Using the 'Expert Performance Approach' as a Framework for Improving Understanding of Expert Learning

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Abstract

The expert performance approach, initially proposed by Ericsson and Smith (1991), is reviewed as a systematic framework for the study of 'expert' learning. The need to develop representative tasks to capture learning is discussed, as is the need to employ process-tracing measures during acquisition to examine what actually changes during learning. We recommend the use of realistic retention and transfer tests to infer what has been learned, so that the effects of various interventions on learning may be evaluated. A focus on individual differences in learning within groups of expert performers is considered as a way to identify the characteristics of more efficient and effective learners. The identification and study of expert (or good) learners will enhance our understanding of skill acquisition and how this may be promoted using instructional interventions and practice opportunities. Although these ideas are predicated on our research on perceptual-cognitive expertise in sport, we argue that these ideas have general merit beyond this domain. The challenge for scientists is to generate new knowledge that helps those involved in developing learners who can acquire and refine skills more efficiently and effectively across professional domains.

Keywords: perceptual-cognitive training; skill acquisition; representative task-design; process-tracing measures; deliberate practice

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1.   Introduction

Over recent decades there has been a significant growth of interest in the study of expert performance, with a specific focus on perceptual-cognitive expertise (for up-to-date reviews, see Baker & Farrow, 2015; Ericsson, Hoffman, Aaron, & Williams, in press; Farrow, Baker & MacMahon, 2013; Hodges & Williams, 2012). The growth of interest in topics such as anticipation and decision making has spanned multiple domains including sport (Williams & Abernethy, 2012), medicine (McRobert, Causer, Vasiliadus, Watterson, & Williams, 2013), aviation (Kennedy, Taylor, Reade, & Yesavage, 2010), and automobile driving (Stahl, Donmez, & Jamieson, 2016). The typical finding is that experts can be differentiated from less expert or novice counterparts based on a number of domain-specific, perceptual-cognitive skills. These skills include the ability to pick up biological motion information from the movements of others (e.g., Abernethy & Zawi, 2007), a capacity to identify familiarity or patterns in structured displays (e.g., North, Ward, Ericsson, & Williams, 2011), and a more refined knowledge of likely situational or event probabilities (e.g., Ward, Ericsson, & Williams, 2013). Systematic differences have been reported in the gaze behaviours underpinning these perceptual-cognitive skills, with the specific strategies employed being task and context specific (see Roca, Ford, & Williams, 2013). In contrast, evidence pointing towards individual differences in measures of basic visual and cognitive functions (i.e., domain-generic skills) is relatively weak or at best mixed (Voss, Kramer, Basak, Prakash, Roberts, 2010). The suggestion is that expertise arises through adaptations that are mostly specific to the target domain of expertise (Ericsson & Kintsch, 1995). In this paper, we consider how research on expertise in sport, particularly related to perceptual-cognitive expertise, could impact how we study expert performance in general and 'expert' or good learning more specifically. We argue that a distinction between expert performance and expert learning could provide significant insight into the process of skill acquisition.

Although the number of published reports on expertise has grown substantially, there remain significant shortcomings with existing literature. First, while the vast majority of researchers have used the traditional expert-novice paradigm to examine differences as a function of performance, there has been a paucity of published papers focusing on expertise within the context of learning in contrast to expertise in terms of performance on the task itself. There are numerous questions that remain unanswered. Is it true that expert performers are always expert learners? What is the relationship between performance and the ability or receptiveness to acquire skills efficiently and effectively? Are there individual differences with respect to how skills are acquired and refined that distinguish individuals even within skill groups? What is the relationship between skill acquisition processes, for component skills, and eventual skilled performance/expertise? What are the perceptual-cognitive skills that might underpin superior learning and how do we translate this knowledge into training programmes that facilitate the more rapid and effective acquisition of perceptual-cognitive expertise?

