THE CAMBRIDGE HANDBOOK OF

EXPERTISE AND EXPERT PERFORMANCE

Edited by K. Anders Ericsson, Robert R. Hoffman, Aaron Kozbelt and A. Mark Williams

SECOND EDITION

The Cambridge Handbook of Expertise and Expert Performance

Second Edition

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Part I
Introduction and Perspectives

1 An Introduction to the Second Edition of *The Cambridge Handbook of Expertise and Expert Performance*: Its Development, Organization, and Content

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The study of expertise and expert performance reached a significant milestone in 2006 when its first handbook was published (Ericsson, Charness, Hoffman, & Feltovich, 2006). In the ten subsequent years, the handbook surpassed 10,000 copies sold, which is pretty impressive for a book of almost 1,000 pages. During this last decade there has been a dramatic increase in articles and books reporting on expertise and expert performance. There are several edited books written about particular domains of expertise, such as sports expertise (Baker & Farrow, 2015) and developing sports expertise (Farrow & Baker, 2013), entrepreneurial expertise (Sarasvathy, 2008), and design expertise (Lawson & Dorst, 2009). Other books have taken more general perspectives on the structure of expertise and its acquisition (Montero, 2016), the social aspects of how expertise is evaluated and experts evaluated (Collins & Evans, 2007), and the relation between skill acquisition and expertise (Johnson & Proctor, 2016). General books on the topics of expertise and expert performance have been published, focusing on professional development (Ericsson, 2009), accelerating the development of expertise (Hoffman et al., 2014), as noted earlier, and expertise in professional decision making (Hoffman, 2007). Another sign of impact is the large number of popular books describing how insights from the study of expertise and expert performance can inform individuals on how to improve their performance. A few examples of such popular books are Colvin (2008), Coyle (2009), Ericsson and Pool (2016), Foer (2011), Gladwell (2008), and Marcus (2012). This new edition of the handbook will update the most active areas of research and provide an up-to-date summary of our knowledge about perspectives, approaches, and methods in the study of expertise and expert performance as well as updated assessments of the knowledge of expertise and expert performance in different domains of expertise. There is also a new section identifying similar mechanisms that mediate expertise and expert performance across different domains, as well as generalizable issues and theoretical frameworks.

Expert, Expertise, and Expert Performance: Dictionary Definitions

Encyclopedias describe an ***Expert*** as “one who is very skillful and well-informed in some special field” (*Webster’s New World Dictionary*, 1968, p. 168), or “someone widely recognized as a reliable source of knowledge, technique, or skill whose judgment is accorded authority and status by the public or his or her peers. Experts have prolonged or intense experience through practice and education in a particular field” (Wikipedia). ***Expertise*** then refers to the characteristics, skills, level of performance (Epstein, 1991). When people were accepted as masters they were held responsible for the quality of the products from their shop and were thereby allowed to take on the training of apprentices (see the chapter by Amirault & Branson, 2006, in the first edition of the handbook on the progression toward expertise and mastery of a domain).

In a similar manner, the scholars' guild was established in the twelfth and thirteenth centuries as "a *univeristas magistribus et pupillorum*," or "guild of masters and students" (Krause, 1996, p. 9). Influenced by the University of Paris, most universities conducted all instruction in Latin, where the students were initially apprenticed as arts students until they successfully completed the preparatory (undergraduate) program and were admitted to the more advanced programs in medicine, law, or theology. To become a master, the advanced students needed to satisfy "a committee of examiners," then publicly defend a thesis, often in the town square and with local grocers and shoemakers asking questions (Krause, 1996, p. 10). The goal of the universities was to accumulate and explain knowledge and in the process masters organized the existing knowledge (see Amirault & Branson, 2006). With the new organization of existing knowledge of a domain, it was no longer necessary for individuals to discover the relevant knowledge and methods by themselves.

Today's experts can rapidly acquire the knowledge originally discovered and accumulated by preceding expert practitioners by enrolling in courses taught by skilled and knowledgeable teachers using specially prepared textbooks. For example, in the thirteenth century Roger Bacon argued that it would be impossible to master mathematics by the then known methods of learning (self-study) in less than 30 to 40 years (Singer, 1958). Today the roughly equivalent material (calculus) is taught in highly organized and accessible form in every high school.

Sir Francis Bacon is generally viewed as one of the architects of the Enlightenment period of Western civilization and one of the main proponents of the benefits of generating new scientific knowledge. In 1620 he described in his book *Novum Organum* his proposal for collecting and organizing all existing knowledge to help our civilization engage in learning to develop a better world. In it, he appended a listing of all topics of knowledge to be included in *Catalogus Historarium Particularium*. It included a long list of skilled crafts, such as "History of weaving, and of ancillary skills associated with it," "History of dyeing," "History of leather-working, tanning, and of associated ancillary skills" (Rees & Wakely, 2004, p. 483).

The guilds guarded their knowledge and their monopoly of production. It is therefore not surprising that the same forces that eventually resulted in the French Revolution were not directed only at the oppression by the king and the nobility, but also against the monopoly of services provided by the members of the guilds. Influenced by Sir Francis Bacon's call for an encyclopedic compilation of human knowledge, Diderot and D'Alembert worked on assembling all available knowledge in the first *Encyclopédie* (Diderot & D'Alembert, 1966–67), which was published in 1751–80.

Diderot was committed to the creation of comprehensive descriptions of the mechanical arts to make their knowledge available to the public and encourage research and development in all stages of production and all types of skills, such as tanning, carpentry, glassmaking, and ironworking (Pannabecker, 1994) along with descriptions of how to sharpen a feather for writing with ink as shown in Figure 1.1. His goal was to describe all the raw materials and tools that were necessary, along with the methods of production. Diderot and his associate contributors had considerable difficulties gaining access to all the information because of the unwillingness of the guild members to answer their questions. Diderot even considered sending some of his assistants to become apprentices in the respective skills to gain access

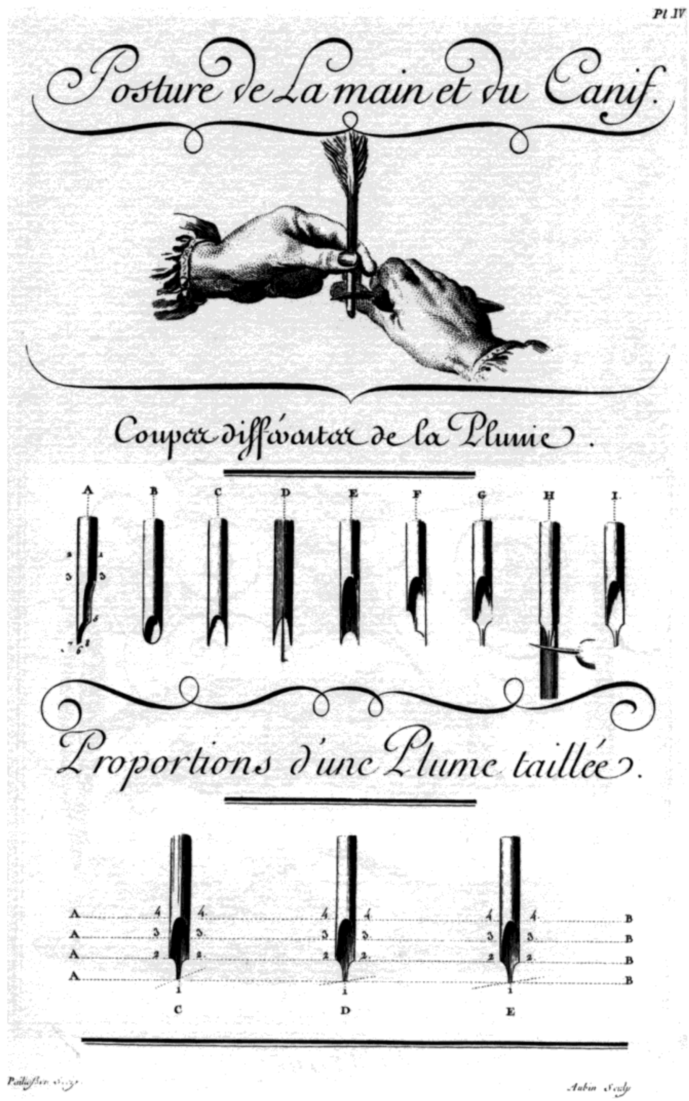

Figure 1.1 An illustration of how to sharpen a goose feather for writing with ink from Plate IV in the entry on "Ecriture" in the 23rd volume of *Encyclopédie ou dictionnare de raisonné des sciences, des arts et des métiers* (Diderot & D'Alembert, 1966–67).

to all the relevant information (Pannabecker, 1994). In spite of all the information and pictures (diagrams of tools, workspaces, procedures, etc. as illustrated in Figure 1.2 showing one of several plates of the process of printing) provided in the *Encyclopédie*, Diderot was under no illusion that the provided information would by itself allow anyone to become a craftsman in any of the described arts and wrote: "It is handicraft that makes the artist, and it is not in Books that one can learn to manipulate" (Pannabecker, 1994, p. 52). In fact, Diderot did not even address the higher levels of cognitive activity, "such as intuitive knowledge, experimentation, perceptual skills,

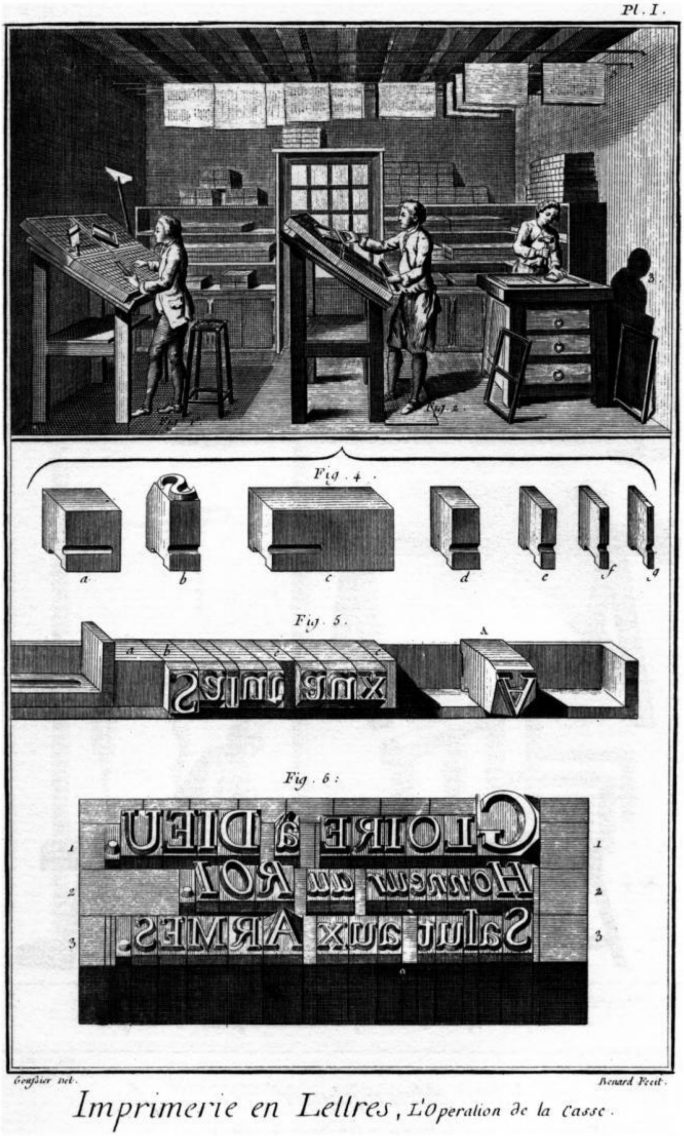

Figure 1.2 An illustration of the workspace of a printer with some of his type elements from Plate I in the entry on "Imprimerie" in the 28th volume of *Encyclopédie ou dictionnare de raisonné des sciences, des arts et des métiers* (Diderot & D'Alembert, 1966–67).

problem-solving, or the analysis of conflicting or alternative technical approaches" (Pannabecker, 1994, p. 52).

