demanding circumstances (e.g., under increased performance pressure). Evidence has been presented indicating that withholding learners from accruing explicit rules about movement execution (i.e., implicit learning) results in performance advantages when performance pressure increases (Liao & Masters, 2001; Masters, 1992; Poolton, Masters, & Maxwell, 2005). Masters (1992) demonstrated that when learners perform a concurrent secondary task during primary skill learning, minimal explicit knowledge about movement execution is accumulated and primary task performance is robust to increases in performance pressure. In addition, several alternative methods of implicit learning have been proposed and tested, such as analogy and errorless learning (see Liao & Masters, 2001; Maxwell, et al., 2001, respectively). In analogy learning, only one simple rule is provided. By following this single rule, learners also forego hypothesis testing about their behavior, leading to little accrual of explicit knowledge about movement execution. For instance, Liao and Masters (2001) provided participants with a triangle analogy to help them learn the table tennis forehand. In particular, they instructed participants to pretend drawing a right-angled triangle and hitting the ball while traveling along the imaginary hypotenuse. It appeared that analogy learners accumulated few explicit rules about movement execution yet demonstrated similar learning performance as explicit learners with the added benefit of robustness to performance pressure.

To explain these findings, it has been argued that under increased performance pressure, stored explicit rules can be activated in working memory to interfere with proceduralized movement control, thereby disrupting fluent and automatized movement execution (Masters & Maxwell, 2004). This line of reasoning is called the ‘reinvestment’ or ‘conscious processing’ hypothesis (Hardy, Mullen & Jones, 1996; Liao & Masters, 2001; Masters, 1992, 2000; Mullen, Hardy & Tattersall, 2005). In sum, it appears that bypassing the declarative stage through implicit learning techniques not only installs more automated control mechanisms compared to more traditional explicit learning techniques, it also prevents falling back to a
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conscious mode of control under increased performance pressure.

Performance time
A third example is the anecdotal evidence of tennis players that miss very easy overhead smashes from towering defensive lobs or soccer players that miss an easy score when they seemingly have ‘all the time in the world’. Beilock et al. (2004) showed the same effect by manipulating the time available for movement preparation and execution in a speeded (maximum 3 s to complete each putt) versus an accuracy condition (take as much time as you need). The quicker skilled players took to putt, the better they performed. Beilock, Bertenthal, Hoerger, and Carr (2008) recently isolated this effect to the amount of time spent in putt preparation (the period before stroke initiation). Beilock and colleagues contended that extending the time available to experts during performance heightens the opportunity to attend to movement execution, disrupting “automated processes that normally run as uninterrupted routines” (p. 373).

Interference effects in learning and performing similar movement sequences
Whereas the preceding examples of deautomatization can be all considered involuntary, or negative, in some cases deautomatization might be voluntary or necessary. In situations when a skill is already fully automated but still results in suboptimal performance, resorting to conscious control processes may be a blessing rather than a curse. Bernstein (1996) argued that in automated movements “background corrections” are instantiated at lower levels of the motor hierarchy that occur largely autonomously without interference from the higher levels. In order to breakdown established automatisms it will be necessary to cognitively overrule these lower levels of organization and to consciously correct the execution of the movements, that is, to temporarily substitute the background corrections with foreground corrections. For instance, Masters (1992, 2000) only highlighted the negative effects of explicit knowledge, suggesting that implicit learning is always superior. Both Beek (2000) and Bennett (2000), however, argue that explicit knowledge may sometimes give the performer the ability to overrule or circumvent the automatisms in his or her performance, for instance, when an old injury plays up, or when certain imperfections have become ingrained in the technique during the automatization process. In reshaping imperfect automatisms attention might also play a key role. As argued in the preceding, it is well appreciated that an external focus of attention is more beneficial in learning new perceptual-motor skills than an internal focus (Wulf et al., 1998; Wulf et al., 1999). However, an internal focus of attention might be indispensable in order to override a fully automated movement and adapt, change or improve on it. Hanin, Korjus, Jouste, and Baxter (2002), who
studied learning strategies to correct established errors in technique with elite athletes, also argued that kinesthetic awareness is a prerequisite to change from an old, less effective technique to a new and improved technique.

Outline of the present thesis
The main aim of this thesis is to contribute to our understanding of the role of cognition in motor performance and learning in a number of ways. Chapters 2 and 3 will test the hypothesis introduced by Masters (1992) and others that explicit rules are reinvested when an athlete has to perform under pressure. More specifically, the objective of Chapter 2 was to examine the respective roles of explicit rules and focus of attention in learning, automatization, and performance under pressure. Furthermore, sufficiently long longitudinal studies examining the perceptual-motor consequences of implicit and explicit learning techniques have been lacking, a lacuna that is filled by the study reported in Chapter 3.

A second aim of the thesis is to generate more general insights into skill deautomatization. Therefore we looked at conditions in which deautomatization processes might occur, such as under skill-focus instructions (Chapters 2 and 4), increased psychological pressure (Chapters 2 and 3), shortening and lengthening of movement preparation and performance time (Chapter 4), and in learning similar movement sequences (Chapter 5). Specifically, in Chapter 4 we looked into the effects of expertise and instruction (explicit instructions vs. an analogy instruction) on performance in environments that encourage attention towards movement preparation and execution (i.e., skill-focus instructions or lengthy movement preparation periods) in contrast to environments that minimize the opportunity to attend to movement preparation and execution (i.e., dual-task conditions or high temporal constraints). In Chapter 5 we undertook three experiments to gain insight into the processes involved in the learning of two similar movement sequences with a particular interest in how automaticity of sequential performance influences interference effects between similar movement sequences. The series of experiments reported in Chapter 5 would serve as a possible foundation for future questions such as the possible roles of the direction of attention or the role of explicit knowledge in reshaping movement sequences. Finally, in the epilogue (Chapter 6) the results of the performed experiments are discussed and evaluated within relevant frameworks.
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70, 120-126.