In this review article, the merits of using the 'expert performance approach' as a framework to study expert learning rather than expert performance per se are highlighted. Generally, research into skill development and learning has lacked a systematic framework (including methods and measures) for the study of perceptual-cognitive expertise and, equally importantly, its acquisition. While the expert performance approach is not new, having originally been proposed more than two decades ago (see Ericsson & Smith, 1991), it does offer a framework to study how skills are learned as well as performed. We acknowledge that this approach puts a focus on the acquisition of new skills, rather than their refinement, with the supposition that intentional learning and factors related to skill learning are likely different to the background corrections (Bernstein, 1967/1996) and refinements in skill that might take place at a more implicit/non-conscious or subcortical level. In the following sections, the three stages outlined in the expert performance approach are introduced with some examples of how the framework has been used successfully to evaluate expertise across domains. In the second half of the article, the focus shifts to examining how the expert performance approach may be used to evaluate expert learning rather than expert performance. Our intention is that some of the questions, issues and ideas we raise in this paper will encourage those working in the learning sciences to adopt this approach (or at least consider these issues) as they pursue further research in this area.

2.   The Expert Performance Approach

The expert performance approach was first presented by Ericsson and Smith in 1991. The three-stage approach to studying expert performance is highlighted in Figure 1, with each stage described in detail below.
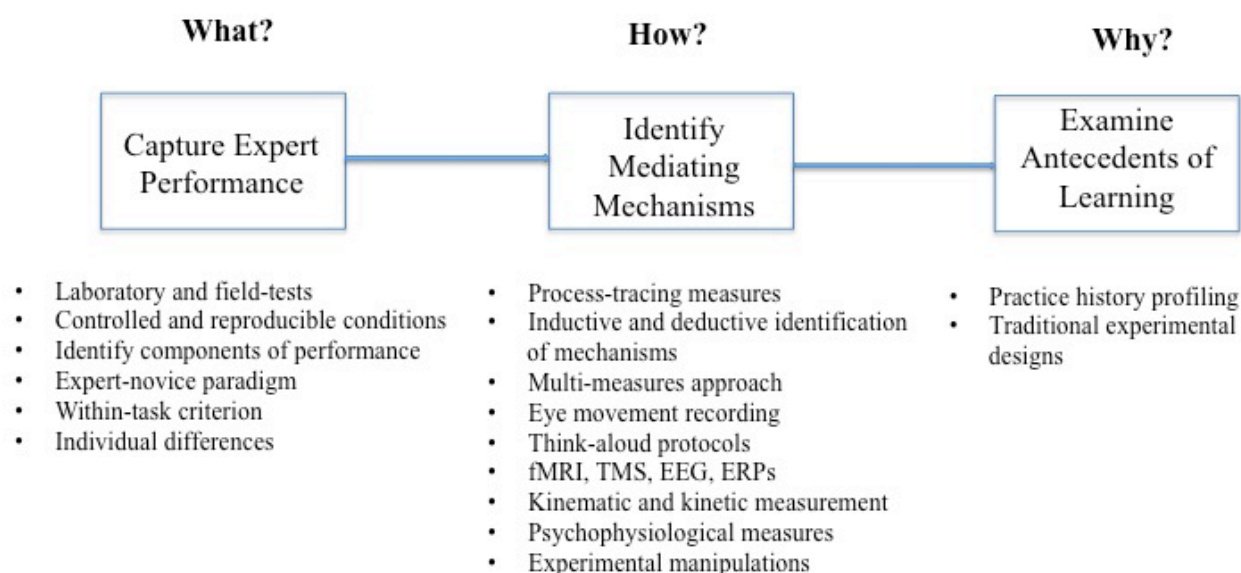

Figure 1. The expert performance approach proposed by Ericsson and Smith (1991). Adapted from Williams and Ericsson (2005).

2.1   Stage 1 – Capturing expert performance: What factors discriminate?

In the first stage, the aim is to develop a representative task that enables expert performance to be captured in a reliable and objective manner. Performance may be captured under controlled conditions in the laboratory or using appropriate measurement systems in the field (Williams & Ericsson, 2005). The goal is to develop tests that discriminate at an empirical level those who are skilled from those less skilled on the task(s). The stable and reliable aspects of performance are captured in a repeated manner. Initially, researchers focused primarily on cognitive tasks representative of performance in domains such as chess or mathematics. More recently, there have been efforts to determine representative tasks for both perceptual-cognitive and perceptual-motor skills (Williams, Ford, Eccles, & Ward, 2011). For example, in sport, these latter efforts have focused both on capturing performance in the field using player and motion tracking systems or by recreating realistic simulations of performance situations using film- or virtual-reality simulations (Williams & Abernethy, 2012). Figure 2 presents a typical example of a film-based simulation set up designed to capture anticipation and decision making in tennis. The advantage with such methods is that they enable performance on the task to be measured accurately such that groups of participants varying in expertise may be compared under standardised and reproducible test conditions.