A couple of years after the French Revolution the monopoly of the guilds was eliminated (Fitzsimmons, 2003) including the restrictions on the practice of medicine and law. After the American Revolution and the creation of the United States of America laws were initially created to require that doctors and lawyers be highly trained based on the apprenticeship model, but pressure to eliminate elitist tendencies led to the repeal of those laws. From 1840 to the end of the nineteenth century there was no requirement for certification to practice medicine and law in the USA (Krause, 1996). However, with time both France and the USA realized the need to restrict vital medical and legal services to qualified professionals and developed procedures for training and certification.

Over the last couple of centuries there have been several major changes in the relation between master and apprentice. For example, before the middle of the nineteenth century children of poor families would often be taken on by teachers in exchange for a contractual claim for part of the future dancers', singers', or musicians' earnings as an adult (Rosselli, 1991). Since then the state has gotten more involved in the training of their expert performers, even outside the traditional areas of academia and professional training in medicine, law, business, and engineering. In the late nineteenth century public institutions, such as the Royal Academy of Music, were established to promote the development of very high levels of skill in music to allow native students to compete with better trained immigrants (Rohr, 2001). In a similar manner during the latter part of the twentieth century, many countries invested in schools and academies for the development of highly skilled athletes for improved success in competitions during the Olympic Games and World Championships (Bloomfield, 2004).

More generally, over the last century there have been economic developments with public broadcasts of competitions and performances that generate sufficient revenue for a number of domains of expertise, such as sports and chess, to support professional full-time performers as well as coaches, trainers, and teachers. In these new domains, along with the traditional professions, current and past expert performers continue to be the primary teachers at advanced levels (masters) and their professional associations have the responsibility for certifying acceptable performance and the permission to practice. Thus they have the clout to influence training in professional schools, such as law, medical, nursing, and business schools – "testing is the tail that wags the dog" (Feltovich, personal communication). The accumulation of knowledge about the structure and acquisition of expertise in a given domain as well as knowledge about instruction and training of future professionals have, until quite recently, occurred almost exclusively within each domain, with little cross-fertilization of domains in terms of teaching, learning methods, and skill training techniques.

It is not immediately apparent what is generalizable across such diverse domains of expertise as music, sport, medicine, and chess. What could possibly be shared by the skills of playing difficult pieces by Chopin, running a mile in less than four minutes, and playing chess at a high level? The premise for a field studying expertise and expert performance is that there are sufficient similarities in the theoretical principles mediating the phenomena and the methods for studying them in different domains that it would be possible to propose a general theory of expertise and expert performance. All of these domains of expertise have been created by humans and thus the accumulated knowledge and skills are likely to reflect similarities in structure reflecting human biological and psychological factors as well as cultural factors. This raises many challenging problems for methodologies seeking to describe the organization of knowledge and to identify the mechanisms mediating expert performance that generalize across domains.

Once we know how experts organize their knowledge and their performance, is it possible to improve the efficiency of learning to reach higher levels of expert performance in these domains? It should also be possible to determine why different individuals improve their performance at different rates and why different people reach very different levels of final achievement. Would a deeper understanding of the development and its mediating mechanisms make it possible to select individuals with unusual potential and to design better developmental environments to increase the proportion of performers who reach the highest levels? Would it even be possible to facilitate the development of those rare individuals who make major creative contributions to their respective domains?

Conceptions of Generalizable Aspects of Expertise

Several different theoretical frameworks have focused on broad issues on attaining expert performance that generalize across different domains of expertise.

Individual Differences in Mental Capacities

A widely accepted theoretical concept argues that general innate mental capacities mediate the attainment of exceptional performance in most domains of expertise. In his famous book, *Hereditary Genius*, Galton (1869/1979) proposed that across a wide range of domains of intellectual activity the same innate factors are required to attain outstanding achievement and designation as a genius. He analyzed eminent individuals in many domains in Great Britain and found that these eminent individuals were very often the offspring of a small number of families – with much higher frequency than could be expected by chance. The descendants from these families were much more likely to make eminent contributions in very diverse domains of activity, such as becoming famous politicians, scientists, judges, musicians, painters, and authors. This observation led Galton to suggest that there must be a heritable potential that allows some people to reach an exceptional level in any one of many different domains. After reviewing the evidence that height and body size were heritable Galton (1869/1979) argued: "Now, if this be the case with stature, then it will be true as regards every other physical feature – as circumference of head, size of brain, weight of gray matter, number of brain fibers, &c.; and thence, by a step on which no physiologist will hesitate, as regards *mental capacity*" (pp. 31–32, emphasis added).

Galton clearly acknowledged the need for training to reach high levels of performance in any domain. However, he argued that improvements are rapid only in the *beginning* of training and that subsequent increases become increasingly smaller, until "maximal performance becomes a rigidly determinate quantity" (p. 15). Galton developed a number of different mental tests of individual differences in mental capacity. Although he never related these measures to objective performance of experts on particular real-world tasks, his views led to the common practice of using psychometric tests for admitting students into professional schools and academies for arts and sports with severely limited availability of slots. These tests of basic ability and talent were believed to identify the students with the capacity for reaching the highest levels.

In the twentieth century scientists began testing large groups of experts to measure their powers of mental speed, memory, and intelligence with psychometric tests. When the experts' performances were compared to control groups of comparable education there was no evidence supporting Galton's hypothesis of a general superiority for experts, because the demonstrated superiority of experts was found to be specific to certain aspects related to the particular domain of expertise. For example, the superiority of the chess expert's memory was constrained to regular chess positions and did not generalize to other types of materials (Djakow, Petrowski, & Rudik, 1927). Not even IQ could distinguish the best among chess players (Doll & Mayr, 1987) nor the most successful and creative among artists and scientists (Taylor, 1975).

In an article in the *Annual Review of Psychology*, Ericsson and Lehmann (1996) found that (1) measures of basic mental capacities are not valid predictors of attainment of expert performance in respond to representative situations from their domain (Ericsson, Chapter 12). These verbalized thoughts have raised issues about how experts have acquired memory skills to allow them to maintain efficient access to diverse information relevant to the generation of performance (long-term working memory, Ericsson, Chapter 36, and situational awareness, Endsley, Chapter 37). This latter evidence on expertise suggests that expert performers have to actively retain and refine their mental representations for monitoring and controlling their performance.

Expertise as Elite Achievement Resulting from Superior Learning Environments

There are other approaches to the study of expertise that have focused on objective achievement. There is a long tradition of influential studies with interviews of peer-nominated eminent scientists (Roe, 1952) and analyses of biographical data on Nobel Prize winners (Zuckerman, 1977) (see Simonton, 1994, for a more extensive account). In a seminal study, Benjamin Bloom and his colleagues (Bloom, 1985a) interviewed international-level performers from six different domains of expertise ranging from swimming to molecular genetics. All of the 120 participants had won prizes at international competitions in their respective domains. They were all interviewed about their development, along with their parents, teachers, and coaches. For example, Bloom and his colleagues collected information on the development of athletes who had won international competitions in swimming and tennis. They also interviewed artists who had won international competitions in sculpting and piano playing and scientists who had won international awards in mathematics and molecular biology. In each of these six domains Bloom (1985b) found evidence for uniformly favorable learning environments for the participants in all the domains. Bloom (1985b) concluded that the availability of early instruction and support by their families appeared to be necessary for attaining an international level of performance as an adult. He found that the elite performers typically started early to engage in relevant training activities in the domain and were supported both by exceptional teachers and by committed parents. These topics are covered in this handbook through up-to-date reviews of historiometric approaches to the development of professional excellence (Simonton, Chapter 18) and of case studies of experts (Mumford, McIntosh, & Mulhearn, Chapter 17). In a new addition to the handbook Elferink-Gemser, te Wierike, and Visscher (Chapter 16) review longitudinal studies of large groups of expert performers.

Expertise as Reliably Superior (Expert) Performance on Representative Tasks

It is difficult to identify the many mediating factors that might have been responsible for an elite performer to win an award and to write a groundbreaking book. When eminence and expertise are based on a singular or small number of unique creative products, such as books, paintings, or music compositions, it is rarely possible to identify and scientifically study the key factors that allowed these people to produce these achievements. Consequently, Ericsson and Smith (1991) proposed that the study of expertise with laboratory rigor requires representative tasks that capture the essence of expert performance in a specific domain of expertise. For example, a world-class sprinter will be able to reproduce superior running performance on many tracks and even indoors in a large laboratory. Similarly, de Groot (1978) found that the ability to select the best move for presented chess positions is the best correlate of chess ratings and performance at chess tournaments – a finding that was replicated (van der Maas & Wagenmakers, 2005). Once it is possible to reproduce the reliably superior performance of experts in a controlled setting, such as a laboratory, it then becomes feasible to examine the specific mediating mechanisms with experiments and process-tracing techniques, such as think-aloud verbal reports (see Ericsson, Chapter 12, in this volume, and Ericsson & Smith, 1991). The discovery of representative tasks that measure adult expert performance under standardized conditions in a controlled setting, such as a laboratory, makes it possible to measure and compare the performance of less skilled individuals on the same tasks. Even more importantly, it allows scientists to test aspiring performers many times during their development of expertise, allowing the measurement of gradual increases in performance.

The new focus on measurement of expert performance with standardized tasks revealed that "experts," i.e. individuals identified by their reputation or their extensive experience, are not always able to exhibit reliably superior performance. There are at least some domains where "experts" perform no better than less trained individuals and that sometimes experts' decisions are no more accurate than beginners' decisions and simple decision aids (Bolger & Wright, 1992; Camerer & Johnson, 1991). Most individuals who start as active professionals or as beginners in a domain change their behavior and increase their performance for a limited time until they reach an acceptable level. Beyond this point, however, further improvements appear to be unpredictable and the number of years of work and leisure experience in a domain is a poor predictor of attained performance (Ericsson & Lehmann, 1996). Hence, continued improvements (changes) in achievement are not automatic consequences of more experience and, in those domains where performance consistently increases, aspiring experts seek out particular kinds of training tasks designed for the particular performers by their teachers and coaches (deliberate practice) (Ericsson, Krampe, & Tesch-Römer, 1993). Several chapters in this revised handbook describe how deliberate practice can change the mechanisms mediating the experts' superior performance and that the accumulated amounts of deliberate practice are related to attained level of performance (see Ericsson, Chapter 38). Baker, Hodges, and Wilson (Chapter 15) review methods for collecting information about practice activities using concurrent and retrospective methods.