2.2   Stage 2 – Identifying mechanisms underpinning expert performance: How do experts perform better?

In the second stage, the aim is to identify the processes and mechanisms underpinning superior performance. Process-tracing measures such as eye movement recording and think-aloud verbal protocols are

employed to examine the perceptual-cognitive processes underlying expert performance (e.g. McRobert, Ward, Eccles, & Williams, 2011; Roca, Ford, McRobert, & Williams, 2013). Neurophysiological techniques, such as transcranial magnetic stimulation (TMS), electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) can be employed to identify and relate areas of brain activity to performance (e.g., Balser et al., 2014; Dennis, Rowe, Williams, & Milne, in press; Wright, Bishop, Jackson, & Abernethy, 2010, 2011). Psycho-physiological measures such as pupil diameter, inter-beat heart rate intervals, electromyography (EMG), and galvanic skin response may be recorded to examine changes in mental effort or stress/anxiety as a function of skill on the task (e.g., Vater, Roca, & Williams, 2015). Biomechanical measurement tools can also be employed to record kinetic and kinematic variables that give insight into movement planning and execution processes (e.g., Müller, Brenton, Dempsey, Harbaugh & Reid, 2015; Smeeton & Williams, 2012). Finally, various behavioural manipulations, such as dual-task paradigms, can be used to determine the type of processes engaged during anticipation and decision making (e.g., Mulligan, Lohse & Hodges, 2016a,b) or the cognitive and attentional load associated with a task or skill level (e.g., Broadbent, Causer, Williams, & Ford, in press). A combination of different process-tracing measures may be needed to cross-validate findings and to provide a more complete picture of the important processes that mediate expert performance. The challenge is to identify how experts demonstrate superior performance on the task compared to less expert individuals with the overall aim of enhancing conceptual and empirical understanding of performance processes.

2.3   Stage 3 – Facilitating the acquisition of expert performance: Why has expertise developed?

The aim in the final stage is to improve understanding of how adaptations occur during the acquisition of expertise and to use the knowledge acquired to develop training interventions that help facilitate the more rapid acquisition of expertise. In regards to understanding how these adaptations occur, the prototypical approach has been to use qualitative and quantitative methods to probe practice histories; such as questionnaires, interviews and practice logs. The deliberate practice theory (Ericsson et al., 1993) is usually used as the framework around which empirical questions are generated and related (e.g., see Ward, Hodges, Starkes, & Williams, 2007; Ford & Williams, 2012). Pre- to post-test intervention designs have also been used to study the efficacy of short- to medium-term training interventions on performance and learning. Such interventions have focused on determining whether the practice behaviours of experts differ from less skilled individuals and how these behaviours relate to current understanding of best practice methods (e.g., Coughlan, Ford, McRobert, & Williams, 2014; Hodges, Edwards, Luttin, & Bowcock, 2011). Other researchers have studied how the perceptual-cognitive skills that underpin anticipation and decision making can be trained using simulation- or field-based interventions (e.g., see Broadbent, Causer, Williams, & Ford, 2015a; Williams, Ward, & Chapman, 2003; Williams, Ward, Knowles, & Smeeton, 2002). The general intention is to develop interventions that facilitate the more rapid and robust acquisition of skills, based on knowledge of what good learners or elite performers do, as well as understanding of how and why this works.

Figure 2. An illustration of a film-based simulation used to evaluate anticipation and decision making in tennis. The participant is required to anticipate the location and type of shot played by the opponent located at the net and to decide on an appropriate response. Verbal or motor responses are recorded (both speed and accuracy), with the latter from pressure sensitive mats placed on the floor around the participant.