General Comments

In summary, there are a broad range of approaches to the study of the structure and acquisition of expertise as well as expert performance. Although individual researchers and editors may be primarily pursuing one of the approaches, this handbook has been designed to cover a wide range of different approaches and research topics in order to allow authors to describe their own views. However, the authors have been encouraged to describe explicitly their empirical criteria for their key concepts, such as expertise, experts, and expert performance. For example, the authors have been asked to report if the cited research findings involve experts identified by social criteria, criteria of lengthy domain-related experience, or criteria based on reproducibly superior performance on a particular set of tasks representative of the individuals' domain of expertise.

General Outline of the Handbook

The second edition of this handbook is organized into seven general sections. First, Part I introduces the handbook with brief accounts of general perspectives on expertise. In addition to this introductory chapter that outlines the organization of the handbook, there are four chapters. All of the four chapters are important new additions to the handbook. Collins and Evans (Chapter 2) give a sociological perspective of expertise based on philosophical analysis, Dall'Alba (Chapter 3) describes expertise from a phenomenological perspective based on the concept of the lifeworld, and Winegard, Winegard, and Geary (Chapter 4) take an evolutionary perspective on expertise and distinguish natural expertise, such as hunting, from non-functional expertise, such as chess. Finally Helton and Helton (Chapter 5) describe expertise displayed by non-humans, such as trained dogs detecting illegal drugs or herding livestock.

Part II of the revised handbook contains reviews of the historical development of the study of expertise from the perspective of different disciplines. Feltovich, Prietula, and Ericsson (Chapter 6) review the recurrent themes in the study of expertise from a psychological perspective. Buchanan, Davis, Smith, and Feigenbaum (Chapter 7) trace the historical development of using computers to model expertise, especially in the form of expert and knowledge-based systems. Billett, Harteis, and Gruber (Chapter 8) describe occupational expertise and its development based on experiences in the workplace. Finally, Mieg and Evetts (Chapter 9) describe the historical development of professionals and experts from a social perspective.

The next two sections of the handbook review the core methods for studying the structure (Part III) and acquisition (Part IV) of expertise and expert performance. Part III focuses on how expertise and expert performance can be explained by observable differences between experts and novices. In the first chapter in this section David Landy (Chapter 10) describes how the development of expertise can influence even processes of perception. Lintern et al. (Chapter 11) describe how the knowledge of experts has been elicited using the critical incident method, concept maps, and decision ladders. Ericsson (Chapter 12) describes the method of protocol analysis, which involves eliciting and recording the thought processes of experts when they respond to representative tasks from their domain of expertise. Ackerman and Beier (Chapter 13) describe psychometric approaches to expertise and identifying traits (cognitive, affective, and conative) that predict individual differences in its development. Finally Bilalić and Campitelli (Chapter 14) review methods to study changes in the neural structure and pattern of activation of the brain associated with expertise.

Part IV contains chapters examining methods for studying how skill, expertise, and expert performance develop and their relation to practice and other types of activities during the development. In the first chapter, Baker et al. (Chapter 15) describe methods and findings related to concurrent and retrospective assessment of these activities to performance. Elferink-Gemser et al. (Chapter 16) review the methodology and findings from longitudinal studies of groups of individuals developing achievement and performance. Mumford et al. (Chapter 17) describe how the case method for studying individuals' development can inform about the acquisition of expertise and expert performance. In the final chapter of this section, Dean Simonton (Chapter 18) reviews the methods of historiometrics and how data about the development of eminent performers can be collected and analyzed.

Part V consists of 16 chapters that provide up-to-date reviews of our current knowledge about expertise and expert performance in particular domains and represents the core of this handbook. The chapters in Part V have been broken down into two subsections. Part V.I is focused on different types of professional expertise. In the first chapter Norman, Grierson, Sherbino, Hamstra, Schmidt, and Mamede (Chapter 19) review our rapidly expanding knowledge about expertise in medicine and surgery as well as new training methods including simulators. Durso, Dattel, and Pop (Chapter 20) review the new research on expertise in transportation, especially driving and the effect of experience and training on hazard perception. In a completely new addition to the handbook Cross (Chapter 21) describes the new emerging domain of expertise in design based on studies with interviews and protocol analysis. In another new addition Dew, Ramesh, Read, and Sarasvathy (Chapter 22) review the knowledge of expertise among entrepreneurs and focus on the skill of requesting resources for new projects (The Ask). Kellogg (Chapter 23) has updated and expanded his review of expertise among professional writers and emphasizes the importance of other factors than writing ability such as knowledge of the topic and accessible memory for the already generated text. In a new addition Stigler and Miller (Chapter 24) review the societally important topic of expertise among teachers and identify the "pseudo expertise in teaching" as an obstacle to progress and outline how teachers can be helped to become more effective in improving their students' performance. Mosier, Fischer, Hoffman, and Klein (Chapter 25) describe the Naturalistic Decision Making approach to the examination and training of expert decision making in complex dynamic situations in everyday life. In a new addition to the handbook Cokely, Feltz, Ghazal, Allan, Petrova, and Garcia-Retamero (Chapter 26) review evidence on general decision making abilities that generalize across everyday contexts, finding that superior decision performance among both experts and non-experts primarily results from acquired specialized knowledge and probabilistic inductive reasoning skills (statistical numeracy and risk literacy). In the last chapter of Part V.I Sonesh, Lacerenza, Marlow, and Salas (Chapter 27) review the emerging evidence on how expert teams are more than the sum of all team members' expertise and emphasize the importance of the teams' adaptability, shared cognition, and leadership.

Part V.II contains chapters that review expert performance in the more traditional domains of games, such as chess, the arts, such as music, and sports. In the first chapter of the subsection Lehmann, Gruber, and Kopiez (Chapter 28) provide an updated review on the development of expert performance in music and its relation to the age of starting practice and the quality/quantity of different types of practice. Altenmüller and Furuya (Chapter 29) review evidence for the view that favorable adaptations of the brain are associated with superior performance and how maladaptive changes of the brain due to overtraining can account for the inability to control music playing, such as violinist's cramp. For the domains of drawing and painting Kozbelt and Ostrofsky (Chapter 30) examine the evidence for differences in general and specific perceptual and motor processes as a function of level of artistic skill. The classic domain of chess expertise is reviewed by Gobet and Charness (Chapter 31), who examine factors associated with individual differences in the ability to select superior chess moves, such as age of starting practice and amount of accumulated practice. Butterworth (Chapter 32) describes the evidence primarily on the development of expertise in mathematical calculation and discusses the effects of mental ability (natural ability), motivation (zeal), and practice (hard work). In a new addition to the handbook Macis, Garnier, Vilkaitė, and Schmitt (Chapter 33) review evidence on expertise in a foreign language by examining the development of learning and mastery of the critical vocabulary. In the final chapter of Part V.II Williams, Ford, Hodges, and Ward (Chapter 34) review expertise in sports and focus on the specificity and adaptability of expert athletes.

Part VI of the handbook is a new addition and addresses an important issue in the study of expertise and expert performance. In spite of the specificity of superior performance in a given domain, is it possible to identify mechanisms mediating performance in different domains which reveal a similar abstract structure? In the first chapter of this section Abernethy et al. (Chapter 35) show how the superior speed of reacting by experts compared to less skilled individuals can be accounted for by earlier anticipation of opponents' actions and better control and organization of their acquired motor processes. Ericsson (Chapter 36) shows how experts develop skills to maintain rapid access to information relevant to their current situations (long-term working memory). In the last chapter of Part VI Endsley (Chapter 37) reviews the research on experts' superior mental models based on perception, comprehension of the current situation, and prediction of future situations (situation awareness).

In Part VII the focus is on general theoretical issues that cut across different domains of expertise to provide reviews of the current state of knowledge. The first chapter, by Ericsson (Chapter 38), reviews the effects on attained performance from engagement in different types of domain-related activities, such as playing games, professional experience, solitary practice, and deliberate practice led by a teacher or coach. Cianciolo and Sternberg (Chapter 39) provide an updated review of the relation between expertise and central concepts/frameworks, such as practical intelligence, tacit knowledge, and related ecological theories. In a new addition Kalyuga and Sweller (Chapter 40) describe how instructional supports reduce cognitive load and improve learning for novice learners, but the same supports reduce the rate of further learning by more knowledgeable individuals and experts (the expertise reversal effect). Weisberg (Chapter 41) discusses the mechanisms mediating creative advances and shows how the expertise view provides superior accounts of the source of creativity. In the last chapter of the handbook, Krampe and Charness (Chapter 42) review the effects of aging deficits on tests of general cognitive ability for older participants. They find that these types of reduced performance on tests do not inevitably lead to reduced performance of experts, who are able to counteract reduction in the performance effects of aging with goal-directed practice.

Conclusion

This second edition of the handbook was designed to provide researchers, students, teachers, coaches, and anyone interested in attaining expertise with an up-to-date comprehensive reference to methods, findings, mechanisms, and theories related to expertise and expert performance. It is designed to be an essential tool for researchers, professionals, and students involved in the study or the training of expert performance and a necessary source for college and university libraries as well as public libraries. In addition, the volume is designed to provide a suitable text for graduate courses on expertise and expert performance. More generally, it is likely that professionals, graduate students, and even undergraduates who aspire to higher levels of performance in a given field can learn from experts' pathways to superior performance in similar domains.

Many researchers studying expertise and expert performance are excited and personally curious about the established research finding that most types of traditional expertise in competitive activities require years and decades of extended efforts to improve in order to acquire the mechanisms mediating world-class performance. There is considerable knowledge that is accumulating across many domains about the acquisition and refinement of these mechanisms during an extended period of training and practice. The generalizable insights range from the characteristics of ideal training environments with teachers and coaches, to the methods for fostering motivation by providing both emotional support and attainable training tasks of a suitable difficulty level. This theoretical framework has several implications.

It implies that if someone is interested in the upper limits of human performance, and the most effective training to achieve the highest attainable levels, they should study the training techniques and performance limits of experts who have spent their entire life striving to maximize their performance in a particular domain. This assumption also implies that the study of expert performance will provide us with the best current evidence on what is humanly possible to change and improve with today's methods of training and how these elite performers are able to achieve their highest

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2 A Sociological/Philosophical Perspective on Expertise: The Acquisition of Expertise through Socialization

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The sociological literature makes a distinction between expertise as a "performance" and expertise as a "property." We begin with a summary of the relational or performative understanding of expertise but the larger part of the chapter treats expertise as a capacity or property acquired by socialization within the relevant social group. This alternative approach supports a detailed typology of expertise and touches on philosophical debates including the relationship between ideas and actions, the nature of tacit and explicit knowledge, and the role of the body in the acquisition of expertise. Focusing on socialization as the foundation of expertise also leads to the identification of a new kind of expertise – interactional expertise – that is acquired through linguistic socialization. We explain this idea in some detail, showing how interactional expertise makes language more central to the *understanding* of practical matters than practice itself. We conclude by summarizing the approach in a three-dimensional model of expertise.