3.   Applying the Expert Performance to the Study of Expert Learners

The expert performance approach has been used to study differences between expert and less expert or novice performers. However, the approach has not been used systematically to evaluate how skilled individuals acquire (and refine) skills. There are many factors which are likely to affect the rate of acquisition and retention of skills, including the dispositional characteristics of the performer and exposure to previous learning experiences (e.g., Hodges et al., 2014), existing skill sets (e.g., Hodges et al., 2011), motivation (Wulf, Shea, & Lewthwaite, 2010), and potentially, individual differences related to intelligence or other factors (e.g., Ackerman, 1987). The expert performance approach offers a framework to address issues concerning how experts learn and engage in practice to acquire new skills, characteristics that define good learners with respect to factors such as efficiency in rate of skill acquisition and potentially transferability of skills to new conditions, as well as to assess relationships between current performance and learning. As such, by studying how expert performers learn and what factors distinguish the best learners from the worst, we might learn more about best practice principles for more elite performers and about processes of learning in general that could impact conceptual understanding and applied interventions.

3.1   How can we capture learning and how do we define 'expert' and 'less expert' learners?

Learning is differentiated from performance during practice on the grounds that the latter is evaluated through observation of current behaviour, whereas estimates of learning usually involve both a measure of skill retention (to measure the longevity of the change in performance) and an assessment of transfer to probe what has been learned and the robustness of learning (Schmidt & Lee, 2013). Typically, learning is assessed at least 24 hours after the end of practice (i.e., after a period of sleep consolidation, Walker et al., 2002), under equitable conditions for all groups (such as in the absence of feedback). Thus far, however, limited attention has been paid to the efficiency of learning and how it differs within or between individuals. The general focus has been on testing how various interventions facilitate, or not, learning at the group rather than individual level. In fact, the process of collating mean scores across both trials and individuals and summating these largely eliminates what may be interesting variability in the data, which may be a functional component of learning (Davids, Bennett, & Newell, 2006).

The rate of learning may be negatively related to long-term retention. For example, in short-term adaptation studies, where individuals practice making novel aiming movements in visually-rotated conditions, there is evidence for both fast and slow adaptation processes, with the slow process being more robust over time and arguably predictive of better learning (Smith, Ghazizadeh & Shadmehr, 2006). This slow process is more implicit in nature, showing little sensitivity to error, in comparison to the fast process that is more explicitly-driven and highly responsive to errors. In a study of sequence learning, where individuals practiced three different sequences in a serially repeating order, there was evidence that slower learners, or the ones who spent more time in what was termed the cognitive phase of skill acquisition, had better retention (Wadden, Hodges, De Asis, Neva & Boyd, 2017). These data seem to support an efficiency-effectiveness trade-off in learning, which is underscored by current conceptualizations of practice and learning relating to the need for 'challenge points' during practice (Guadagnoli & Lee, 2004) and the promotion of desirable difficulties (Bjork & Bjork, 2011). However, there are individuals that show both fast acquisition and good retention and "good" learners do not always adhere to established principles of practice. For example, when learners are allowed to schedule their own practice, a useful method to assess characteristics of good or expert learners, the best learners are not always the ones who adhere to good practice principles (such as high contextual interference between attempts of different skills). As long as practice is self-determined, low levels of switching (i.e., contextual interference) between to-be-acquired skills can also produce good learning, without accuracy costs in acquisition (Hodges et al., 2011, 2014; Keetch & Lee, 2007). Also, there has been resistance to methods which have a negative impact on performance in the short-term (in order to benefit retention), as these can discourage change, demotivate learners and of course have a cost function in terms of amount or duration of practice (especially pertinent when practice time is limited or safety concerns are at play, see Lee & Wishart, 2005). Systematic investigations of experts acquiring new skills (or studying good learners who are able to circumvent practice time) may help to give us insights into this efficiency-effectiveness relationship and any individual differences that might impact these variables.