Expertise as Performance

Treating expertise as a something that is "performed" means treating it as a relational or network phenomenon (Eyal, 2013) that is produced through its enactment in social settings. In this view, expertise is a status that individuals and organizations struggle to have attributed to them by others and which they must work to retain (Hilgartner, 2000). This, in turn, links expertise to issues of power and control with Foucault providing the classic exposition of "power/knowledge" (e.g. Foucault, 1978). Carr (2010) classifies sociological and anthropological work in this tradition into four main areas:

- **Apprenticeship, training, and socialization**, where the aim is to describe the methods by which novices are initiated into a domain of skilled practice and the boundaries that define the group are maintained. In some cases (e.g. Lave & Wenger, 1991) this approach can serve to bolster the value of more traditional forms of learning; in others (e.g. Gieryn, 1999) it can be used to show the socially constructed, and hence contestable, nature of expert authority.
- **Authentication and evaluation**, where the focus is on explicating the ways in which expert status, and hence the distinction between expert and non-expert, is enacted and legitimated in social settings. For example, researchers working within the ethnomethodological tradition of sociology might focus on the minutiae of interactions in order to reveal how the structure and topics of utterances, combined with non-verbal behaviors, are used to project authority and claim expert status (e.g. Lynch & Cole, 2005; Matoesian, 1999, 2008). Such work typically makes no claim to judge whether or not participants' attributions of expertise are justified by

any independent criteria. Instead, the point is to reveal the methods social actors use to construct and contest expert status (Coopmans & Button, 2014).

- **Institutions and authorization**, where the emphasis is on how expert knowledge is stabilized in both formal institutions and everyday practices. This might include studies of professions and the autonomy they are able to claim (e.g. Abbott, 1988; Turner, 2001), the difficulties of collaboration between specialists as exemplified by scientific research (e.g. Fisher et al., 2015; Galison, 1997), or the incorporation of science and technology into everyday practices like waste management (e.g. Woolgar & Neyland, 2013).
- **Naturalization**, where research uses the social constructivist approach to highlight the cultural and political assumptions that are embedded within dominant forms of expertise but which are so taken for granted that they are rarely questioned. Again, the field of science studies provides a good example of this kind of work with typical topics being the way problems are framed and what is allowed to count as evidence in situations of conflict (e.g. Delborne, 2008; Irwin, 1995; Shapin, 2007; Wynne, 1992).

Epistemic Injustice and the Limits of Attribution

The network or relational model of expertise is normative insofar as it aims to reveal the contingent ways in which "particular claims and attributions of expertise come into being and are sustained and what the implications are for truth and justice" (Jasanoff, 2003, p. 398). The analysis typically documents how different social groups mobilize cultural and epistemic resources to challenge established ways of defining problems and is often framed as a critique of elite, top-down, or technocratic decision making (Callon, 1986; Fischer, 2009; Turner, 2003). One particularly striking outcome of this work has been to show that even the most privileged networks of expertise can be effectively challenged by organized groups of lay citizens and stakeholders (e.g. Epstein, 1996; Ottinger, 2010).

Epistemic and political issues are often considered alongside each other in these studies. The same boundary work (Gieryn, 1999) that discredits local, experiential, or traditional knowledge also reinforces the social and technological outcomes that put indigenous or minority communities at increased risk, with Love Canal (Mazur, 1998) and the Union Carbide disaster in Bhopal (Fortun, 2001) providing two of the most well-known cases. As the critique starts from the idea that both the expertise and the interests – the two are seen as inseparable – of particular social groups have been ignored, the solution that is invariably proposed is the creation of more inclusive decision making forums in which a wider cross-section of communities can be represented (e.g. Douglas, 2009; Schot & Rip, 1997). Sociological interest in the enactment of expertise thus fits neatly with arguments for the democratization of expertise (e.g. Funtowicz & Ravetz, 1993; Jasanoff, 2003; Maasen & Weingart, 2008).

A different way of understanding this critique of technocracy is through the idea of "epistemic injustice." First coined by Miranda Fricker (2007), "epistemic injustice" refers to the wrong that is done when there is a refusal to recognize a "bona fide knower," or community of knowers. Epistemic injustices can be inflicted on both high and low status groups and, although it is true that many marginal or low status social groups continue to have their knowledge unfairly discounted, the same is now happening to higher status professions and institutions (Collins, 2014; Collins & Evans, 2002; Prior, 2003). Well-known examples of this phenomenon include controversies over vaccines, in which parents reject consensual medical evidence (Boyce, 2006; Laurent-Ledru, Thomson, & Monsonego, 2011; Sheldon, 2009) and the decision of the South African government in 1999 not to use AZT to reduce the risk of mother-to-child transmission of HIV (Nattrass, 2012; Weinel, 2007). Focusing purely on the enactment of expertise makes it difficult to offer a critique of these events because, within the constructivist framework that characterizes this approach, the legitimate sources of expertise are whatever the relevant social actors take them to be.

Expertise as Property

The alternative is to see expertise as the property of an individual or group (Collins & Evans, 2007). By foregrounding the notion of socialization this approach links the acquisition of expertise to participation in the relevant social practices. Where there is participation – i.e. experience – there can be expertise; where there is no participation there can be no expertise because there has been no opportunity to acquire the relevant tacit knowledge. Known as Studies of Expertise and Experience (SEE), this approach allows the social scientist to examine the social groups in which individuals have participated and, on this basis, to conclude whether expert status has been wrongly denied or wrongly attributed and, in so doing, to challenge the conclusions reached by participants (Collins, 2008; Collins & Evans, 2002, 2014a).

Expertise as Real

Arguments about who is an expert and who is not are the stuff of professional life so how can an outside analyst claim to know that, say, "X really is an expert in A but Y is not"? Well-known approaches such as the "five stage model" of Dreyfus and Dreyfus provide a starting point by showing that it is possible to identify different levels of expertise within a domain of practice (Dreyfus, 2004; Dreyfus & Dreyfus, 1986). Under the Dreyfus approach the initiate starts as a novice, self-consciously applying explicit rules but unable to grasp the nuances of context, and gradually works toward the expert stage, in which he or she is able intuitively to identify the salient features of the situation and the actions that should follow. The expert is, then, an individual who has gradually acquired skills through sustained practice. The sociological twist to this phenomenological account is to specify social embedding in an expert community as a necessary condition for developing these skills. This leads to an enculturation or apprenticeship model of learning that can be theorized in several ways, including the "situated learning" or "communities of practice" associated with Lave and Wenger (Lave & Wenger, 1991), Thomas Kuhn's idea of a scientific paradigm (Kuhn, 1962), and the idea of "form of life" (Bloor, 1983; Winch, 1958; Wittgenstein, 1953) used in Science and Technology Studies and by SEE in particular.

The common element in these models is that expertise is held in, and sustained by, the activities of a social group. Gaining the skills needed to become an expert means becoming a full and active member of that group and learning to act in ways that other group members will recognize as appropriate or, at least, not inappropriate, when actors are confronted with new or novel problems. In some cases, the expected standards are codified with acceptance as an expert predicated on "reproducible performances of representative tasks that capture the essence of the respective domain" (Ericsson, 2006, p. 3). Examples of this include professions like medicine or law, where entry is via formal examinations and any subsequent work is expected to maintain appropriate levels of competence. Likewise, athletes and artists display their expertise though consistently performing well in competitions and giving performances that go beyond what "normal" or "ordinary" people can achieve.

In other cases, the requirements are much less explicit and what counts as the standard is shared tacitly and only revealed through the group's practices. The paradigm case here is natural language speaking, where the rules of grammar are notoriously hard to specify, but all native speakers know how to create an intelligible utterance. In fact, this is closer to the general case as even formal rules need informal meta-rules to determine how they should be applied in each new context (Collins, 1990). Thus, "thou shalt not kill" is generally a good rule but there are exceptions (e.g. on a battlefield, in self-defense, in order to save another life, and so on) and these exceptions will need meta-meta-rules as well (e.g. is this self-defense?).

This idea of rules as essentially incomplete is crucial to the sociological understanding of expertise. According to this view, the meaning of an idea or word is revealed in the way it is used (Bloor, 1983; Winch, 1958). This makes expertise both context-sensitive and dependent on tacit knowledge. The apprenticeship model of learning is then necessary because only socialization can enable the individual to share the collective understandings of the group and so develop the tacit skills needed to apply them in new settings (Collins, 2010; Collins & Kusch, 1998; Dreyfus, 1979; Polanyi, 1962, 1966).

The Periodic Table of Expertises

If expertise is the outcome of successful socialization, then an individual's expertises are the accumulation of what has been acquired from the social groups in which he or she is a successful participant (Collins & Evans, 2017). As different individuals participate in different combinations of social groups, there must be a distribution of expertises that reflects these different experiences (Evans, 2011). These ideas are captured in a typology known as the "periodic table of expertises" (Collins & Evans, 2007), which is shown in Table 2.1.

The structure of the table is given by different kinds of participation. Working from the top, the first two rows identify the society-wide *ubiquitous expertises* and *dispositions* (personal

Table 2.1 The periodic table of expertises.

UBIQUITOUS EXPERTISES					
DISPOSITIONS				Interactive Ability	Reflective Ability
SPECIALIST EXPERTISES	UBIQUITOUS TACIT KNOWLEDGE			SPECIALIST TACIT KNOWLEDGE	
	Beer-mat Knowledge	Popular Understanding	Primary Source Knowledge	Interactional Expertise	Contributory Expertise
				Polimorphic	Mimeomorphic
META-EXPERTISES	EXTERNAL		INTERNAL		
	Ubiquitous Discrimination	Local Discrimination	Technical Connoisseurship	Downward Discrimination	Referred Expertise
META-CRITERIA	Credentials		Experience		Track-Record

Source: Collins & Evans (2007).

understand the discourse of those subfields. Note that acquiring interactional expertise is not the same as reading about a domain of practice in texts or on the Internet, it involves long and deep immersion in the flux of linguistic discourse; such immersion is a means of acquiring tacit knowledge. This, incidentally, resolves the enigma of how it is possible for management of technical domains to work; to understand the domain they are managing, and to make recognizably good technical judgments within that domain, managers do not have to be front-line practical experts (Collins & Sanders, 2007).

Outside workplace settings, the same problem arises: how do members of one social group come to understand the experiences of other groups? In some cases this will be via representations in the media or other forms of explicit knowledge but in others, and particularly where genuine understanding is needed, it will be best achieved by talking deeply to members of those groups about their experiences (Collins & Evans, 2014b). That said, the difficult and time-consuming process of acquiring a high level of interactional expertise in an esoteric domain should not be underestimated (Collins & Evans, 2015). For attempts to widen the notion of interactional expertise so as to make it less difficult to acquire see Goddiksen (2014) and Plaisance and Kennedy (2014). For resistance to such moves see Reyes-Galindo and Duarte (2015) and Collins, Evans, and Weinel (2016).

These ideas have also given rise to a new research method based on the Turing Test (Collins et al., 2017; Collins, Evans, Ribeiro, & Hall, 2006; Evans & Collins, 2010). Known as the Imitation Game, the method explores both the content and distribution of interactional expertise by asking participants to pretend to be members of a different social group referred to as the "target group" (e.g. men might pretend to be women). Members of the target group (women in this example) then compare these answers to answers provided by genuine members of the target group to the same questions and try to work out which were produced by the pretender and which by the real women. Examining the questions asked and how they are answered by each group reveals what members of a social group think defines their culture and how well this is understood by other social groups. Research to date has included physiological topics such as color-blindness (Collins et al., 2006) and sociological topics such as gender and sexuality (Collins & Evans, 2014b). It has also been used to explore the extent to which medical practitioners are able to take the patient's perspective (Evans & Crocker, 2013; Wehrens, 2014) and how well social scientists understand their fieldwork setting (Collins, 2016a; Giles, 2006).

Three Dimensions of Expertise

The sociological model of expertise as social fluency put forward in this chapter can be summarized as operationalizing expertise along three different dimensions (Collins 2013b):

1. *Individual accomplishment*: this is similar to the approach of the stage models championed by such as Dreyfus and Dreyfus (1986) or Chi (2006) and captures the proficiency of the individual or group with respect to the domain of expertise in question.
2. *Esotericity*: this captures the extent to which access to the social collectivity that holds the expertise is open or closed.
3. *Exposure to tacit knowledge*: this describes the type of exposure that the learner has to the domain, ranging from published sources, through linguistic interaction to full participation.

Combining these gives the three-dimensional expertise space shown in Figure 2.1, in which domains of expertise and individual practitioners can be placed.

This model allows a much richer description of the types of expertise available and the ways in which they develop and spread over time than the one-dimensional view of expertise as the mastery of esoteric skills. For example, it is possible to see

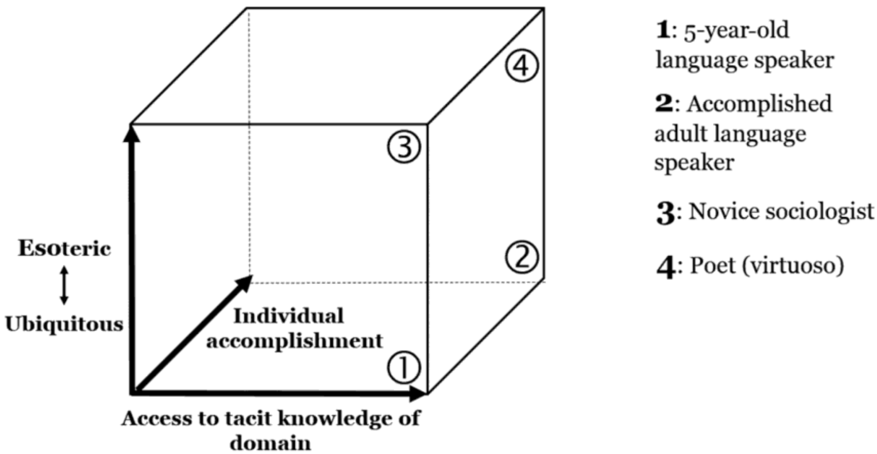

Figure 2.1 Three dimensions of expertise.

how some expertises can be ubiquitous (e.g. natural language speaking), whilst others are esoteric (e.g. the virtuoso poet). It also enables individual accomplishment and practice to be set within a broader scheme that suggests what kind of practice is needed – thus, if full mastery means reaching the right-hand edge of the back wall, then practice must involve social interaction with the relevant community as, without this, the tacit knowledge of the domain can never be attained.

Summary

In this chapter we have focused on the analysis of expertise as a property of social groups that is acquired by individuals through their participation in those groups. The success of this process is measured by the increasing social fluency of the learner as they acquire the tacit knowledge needed to use their knowledge in ways that other group members recognize as correct.

We have also argued that it is possible to distinguish between different types of expertise based on these different socialization experiences. Within this classification, the distinction between contributory and interactional expertises, and hence between the linguistic and physical aspects of socialization, reaches deep into philosophical debates about the embodiment of human knowledge. Although these debates continue, the model of expertise we defend suggests that socialization not embodiment is what underpins expertise. This, in turn, leads to a range of more practical and normative suggestions in which participation in the linguistic discourse, rather than the physical practice, of the relevant community is the key determinant of whether or not an individual knows what they are talking about. Practice, of course, remains the key to practical accomplishment but it is no longer the only source of good judgment.

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skills organized in cognitive structure, could expertise principally consist of *something other than* knowledge and skills in cognitive structure?

Given the challenges to current theory, my aim in this chapter is to point to a way forward in reframing expertise and its development. This reframing necessitates adopting assumptions that differ from those prevalent within a model of cognitive structures in the mind or, in other words, it assumes a different ontological ground. Below I outline a theoretical framework that opens new avenues for researching expertise and its development, while also contending with the challenges noted above. This framework has as its source the notion of the lifeworld, or entwinement of life with world, from phenomenology, as I outline in what follows.

Rethinking Expert Knowledge and Expertise

In much conventional expertise research, experts are seen as possessing and/or applying extensive knowledge in their domain of expertise. Experts, their knowledge, and domains of expertise are typically seen as separable and independent of each other. This assumption of separateness can be called into question, however. It makes no sense to talk of expert knowledge in the absence of experts or domains of expertise. For instance, expert knowledge about teaching only makes sense in the context of learners who are being taught by teachers. In contrast to an assumption of separateness, we can think of them as comprising an inescapable entwinement (Dall'Alba, 2009).

The concept of the lifeworld, proposed by Edmund Husserl (1936/1970) who is considered the founder of phenomenology, captures this inevitable entwinement of persons with their world. Rather than either external stimuli or cognitive structures in the mind, the lifeworld highlights the inescapable relation between persons and world. In other words, we are *always already entwined with others and things* in our world; we cannot step outside this entwinement with world. The lifeworld is not limited, then, to either an "inner world" of cognitions or an external world of stimuli. Instead, it is simultaneously my world and a world shared with others and things—a world we individually and collectively inhabit. The lifeworld is the everyday world we take for granted and from where all our endeavors arise, so it is both pre-scientific and pre-reflective. This concept of the lifeworld is common to the various branches of phenomenology that developed following Husserl, each with its own knowledge interest (see Spiegelberg, 1982).

The concept of the lifeworld is further developed through Martin Heidegger's (1927/1962) notion of "being-in-the-world." Heidegger considered our domains of knowledge, such as architecture, history, and visual arts, as ways of being-in-the-world (p. 408). In other words, we enact our knowing in our ways of teaching, engineering, nursing, and so on. This emphasis directs attention not simply to an individual expert's knowledge and skills, but to what is entailed in being expert in a specific domain. Being expert is not limited to knowledge and skills of individuals, but expert performance is inseparable from individual and collective activities, concerns, equipment, and endeavors in particular domains. So, the relation between experts and their domain of expertise is again highlighted, albeit with an ontological emphasis on being expert in a particular domain, as further elaborated below.

While Heidegger gave the concept of the lifeworld an ontological emphasis, Maurice Merleau-Ponty (1945/1962) proposed that our being in the world is made possible through the perceiving body. Highlighting the relation between person and world, he argued that "consciousness is being-towards-the-thing through the intermediary of the body . . . and to move one's body is to aim at things through it; it is to allow oneself to respond to their call, which is made upon it independently of any representation" (pp. 138–139). He pointed out that "movement is not thought about movement, and bodily space is not space thought of or represented" (p. 137). Emphasizing the mediating role of the body, he argued that "the body is the vehicle of being in the world" (p. 146). This body is not limited to interrelated systems of organs, but is the body as *lived*, as continually engaged in the world.

For Merleau-Ponty, "perception and action are therefore essential collaborators with each other from our first embodied moments" which "dissolves the traditional conceptual split between the mental and the material" (Scully, 2012, p. 145). Merleau-Ponty's concept of the "lived body" overcomes the problem of a gap between contents of the mind and expert performance. It shifts the focus of attention from the construct of "mind" to bodily perceptions, sensations, and movement about the world, which form the basis for habituated actions and, subsequently, for thought. For instance, "for us to be able to conceive space, it is in the first place necessary that we should have been thrust into it with our body" (Merleau-Ponty, 1945/1962, p. 142).

Over time, bodily perceptions, sensations, and movement develop into habits based on experience of the material, socio-cultural world. These habits, enacted through the body, allow us to make our way about the world without being compelled to continually think in advance about everything we are doing. For Merleau-Ponty, "bodily actions or habits make thinking possible in the first place. And so the body and its habitual actions constitute forms of knowledge in themselves about how to be particular kinds of human beings in particular social settings" (Scully, 2012, p. 144).

Drawing on Heidegger's and Merleau-Ponty's phenomenology, I argue that expertise and its development are not primarily dependent upon knowledge and skills in cognitive structure, but on embodied being in the world, inescapably entwined with others and things. In the section that follows, I explore what such a notion of expertise means for developing expert performance.

Developing Expert Performance

From a lifeworld perspective, expertise and expert performance are enacted and embodied, rather than possessed or applied as independent entities. Developing expertise relies upon this embodied being in the world. More specifically, developing expert performance requires integration of knowledge and skills into particular ways of being in the world (Dall'Alba, 2009), such as being economists, biologists, or social workers. This means it is insufficient simply to possess knowledge and skills, or to apply them to specific tasks or problems, however complex these may be. Possession or application of knowledge and skills is not sufficient to constitute expertise. Instead, knowledge and skills must become integrated into being expert, as I discuss below.

If we seek to promote the development of expertise, then, what would this entail? An important consideration is enhancing not only what aspiring experts know and can do (an epistemological dimension), but also how they are learning to be (an ontological dimension) in relation to the domain in question (see Dall'Alba, 2009, for elaboration). To date, research on expertise and associated efforts to develop expert performance have had largely an epistemological emphasis. Developing expertise requires, then, an "ontological turn" through adopting a relational focus (Heidegger, 1998; see also Barnett, 2004; Dall'Alba & Barnacle, 2007). Developing expert performance involves not simply increasing knowledge and skills, but integrating these knowledge and skills into expert ways of being in a specific domain. The inevitable entwinement of (aspiring) experts with their world is foregrounded. Developing expertise can be conceptualized, then, as a continuing process of becoming; never entirely complete, nor achieved once and for all.

Simply disseminating knowledge and skills, even by enthusiastic experts, falls short of promoting such a process of becoming. Indeed, the problem of knowledge "transfer" has itself arguably been created through an assumption of separate, independent components of expertise. While efforts to educate aspiring scientists in "thinking like scientists" recognize limitations in disseminating knowledge and skills, they typically fall short of a clear focus on developing embodied ways of being scientists.