In order to enhance measurement sensitivity, it is necessary to consider the variability in learning across participants to determine how individuals differ in the amount of learning that has occurred (perhaps in response to varying instructions or demonstrations). Such an analysis is important if we are to better understand the subtle differences that may exist between 'expert' and 'less expert' learners. One approach would be to classify performers based on the amount of learning that has occurred by looking at either absolute retention, change in performance (from pre- to retention tests) or learning efficiency, with respect to the relationship or ratio between rate of acquisition and retention. With respect to this latter measure, those with the best ratio (i.e., efficient and effective) would be classified as a more 'expert learner' (or the best within the group). If a sufficiently large sample is used, more and less expert learning groups may be created using a quartile- or median-split approach or alternatively, regression analyses may be used, with all participants included, to examine changes in performance and how these ultimately may be linked to changes in process measures. Such an approach has been used previously to stratify participants into high and low performing individuals based on their perceptual-cognitive expertise (e.g., Bourne, Bourne, Bennett, Hayes, & Williams, 2011; Savelsbergh, van der Kamp, Williams, & Ward, 2006; Williams, Ward, Bell-Walker, & Ford, 2011), yet, thus far, the approach has not been employed to stratify participants based on their proficiency in learning a skill.

It is often difficult to assess performance directly in many domains, making it hard to measure the amount of improvement that occurs during learning. When performance can be evaluated using standard units of assessment (e.g., time and distance), it is relatively straightforward to evaluate learning. Yet, in domains such as in team sports, the military and emergency room medicine, performance is hard to measure as it is not expressed through a single unit of measurement. In such scenarios, performance is typically made up of several individual components that could interact. As such, particularly when the components are more independent, a sensitive assessment could be provided through measurement of an isolated component of performance. For example, a specific test of decision making could be designed, such that performance on this component can be isolated for assessment in the laboratory. A within-task criterion (i.e., actual score on the test) may then be used to identify those who are high or low on decision making, rather than general performance in the domain. An advantage of this method is that the efficiency and effectiveness of learning on a specific component of

performance may be identified, allowing identification of participants who are more or less able to learn and improve on that component.

3.2 Identifying the processes and mechanisms that mediate expert learning

When conducting traditional experimental work on skill learning, the vast majority of researchers have relied almost exclusively on changes in outcome measures of performance. Process-tracing measures, although used, have been employed far less frequently. The difficulty in relying on outcome measures is often we have limited understanding of what actually changes during learning and neglect the fact that positive changes in process may not necessarily be (immediately) reflected in changes in outcomes (Schmidt & Lee, 2013). Eysenck and Calvo (1995), in their Processing Efficiency Theory, present a conceptual account of the effects of anxiety on performance. The model differentiates between changes in processing efficiency and processing effectiveness. As participants become anxious often there is no immediate change in effectiveness, but there may be an increase in the amount of mental effort or resources that need to be devoted to the task, thereby decreasing performance efficiency. At higher levels of anxiety, the cognitive resources needed for task execution may exceed available resource capacity, leading to declines in both efficiency and effectiveness. We argue that the process of learning may function in a similar way such that the efficiency and effectiveness of learning may not necessarily be highly correlated. A call is therefore made for the use of process-tracing measures in conjunction with outcome measures in skill acquisition research. It could be argued that the collection of process-measures to study learning may be as important as the adoption of measures of retention and transfer proved to be in the motor learning literature in the late 1980s (Williams & Ericsson, 2007). We need to better differentiate between the process and product of learning and to ascertain the efficiency and effectiveness gains (or trade-offs) that may be obtained through different interventions.