In learning to enact what we know, we embody ways of being in the world. Knowledge and skills are formed and organized into embodied ways of being, which serve to direct further development of expertise. For example, when teaching is enacted as knowledge dissemination, efforts to develop expertise in teaching tend to concentrate on teachers' presentation of content. Developing knowledge and skills that improve content presentation comes into focus. When teaching, instead, actively seeks to facilitate learning, developing expertise becomes concerned with monitoring and enhancing learning as it occurs (see, for example, Borko, Davinroy, Bliem, & Cumbo, 2000). The knowledge and skills that become integrated into facilitating learning center on understanding what learning involves for learners in a particular setting, how this learning can be monitored, and embodying what can be done to enhance this learning. Ways of being teachers such as these are enacted in how teaching is performed and developed, both individually and collectively.

Current ways of being can present obstacles to achieving expert performance, even when extensive knowledge and skills are accumulated in a conventional sense (e.g. see Benner, Tanner, & Chesla, 1996; Borko et al., 2000; Dall'Alba, 2009). For instance, if expertise in teaching requires careful attention to learning, then primarily improving presentation of content stands in the way of enacting expert teaching, regardless of the extent of acquired knowledge or skill (e.g. see Borko et al., 2000). It follows, therefore, that if targeted, deliberate practice does not take into account current ways of being, it may be ineffective. Development can consist of merely reinforcing and refining existing ways of teaching, without the transformation that would be required in being teachers focused on monitoring and enhancing learning (for examples, see Borko et al., 2000; for examples in learning to be medical practitioners, see Dall'Alba, 2009, and Dall'Alba & Sandberg, 2006).

Such qualitative differences in expertise – of the kind outlined above for teaching – form the basis for Hubert and Stuart Dreyfus's (1986) influential stage model of development from novice to expert. However, this stage model does not account for differences that are evident at a single stage of development (see Dall'Alba & Sandberg, 2006, for elaboration). Depending upon embodied experiences built up over time and responses to these experiences, novices can show similarities to expert ways of being, albeit usually less fluent and refined in the enactment due to fewer, less varied experiences. For instance, both expert and novice teachers can be attuned to learning by learners, although they are likely to differ in their repertoire for responding to those attunements.

When we identify experts in a particular domain, we expect them consistently to demonstrate more accomplished performance than most others. Indeed, such high-level performance is inherent in the notion of being expert (see also Ericsson, 2006; Sonnentag, Niessen, & Volmer, 2006). We also recognize that some never attain this expert status, despite extensive knowledge or years of experience (Benner et al., 1996; Dreyfus & Dreyfus, 1986). Being expert entails, then, something other than simply increasing knowledge and skills. It requires consistently demonstrating high-level performance through responding in attuned ways to the particular setting and issues at hand. This "attuned responsiveness" (Dall'Alba, 2009, p. 68) includes taking an informed and responsible stand on the varied situations and issues encountered. It would be a contradiction in terms to speak of an uninformed or irresponsible expert. We expect experts to display not only substantial knowledge and skills, but also a capacity for critical reflection, while exercising responsible judgment. In other words, we expect not only expert knowledge, but expert ways of being.

Such attuned responsiveness to the circumstances and issues at hand is not readily addressed through standardized performance measures, as evident in the risk of teaching to the test in ways that can limit learning. What is considered to be attuned, high-level performance in particular settings also alters over time, as expertise and its related domains develop. For instance, in recent years, promoting literacy in the use of information and communication technologies among learners has increasingly become an expectation held of teachers in schools. As developments occur in domains of expertise over time, it follows that standardized, generic measures of performance cannot fully capture performance once and for all, as controversy over efforts to measure intelligence has also made manifest (e.g. see Kaufman, 2009).

Ways of being in a particular domain also show some variation from one socio-cultural, material context to another. For instance, the teaching required of a teacher with chalk, a blackboard, and a few books in a remote village contrasts with the teaching demanded in a richly resourced virtual environment. Similarly, ways of being teachers can vary from one classroom to an adjacent classroom. This is because expertise is dynamic, embodied, intersubjective, and plural, in line with the inseparable relation between persons and world. A limitation of expertise research carried out in controlled, laboratory conditions with standardized tasks is that it does not account for this plurality (as Micheline Chi acknowledges: Chi, 2006; see also Clancey, 2006; Ross, Shafer, & Klein, 2006; and Norman, Eva, Brooks, & Hamstra, 2006, on the importance of the situation or context). In the everyday world, variations occur as situations alter and requirements change. At the same time, if it is to be considered teaching, there will be some commonalities across time and settings, such as teachers, learners, and material to be learned with relevance to the context.

It is crucial, then, that developing expertise attends not only to knowledge and skills, but also to attuned responsiveness to others and things in the surrounding environment, across variations in time and place. In other words, ways of being in the world are to be in focus through integrating knowing, acting, and being experts in the domain in question (Dall'Alba, 2009; Dall'Alba & Barnacle, 2007).

Concluding Remarks

In some respects, both behaviorism and the later cognitive turn each pointed to important features of expertise. On the one hand, behaviorism indicated the perceived world (while underestimating the perceiving body). On the other hand, the cognitive turn signaled active involvement of the mind (while downplaying the world calling forth this response). These are two sides of a common coin, each incomplete in its own way.

A lifeworld perspective from phenomenology calls into question the usefulness of cognitive structures in the mind as "a theoretical construct, a model of a possible interface between body and behaviour" (Teubert, 2010, p. 43) for contending with the challenges to theory in exploring expertise into the future. This model displaces attention from the embodied way in which expertise is enacted in addressing specific tasks and concerns in particular settings, while creating an unbridgeable gap between mental content and expert performance. This gap is removed when a lifeworld perspective is adopted. Similarly, a relational, ontological perspective on ways of being in the world exposes the problem of knowledge "transfer" as an inadequate conceptualization, while demonstrating multiplicity in ways of being at any given level of experience.

In order to advance understanding of expertise and its development, the earlier shift in focus from external stimuli to cognitive structures in the mind arguably now demands a shift in ontological ground, toward recognizing the centrality of the inescapable relation between persons and world. The notion of the lifeworld in phenomenology highlights this *inevitable entwinement of persons with world*, providing novel resources for further research and development in expert performance.

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form broad multilevel networks with kin and non-kin (Chapais, 2010). They transmit information in unusually complex ways (e.g. language) and do so, in part, to coordinate group activities and divide into specialized roles (Geary, 2005; Pinker, 2010). These peculiar capacities likely allowed a small and unintimidating ape to spread into multiple continents and to cope with disparate ecologies, from the unforgiving winters of the north to the sun-beaten deserts and humid forests of the equator. Scholars have put forward many theories to explain the evolution of humans' novel nexus of traits. We believe that Alexander's (1990) ecological dominance and social competition theory (EDSC) is among the best (see also Flinn, Geary, & Ward, 2005; Geary, 2005).

According to EDSC, at some point in hominid evolution, our ancestors achieved a significant ability to control ecological selection pressures such as pathogens, climate, and prey. They did this in myriad ways. For example, the control of fire better allowed humans to avoid consuming pathogens, gave them rapid access to nutrient-rich foods, and may have served as a deterrent to predators, especially at night (Wrangham & Carmody, 2010). Humans also learned to make more effective tools which increased hunting and fishing efficiency and also allowed for the making of better shelters (Ambrose, 2001). The reduction of these ecological pressures allowed for rapid population growth and changed the central target of selection forces from starvation, disease, and predation to social pressures, such as ability to learn rapidly and outsmart conspecifics (Geary, 2005). That is, at some point our ancestors became their own chief selective forces, competing intensively against each other (sometimes by cooperating in groups) for resource control and social influence. The resulting within-species arms race is arguably the best explanation for the unprecedented increase in hominid brain size (Bailey & Geary, 2009), and the human cognitive and social competencies that differentiate us from other species.

Researchers have proposed that one key result was the expansion of social, behavioral, and cognitive plasticity to cope with variation and change (Geary, 2005). Other people's unpredictable and self-interested behaviors are the most critical sources of this variation. To anticipate and cope with fluid social dynamics, humans have evolved the capacity to generate mental models or run imaginary scenarios: "If he does this, and I do that, then this will happen." Moving up a social hierarchy is very different from extracting fruit from a tree. The second problem is stable across generations and within lifetimes and thus evolution could solve it with a system of rigid, straightforward algorithms (hard modules). The first problem, though, changes with different constellations of people and groups of people, and individuals with rigid, straightforward social algorithms would be quickly outmaneuvered. Geary (2005, 2007) outlined how this arms race and the attendant use of mental models, combined with modular plasticity (below), could have resulted in the evolution of general fluid intelligence and the ability to create and learn evolutionarily novel things, such as writing systems and chess.

An alternative, but not necessarily mutually opposed perspective, posits that environmental variability was an important driver of human cognitive capacity and behavioral flexibility (Potts, 1998). Variable environments place strains on organisms and select for behavioral plasticity and can lead to adaptive versatility (Potts, 2013). Some evidence supports the hypothesis that climatic variation contributed to human brain expansion (Shultz & Maslin, 2013). In this view, the attainment of high quality food did in fact place tremendous cognitive stress on hominins because the environment changed relatively rapidly, thus a hard modular system would lead to inefficient foraging and place less intelligent and behaviorally inflexible individuals at greater risk for starvation.

Whatever the exact truth of these perspectives, and we suspect both ecological climate and social climate played a role in human uniqueness (see Bailey & Geary, 2009), the end product is the same: an organism that is uniquely intelligent, able to learn novel skills, and to behave flexibly. An organism, in other words, that has entered the cognitive niche (Pinker, 2010).

Models of Human Cognition

For much of the twentieth century, many thinkers assumed human minds were extremely malleable (Pinker, 2002). This "blank slate" perspective was popular among behavioral psychologists and in the social sciences more generally. In the 1950s, the blank slate view was questioned by a number of psychologists, philosophers, and linguists, ushering in the cognitive revolution. Notable in the ensuing paradigm shift was Fodor's (1983) argument that the mind was probably composed of computationally distinct mechanisms, each devoted to solving specific problems in straightforward, algorithmic ways. This gave rise to a "hard modularity" approach to cognition, whereby the mind is composed of a system of unique modules, each using specific algorithms to solve evolutionarily recurrent problems, such as detecting predators and social cheaters (e.g. see Tooby & Cosmides, 1992).

We believe that neither the blank slate nor the hard modularity approaches are sufficient for understanding expert performance. Rather, a "soft" modularity approach, one that relies upon a distinction between primary (evolved) and secondary (learned, culturally specific) competencies affords a more nuanced understanding of the human mind (Geary, 1995; Geary & Huffman, 2002). On this view, the human mind is composed of basic modular functions that support universal, primary competencies. These primary systems require fleshing out and adaptation to local conditions through children's engagement in play, exploration, and social discourse, forms of naturally occurring practice. The eventual results are systems of cognitive competencies organized around the domains of folk psychology, folk biology, and folk physics, as shown in Figure 4.1. These systems enable people to cope with universal social (e.g. developing relationships) and ecological demands (e.g. hunting and navigation), but can be modified (within constraints) through developmental experiences to accommodate the many different social and ecological niches in which humans are situated.