Visual gaze has been used as an index of attention during performance on a specific task (e.g., anticipation), but thus far, only in a few published reports have gaze behaviours been recorded before and after an intervention or practice phase (for exceptions, see Alder, Ford, Causer, & Williams, 2016; Breslin, Hodges, Williams, Kramer, & Curren, 2007; Causer, Holmes, & Williams, 2011). Measures of gaze can help establish whether more stable or efficient patterns of visual search behaviour in some learners (i.e., longer duration fixations on information rich areas of a display) inform what information is being acquired, how improvements in performance are attained, and/or explain "learning" in the absence of performance effects. Such an approach is especially important when studying experts learning, where subtleties in processes may be more evident following practice than (positive) changes in behavioural outcomes. Moreover, there is a paucity of research where verbal reports have been gathered on a pre-test as well as on subsequent retention- and transfer-tests (for an exception, see Coughlan et al., 2014). Whilst kinematic measures are commonly employed on simple tests of motor skill learning, detailed motion analysis is less common for the acquisition of more complex skills, such as those involved in sport. Researchers have tended to focus on changes in motor control by measuring variation in single measures (e.g., range of motion, linear velocity) rather than in global motor coordination patterns (e.g., conjugate cross correlations and angle-angle plots as measures of coordination; see Carling, Reilly, & Williams, 2009). The use of neurophysiological measures such as fMRI, TMS or EEG are reported more frequently as process measures of skill learning in simple, constrained laboratory-based tasks of motor skill (e.g., key press sequencing or single limb adaptation to novel environments; for reviews see Hardwick, Rottschy, Miall, & Eickhoff, 2013; Lohse, Wadden, Boyd, & Hodges, 2014). However, the recording of neurophysiological measures on pre- and retention/transfer-tests following the acquisition of more complex skills has been rare (for an exception, see Bezzola, Merillat, Gaser, & Jancke, 2011). The difficulty is that while we have a reasonable understanding of the effectiveness of different instructional interventions at the outcome level, only limited knowledge has been generated in regards to how changes in process-measures accompany changes in outcome. An interesting question is the extent to which process-tracing measures (such as visual search) may predict changes in learning across and within individuals. Such research would help us better understand the processes underpinning expert learning and how these relate to the development of mechanisms that promote expertise.

3.3 Tracing the development of expert learners

An extensive body of research now exists focusing on deliberate practice and its contribution to expert performance. The findings remain somewhat controversial with wide ranging views regarding the variance in performance across individuals accounted for by hours accumulated in deliberate practice (see Ericsson et al., in press; Hambrick, Altmann, Oswald, Meinz, & Gobet, 2014; McNamara, Hambrick, & Oswald, 2014). Perhaps the most interesting issue is that that variability in the amount of hours accumulated across individuals has been largely unexplored. Numerous researchers have reported extremely large standard deviations in the number of hours athletes accumulate in different types of practices activities during development, implying that practice (at least given issues in measurement) is not the sole factor in developing expertise (e.g., see Ford et al., 2012; Hopwood, MacMahon, Farrow & Baker, 2016). The difficulty with the majority of the existing research on deliberate practice is that it tends to be correlational in nature, rather than prospective or intervention-based. The data may largely be describing the social and cultural backgrounds surrounding a particular cohort or domain, rather than highlighting causal factors which promote excellence.

If the deliberate practice framework is to continue to make a valuable contribution to the learning sciences, better efforts are needed to link engagement in specific types of practice activities with specific improvements in related components of performance. The need to be able to draw firmer inferences about causality may necessitate moving away from retrospective, historical accounts of practice (i.e., the 'bean counting' approach) towards more prospective approaches combining some of the tenants of deliberate practice theory with more traditional, quasi-experimental designs. A published report by Coughlan, Williams, and Ford (2014) nicely illustrates how the tenants of deliberate practice may be studied under controlled conditions involving a traditional learning design, including measures of transfer and retention, and process measures of learning. The need remains to specify not just how much deliberate practice occurs amongst learners, but also how deliberate the learners are during practice itself. Self-regulated learners take control of their learning environment and engage in specific learning strategies to improve (Zimmerman, 2008). The motivation to develop deeper understanding of key concepts and subject matter lead to long-term retention and a greater ability to transfer skills across domains. Similarly, mental toughness, grit and resilience may mediate expert learning as performers must develop new and innovative ways to overcome obstacles and continue to challenge themselves (Hodges, Ford, Hendry, & Williams, in press). Do expert learners simply respond better to challenges in the learning environment or do they create those challenges to push themselves to new heights?

Although research using the deliberate practice framework and cross-sectional, expert-novice type comparisons may be criticised, shortcomings equally exist with more 'traditional' learning designs that rely on an experimental approach. The majority of researchers who study motor-skill learning have employed novice participants who often have no or very little skill (or interest) in the chosen task. Novel tasks are often used, in efforts to equate individuals before practice, which have little applicability to real-world scenarios and relatively short acquisition periods, sometimes not even including a retention and/or transfer test. Moreover, experience and skill are often confounded in the choice of participants, such that, for example, participants high in skill are typically highly experienced making it impossible to disassociate these two factors. The absence of research with more skilled performers is notable, particularly involving real-world tasks. No published reports exist using more and less expert learners. What is needed is a refinement in the methods used by the different camps of researchers and a greater emphasis on using mixed-methods, combining retrospective, experimental and prospective designs and employing processes-tracing measures. The advantages and disadvantages of retrospective practice history profiling, traditional learning studies and prospective designs are highlighted in Table 1.

Table 1

The advantages and disadvantages associated with using retrospective practice history profiles, traditional experimental approaches to learning as well as prospective designs (adapted from Williams & Ericsson, 2005).

Retrospective Practice History Profiling	Traditional Pre- to Post-test Designs	Prospective Designs
Provides a general description of the types of activities performers have engaged in to become expert	Enables the validity of specific instructional interventions and practice schedules to be examined under controlled conditions leading to inferences regarding causality	Can answer questions about why differences exist across individuals and enable causality judgements
Strong emphasis on identifying the macro rather than micro structure of practice	Strong emphasis on the micro-structure of practice, rather than macro-level	Allow subtle measurement of changes in performance with practice that might not be seen in typical behavioural measures
Limited attempts to identify the specific practice activities engaged in and to link these to changes in specific components of performance	Overreliance on simplistic and novel laboratory tasks leading to concerns regarding generalizability of findings (to the real-world and to experts)	Allows tracking of specific activities within a targeted group of individuals
Few attempts to use the approach in conjunction with experimentally-based, pre-post-test designs	Short-term interventions with limited follow-up regarding long-term retention of skills	Assessment of short-term interventions is permitted over long periods of time
Absence of control groups (matched for age and experience)	Applicability of findings somewhat dependent on strengths of transfer tests employed, particularly if stressors such as fatigue and anxiety missing	Prospective designs allow for better reliability and validity in measures/conclusions
Lack of focus on individual differences and large standard deviations in data	Often an absence of retention tests, or the use of short retention periods, and inappropriate use of, or absent, transfer tests	Age can be factored into longitudinal designs, such that comparisons can be made across age groups and across individuals over time
Not possible to imply causality from such data	Majority of published reports involve novice participants with limited focus on expert performers and on expert learners	Prospective designs afford a better focus on changes within individuals and causality statements
Concerns with validity and reliability of retrospective estimates of practice hours	Lack of research studying how instructional variables, practice variables and learner's skill interact, leading to a limited, reductionist approach to exploring skill acquisition	Multiple measures of process and outcome can be integrated to identify efficiency-effectiveness trade-offs and how these change over time

An area of study that has attracted a growing body of research in recent years relates to the use of video and other forms of simulation that enable opportunities for anticipation and decision making to be isolated under controlled conditions in the laboratory, greatly increasing the opportunity for repetition and engagement in deliberate practice (for a recent review, see Broadbent et al., 2015). The prototypical approach involves filming an action sequence (e.g., the serves of opponents in tennis) from the perspective of the player and then replaying the action, which may be occluded at various time intervals before, at or after ball-racket contact. The task for the participant would be to anticipate where and what type of serve the opponents would employ before deciding on the correct return shot. Such an approach would be used for the pre- and post-test, whereas a transfer test would likely involve serves from opponents not previously observed, and potentially some form of on-court data collection. The intervention period would typically require players to view other servers and to receive instruction related to the pick-up of key postural cues to facilitate anticipation. Feedback regarding task performance would be provided (for examples, see Abernethy, Schorer, Jackson, & Hagemann, 2012; Smeeton, Williams, Hodges, & Ward, 2005; Williams et al., 2002).