The plasticity of these systems follows from ecological dominance, climatic variability, and the resulting expansion into novel ecologies and increasing competition from sophisticated conspecifics. Although much remains to be determined, this plasticity likely involves the sensitivity of these systems to a wider range of information than is found in other species and the ability to link systems in top-down and in novel ways (Geary, 2005). The top-down modification of soft modules is supported by the attentional control components of working memory, abstract problem-solving that is a key feature of fluid intelligence, and through practice. The result is the potential to develop evolutionarily novel, secondary competencies. For example, the ability to write poetic verse in iambic pentameter with end rhymes is a secondary competency that is possible through explicit, top-down modification of primary language abilities. These natural rhythms of speech provide the scaffolding for many forms of poetry, the writing of which requires explicit control over language production and multiple cycles of revision to achieve the desired effect. Perfecting the ability to write this form of verse likely requires considerable practice.

Secondary Competencies and Expertise

Expert performance as studied by psychologists is largely focused on secondary domains (e.g. chess, music) (Ericsson & Charness, 1994), and even in domains more closely related to primary abilities, the level of skill development is unusual from an evolutionary perspective (Epstein, 2014).

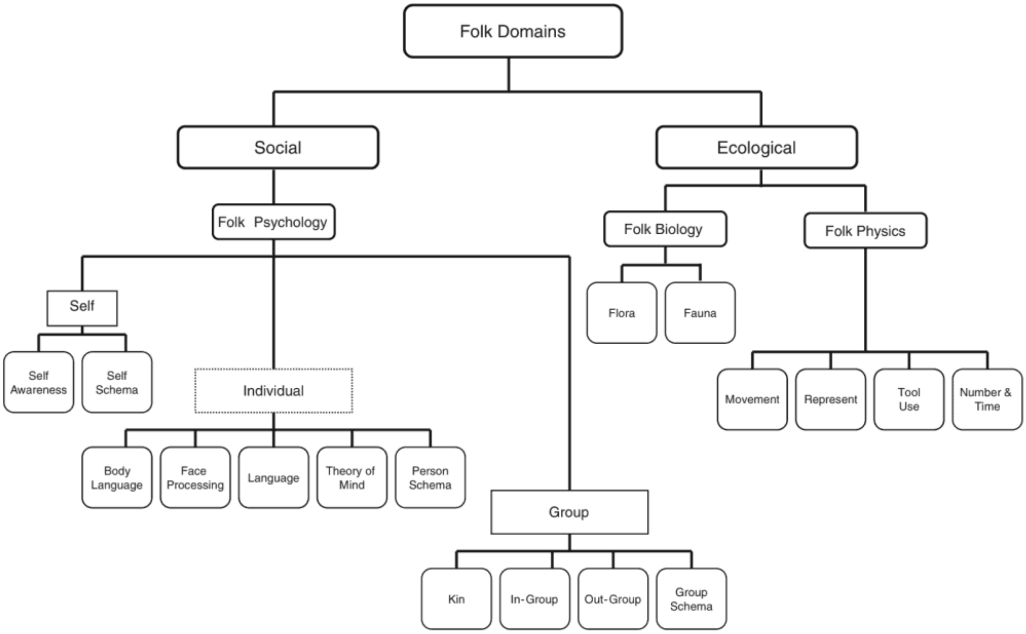

Figure 4.1 Evolutionarily salient information processing domains, and associated cognitive modules that compose the domains of folk psychology, folk biology, and folk physics.Adapted from D. G. Geary, *The origin of mind: Evolution of brain, cognition, and general intelligence*, 2005, p. 129. © 2005 American Psychological Association.

Expert performance requires deliberate practice to achieve; it does not appear to result from the natural play and exploratory behaviors that flesh out primary systems. However, as noted, expert performance does build from the scaffolding of basic modules and primary competencies. Chess, for instance, requires the ability to think about space, movement, time, and to hold a goal in mind, and simulates group-level military conflict and strategy. Chess builds from primary competencies and motivations in folk physics and folk psychology (i.e. "what is my opponent going to do?"), but pulls these together in a novel way. The achievement of chess expertise requires some level of fluid intelligence and attentional focus (Campitelli & Gobet, 2011), along with significant, controlled practice with reliable feedback. By analogy, deliberate practice is to secondary competencies (and expertise, by extension) what play and exploration are for primary competencies (Ericsson, 2008). A key difference is that many of the attentional, cognitive, motivational, and behavioral biases that support the fleshing out of primary systems are built in, but these have to be largely constructed through deliberate, goal-directed activities for the development of competencies in secondary domains.

It is probable that expert performance, like the weather, is dramatically affected by small variation in input variables. That is, small differences in initial physical or cognitive abilities or more likely constellations of them are probably exaggerated as performers reach elite levels (Epstein, 2014). Consider, for an obvious example, height and success in basketball. In lower levels of competitive play, individual differences in height, although important, are not determinative. There are many relatively short players in division one college basketball compared to the NBA (National Basketball Association), and individual differences in height probably do not matter as much. For example, a successful center in college basketball does not have to approach seven feet tall. Productive NBA centers in contrast are typically close to seven feet tall. Today, for example, the shortest center among the top ten in player efficiency, which assesses the impact a player has on the game, is six foot ten inches (ESPN Hollinger Ratings, 2015). What is true for height is probably true for less conspicuous traits such as spatial perception, hand–eye coordination, and short-term memory, among others. Even apparently irrelevant traits such as wrist tendon flexibility might greatly affect the capacity of a person to throw a slider or a curveball. And the difference between an easy to hit and a devastating curveball is probably not large (Epstein, 2014). As we document below, this has implications for thinking about the development of expertise in an evolutionary perspective.

Expertise and Social Signaling

As noted, the development of many forms of expertise appears without evolutionary function. It is hard to understand why a man might practice for thousands of hours just so he can hit a table tennis ball better than another man, allowing him to win 53 percent of his games. And this is especially difficult to understand because the man could be using that time to achieve other goals such as searching for a mate, socializing with friends, working at the office – all of which are more immediately relevant to the evolutionary imperatives of mating and survival (Buss, 1995). We believe that signaling theory can help explain this apparent mystery. In other words, we believe that expert performance is a signal that can attract social partners, romantic partners, and prestige because in modern contexts it communicates the possession of desirable traits, skills, or, even, genes.

Signaling theory explains the logic of animal communication from ornamentation to vocalizations and many previously enigmatic phenomena such as gaudy nests and time-consuming courtship dances (Searcy & Norwicki, 2010; Zahavi & Zahavi, 1997). The basic tenets are straightforward. Trait quality varies among individuals of all sexually reproducing species. The quality of such traits is not always easy to perceive, but trait quality can be reliably indicated by another more perceivable trait. Therefore, both perceivers and senders of the signal can benefit from it; high quality signalers benefit by indicating the quality of their traits, and receivers benefit by being able to discriminate between high and low quality individuals. However, signalers can potentially dissemble high quality traits by enhancing their signals without changing the quality of their underlying trait; therefore, receivers of the signal must remain vigilant against deception. A solution to cheating is the development of costly or hard-to-fake signals, those that impose costs that would-be deceivers cannot bear. And this explains why many signals, especially those sent among animals with potentially competing interests, are elaborate: such signals are costly and therefore make cheating difficult (Zahavi, 1975).

In humans, costly signals are especially important because many culturally important competencies or the ability to develop them are non-physical and thus difficult to directly evaluate. We believe that expertise (or elite performance) often, but not always, functions as a costly signal of some desirable underlying trait (Miller, 2001; Winegard, Winegard, & Geary, 2014). Consider these features of expert performance that make it a good candidate for a costly signal: (1) expert performance is often broadcast publicly; (2) there are enormous individual differences in the domains in which people care about expert performance (music, sports, art), making for obvious rankings between competitors or performers; (3) performances are generally ritualized or organized in such a way that they can be assessed, also facilitating ranking of performers; and (4) expertise is difficult to achieve and quite rare, meaning it is costly and that it relies upon unique constellations of underlying traits and large amounts of leisure time. These traits may consist of, but are not limited to, conscientiousness, athleticism, intelligence, the size of one's social network, and ambition (Hawkes & Bliege Bird, 2002; McAndrew, 2002; Miller, 2001). The signal value of expertise and an ever-expanding population of potential competitors create another within-species arms race that plays out within rather than across lifespans.

Notice a few things that follow from this signaling analysis. The first is that expert performance can only occur in domains in which individual difference variables (including deliberate practice) predict outcomes in performance. There is no such thing as expert performance in tic-tac-toe and other simple games, because high levels of performance are easy to achieve and thus are a weak signal of individual differences in any underlying traits. And second, the prestige that accrues to those who develop expertise motivates people to dedicate the many grueling hours necessary to develop it (Davis & Moore, 1945; Henrich & Gil-White, 2001). Of course, there are other motivating factors, but the prestige that experts obtain, which can improve resource control (e.g. pay) and social influence is certainly a large one, especially in domains valued by the culture (Geary, 2010). Indeed, there is evidence that early humans gained social capital and other resources through the possession of expertise in skills such as flint-knapping, ceramic production, and handaxe production (Ferguson, 2008; Olausson, 2008). This appears to be due to a prestige bias in other human learners who then defer to experts and grant them status in exchange for the valuable knowledge that the experts possess (Henrich & Gil-White, 2001; Mesoudi, 2008).

In general, we would expect people to pursue their comparative advantage when deciding which skills to develop; and we suspect that the pursuit of expertise is not much different from "normal" skill acquisition in secondary domains (Geary, 2007). Consider two people who show the same initial ability to shoot three pointers in basketball. One is five foot four inches and incredibly intelligent. The other is six foot five inches and of average intelligence. Other things equal, the second person is more likely to choose to develop his shooting skills, deliberately practicing and forgoing other activities. Of course, there are many other causes of practice, including parental pressure. But, generally, people should pursue their comparative advantage, meaning that those who practice for many hours in one domain are not a random sample, because only relatively skilled individuals would maintain effortful practice in a domain he or she did not excel in. Note that, from an evolutionary perspective, an individual does not have to be the absolute "best" at a particular skill to gain prestige and resources. All that is required is that he or she is better than local conspecifics. It is only in our modern, evolutionarily novel, environment that individuals compete globally. Thus, an individual's comparative advantage will be context dependent.