While there remain limitations with existing work on perceptual-cognitive training, notably in regards to the measurement of skill transfer, the paradigm has been used to examine the conceptual underpinnings of a range of issues in the learning sciences, including: practice scheduling (Broadbent, Causer, Williams, & Ford, 2015b; Hodges et al., 2011); focus of attention (Abernethy, Schorer, Jackson, & Hagemann, 2012); the effectiveness of imagery (Smeeton, Hibbert, Stevenson, Cumming, & Williams, 2015); perceptual cueing (Ryu, Kim, Abernethy, & Mann, 2012); and training under pressure (Alder et al., 2015). Although there have been attempts to look at individual differences in perceptual-cognitive skills and determine how well these predict performance (e.g., Mangine et al., 2014), such an approach has not been used to examine how elite athletes improve or respond to practice over a relatively short intervention (for an exception, see Faubert, 2013). In terms of differentiating across skill groups, the evidence is pretty mixed regarding the ability of general perceptual-cognitive skills, such as attention or spatial-IQ, to distinguish better from worse athletes (for a review, see Voss et al., 2010). With respect to learning, this general abilities approach may be informative, especially if combined with sport-specific measures of skill. For example, do the athletes who show better recall or recognition for patterns of play specific to their sport, also respond better to practice manipulations designed to improve perceptual cognitive skill in recognizing deceptive plays for example? Whilst there is anecdotal evidence for "good" learners in sports, the reasons for this receptivity have not been explored and as such, studying variables such as current skill level, playing experience, attention or cognitive capacities, might provide insight into variables and characteristics which are most related to continued learning and the overcoming of challenges associated with necessary technique changes (such as in the case of injury or changing demands in the sport).

In addition to the relative short acquisition periods that are employed in laboratory based research on motor learning (e.g., 45-60 min, see Williams, Ward, & Chapman, 2003), there is an absence of longitudinal work. Consequently, we have limited idea of how skill learning progresses and changes over time or the extent to which the typically observed changes are durable and lasting. We know very little about the factors that differentiate someone who learns these skills effectively and efficiently from those who record smaller changes in performance either over time or as a result of the training intervention. The absence of any longitudinal work makes it difficult to judge whether these measures of specific task components (e.g., perceptual-cognitive skills) have any predictive utility from a talent identification perspective. If someone scores well on these tests at an early age does this suggest that performance will continue to be high relative to others in an older age grouping? Moreover, are there key time windows for the acquisition of these skills and how is this linked to general development in young children? Do individuals that demonstrate 'exceptional talent' learn skills more efficiently following brief exposure or is the development of perceptual-cognitive skills non-linear, varying from one stage of development to the next, making prediction difficult?

4.   Conclusions

In this article, the expert performance approach, originally introduced by Ericsson and Smith (1991) was reviewed as a systematic framework for the study of expertise. Over recent decades, this approach has helped to stimulate research in the area of perceptual-cognitive expertise. In contrast to the growing research on expert performance across numerous domains, as well as significant research focusing on the practice history profiles of experts and novices, there remains a need for research on how expert learners continue to learn new skills and refine existing ones. We advocate a more systematic approach to the study of (motor) learning in general, based on process tracing measures and identification of individual differences related to effectiveness and efficiency. Someone who acquires, retains and transfers skill better than another individual may perhaps be categorised as a skilled or more expert learner. The absence of research on this topic largely arises because the prototypical approach has been to use participants classified based on their current level of performance rather than their expertise in learning (which of course requires some formative assessment). This latter approach necessitates the selection of participants (typically retrospectively) based on the level of

performance change observed over time on a particular component of performance. A strong focus on identifying individual differences in learning is essential, rather than relying on group means over practice blocks. The use of process-tracing measures during acquisition will improve understanding of how learning takes place rather than the amount of learning that has occurred, as is the case when relying solely on outcome scores. We suggest that the expert performance approach has considerable potential in offering a framework to identify expert learners across domains and that it offers a systematic, guiding framework for better understanding how experts have learned the skills needed to perform at high levels in their respective domains. A stronger focus on the science of learning is key to enhance knowledge of how skills are acquired and how we then can promote more efficient and effective skill acquisition cross many professional domains.

Keypoints

- The expert performance approach presents a systematic framework for examining how expert learners acquire and refine skills across domains.

- More effort is needed to identify individuals who demonstrate exceptional learning on specific skills (as defined by efficiency and effectiveness in attainment) when compared to norms, if we are to develop more refined methods to accelerate skill learning across domains.

- A stronger focus is needed on exploring individual differences in learning and on using process-tracing measures to evaluate how learning progresses, rather than on an existing overreliance on outcome scores, averaged across individuals.

- Measures of learning efficiency (rate of learning, number of practice trials or days of practice) and effectiveness (i.e., accuracy, consistency, skill quality, speed) are needed to gain a more accurate picture of how experts learn across many domains of professional activity.

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