If our perspective is on the right track, a straightforward prediction is that humans began to exhibit expertise in differentiated domains such as toolmaking, art, ceramics, etc. during the slow process in which humans achieved ecological dominance and began living in more variegated societies marked by a division of labor and specialization (Harari, 2015). Some evidence suggests that this prediction is accurate. While humans have been making tools for roughly 2.6 million years, the complexity of tools increased with the expansion of brain size and it was only 250,000 years ago that humans began producing late Acheulean tools, which required secondary competencies and the ability to use extensive self-control to achieve long-term objectives (Stout, Toth, Schick, & Chaminade, 2008). Around 60,000–30,000 years ago, humans achieved "cultural modernity" which corresponds to a proliferation of symbolically

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5 Expertise in Other Animals: Canines as an Example

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Introduction

Expertise has been suggested as an indicator of the emergence of consciousness in humans (Coolidge & Wynn, 2005; Rossano, 2003; Stout, 2011). Unfortunately, this perspective presupposes expertise is absent in non-human animals (from here on simply animals). This view is likely untenable depending on the definition of expertise actually proposed. If expertise is considered the outcome of deliberate practice and by the term *deliberate* conscious intent is meant, then we face a dilemma. People only attribute full consciousness to adult human language users without controversy. No one would deny the normal state of adult intact people is the capacity for consciousness. Any other attribution of consciousness to any entity besides adult human language users is controversial. Until such a time as a neural correlate of consciousness can be independently measured and validated in humans and other animals, by definition other animals may be excluded from having expertise which requires consciousness. The use of expertise would then be unhelpful for determining when consciousness emerged in the evolution of our or any species (it would be viciously circular), unless expertise could be discerned with indicators other than conscious intent itself. Other definitions of expertise not reliant on internal state attributions seem more encouraging of a broader perspective of expertise which sees expertise potentially as widespread phenomena amongst animals (Helton, 2005, 2007, 2008). Indeed, expertise and its development may be why animals have complex nervous systems. The chapter will relay alternative objective definitions of expertise, demonstrate animals can satisfy these definitions, explain the benefits of a wider comparative perspective, and present some interesting questions raised by animal expertise.

Objective Definitions of Expertise

Non-internal state attribution definitions of expertise have been proposed. These include defining expertise as exceptional performance, a social construction, or the outcome of prolonged learning (Helton, 2008). These definitions are detailed in the following subsections and we provide evidence of where at least some animals appear to satisfy the proposed definition. If issues of consciousness and deliberateness are put aside, then an exploration of animals' expertise and its development may assist in our understanding of expertise and prove practically important. Indeed, examining animals may help with defining expertise or at least refining proposed definitions.

Expertise as Exceptional Performance

Many cognitive scientists propose that expertise is demonstrated, perhaps defined, by objective exceptional performance (Ericsson & Charness, 1994; Ericsson, Charness, Hoffman, &

Feltovich, 2006). If expertise is open to scientific investigation it must be replicable and objective. One path to an objective definition of expertise is to base the definition on objective performance and then use a relative metric of performance to determine who (or what) is an expert. For example, if we examine sprinters we would have their objective running times; we could then scale the sprinters on relative ability and then determine some rough cut-off of expertise. This could be the upper 5 percent or even upper 1 percent. A plausible objection to this definition is that any distribution of performance domains would have an upper percentile of performers; this is a statistical fact. We would probably not want to define into existence expert spark plugs – those spark plugs which perform in the upper percentile. Although objective criteria for expertise are critical, we would need to limit the domain to systems that presumably acquire their expertise via a process of learning and one that presumably is not learned in a limited time (see the third definition regarding prolonged learning). Regardless of these challenges, would other animals qualify based on a performance definition? Undoubtedly for any animal skill we could rank-order animals for their performance and select the upper percentile of performers. This could simply reflect innate differences, so we would have to refine the definition to refer to skills that are acquired over time. In this case we would need to look no further than dogs (*Canis lupus familiaris*). Through training dogs learn to excel at a wide variety of tasks, for example, accelerant detection, blind assistance, epilepsy detection, explosives detection, forensic tracking, guarding, hearing assistance, herding livestock, medical diagnosis, narcotics detection, detection of insect infestations and microbial growth, sprinting, sled-pulling, and fighting (Serpell, 1995). These dogs are sorted on objective performance metrics. Those highly skilled are experts.

Expertise as a Social Construction

Some researchers would advocate that expertise is a socially derived label or in other words a social construction (Sternberg & Ben-Zeev, 2001). Indeed Agnew, Ford, and Hayes (1994) have argued that the minimum criterion for expertise is simply having a large group of people label the individual as an expert. While this social voting criterion may not appeal to all researchers, for those who advocate this perspective would some animals qualify? Yes, the evidence would support this conclusion. Dogs again serve as insightful candidates. First, societal laws have for a long time recognized the distinct value of highly skilled or expert animals. Indeed the Welsh laws of Hywel Dda as early as 945 CE imposed different penalties for killing trained and untrained dogs (Menache, 2000). In the modern United States, most states impose much stiffer penalties for people who either injure or interfere with a service or law enforcement working dog than they would a pet (Randolph, 1997). Indeed the United States Internal Revenue Service even recognizes dog expertise, as assistance dogs are a legitimate medical expense for tax deduction purposes (Treasury Regulation 1.213–1(e)(1)(iii)). Pets, however, are not deductible. The laws are clear: trained animals are different. Second, a variety of animals are given unique awards for their expert performance. Indeed, for military working animals, the British military even created a special award, the Dickin Medal, for exceptional performance and action. Theo, a British springer spaniel, who died in Afghanistan while serving in the British military, was awarded the medal in 2012 for exceptional performance and other exceptional animals (not just dogs) have been similarly recognized. Third, opinion surveys of other professionals indicate the high regard and recognition given to expert animals. Sanquist and colleagues (Sanquist, Mahy, Posse, & Morris, 2006), for example, surveyed 78 security professionals at Pacific Northwest Laboratories, a center for security research, and explosive detection dogs were rated the overall highest security measure available.

Only language users (people) can vote or actually say an individual is an expert, hence, the above examples are of people providing indications that they socially label other animals as exceptional or expert. The examples provided are of dogs, but would hold true for other exceptional animals as well, such as some horses in equestrian sports. Amongst non-language using animals another possibility to consider is the choice animals may make when socially learning a skill. Laland (2004) argues that some animals learn from other animals using a "copy if better" strategy, suggesting some animals are capable of recognizing others more skilled than themselves. So another possibility is conspecifics, even if non-language users, could vote on who is an expert, because they are the ones they try to emulate. This could be explored further, but may be relatively rare amongst animals. Regardless, some non-human animals are socially constructed or labeled as experts.

Expertise as an Outcome of Prolonged Learning

Expertise is the outcome of a prolonged period of learning (Helton, 2009b). This definition provides a solution to the challenges posed by a statistical definition of exceptional performance or one based on social voting mechanisms. A prolonged learning outcome definition rules out innate skills or single-trial learning skills, as these are not likely candidates for expertise. Do other animal have skills that improve with long periods of time, long perhaps relative to their lifespan? Dogs are again a good example; they compete in a number of athletic activities or sports. An investigation of these sports provides direct evidence of long periods of skill improvement (Helton, 2009b). A case in point is the sport of weight-pulling. Readers familiar with the book *Call of the Wild* should be familiar with weight-pulling. In the sport of weight-pulling a dog is harnessed to a heavy sled or cart and is tasked with pulling the weighted vehicle over a relatively short-distance track. The goal of the competition is to see which dog can pull the most weight and the dogs are sorted into weight classes. Weight-pulling is the canine equivalent of the human sports of powerlifting or weightlifting. Research does demonstrate breed body type or muscular skeletal morphology plays some role in weight-pulling performance (Helton, 2011b). There is a genetic contribution. Generally mastiff dog breeds are able to pull more weight for their bodyweight than husky breeds. Nevertheless, even in this relatively simple sport, dogs appear to improve markedly with practice and repeated exposure. To provide a case in point, Bridger, a Swiss mountain dog who was a weight-pulling champion for his weight class in the United States, went from an initial pull of 2800 lb in his first public competition to a pull of 4010 lb a little over a year later. Considering these dogs live at most ten or so years, this represented approximately 10 percent of Bridger's likely lifespan for a 43 percent improvement in performance. For Bridger this was a prolonged period of skill development which resulted in marked performance gains. This definition would require consideration of the lifespan of the animal itself. In people, ten years is often used as a rough rule of thumb and this would translate into roughly 10 percent or more of a person's lifespan. Many animals do not live ten years. So this could be scaled to their lifespan. Some animals may live so briefly that expertise is no longer meaningful when applied to them. This would encourage integrating the expertise literature emerging from cognitive psychology with the life history literature emerging from ecology: a cognitive ecology of expertise.

Benefits of Examining Animal Expertise

Recognizing that other animals have expertise or are capable of developing expertise provides three benefits. First, animals may be studied in a manner untenable with people and this opens new methods to examine expertise and expertise development. Second, examining animals may provide an evolutionary understanding of the emergence of expertise. This raises central and interesting scientific questions. Third, recognizing animal expertise may have practical benefits, regarding the way we employ non-human workers, such as working dogs.

New Methods

Animals may be studied legally in a manner untenable with people. We can, for example, control both the genetics (breeding) and early life experiences of animals in ways that are unthinkable with people. This may open the path to a better understanding of the classic nature–nurture or talent–practice debate which remains controversial in the literature on people (Helton, 2008). For example, some recent work on dogs suggests attributions of inherent talent for trainability may have something to do with genetically influenced properties, but they may not be the cognitive traits (or talents) most people believe are being selected. Instead the selection appears more likely to be for physical shape (Helton, 2010). Alternatively, genetic selection may influence elements of physical and sensory capacities and these can have impacts on skill development in ways which are not always immediately obvious.

While other animals could be examined, dogs in particular provide a useful model for understanding the impact of genetics on expertise development because we have selected for numerous breeds. Consider athletic performance such as running speed; all things equal, dogs with longer legs will run faster than dogs with shorter legs (Helton, 2007). Greyhounds, whippets, and other sight-hounds demonstrate selection for these characteristics and these are the breeds of dogs a person encounters at a race track. Alternatively, dogs for which wrestling and fighting ability have been selected look markedly different, for example, pit-bulls. Indeed, anatomical examinations comparing greyhounds and pit-bulls show clear differences and they have significant genetic components (Kemp, Bachus, Nairn, & Carrier, 2005). For physical based skills the evidence based on dog breeding suggests that genetics is a significant factor in dog physical skill and thus, later expertise development.

On the other hand, there is surprisingly, despite widespread belief, little research suggesting breed differences in actual cognitive abilities. Although people strongly believe breeds differ in intelligence and cognitive ability (Coren, 1994), when controlled tests are made that account for physical differences amongst breeds there is apparently little difference amongst breeds. As Scott and Fuller (1965, p. 258) concluded after a series of cognitive tests conducted on basenjis, beagles, cocker spaniels, fox terriers, and Shetland sheepdogs, "we can conclude that all breeds show about the same average level of performance in problem solving, provided they can be adequately motivated, provided physical differences and handicaps do not affect the tests, and provided interfering emotional reactions such as fear can be eliminated."

Indeed, our own work has found that differences in perceived trainability amongst breeds may have more to do with physical characteristics of dogs than their mental characteristics (Helton, 2010; Helton & Helton, 2010). To summarize our findings, dog breeds perceived to be intelligent are typically not too small and not too big. They are not morphologically specialized. They are not too wide, like fighting dogs, and not too narrow, like running dogs; they are physically just right for cooperative tasks with most people. In simplest terms, breeds of dogs considered smart or easy to train tend to be dogs that have their heads at a height that nicely meets where a typical human hand hangs (the primary instrument for reinforcement and punishment). They are easy to train, because they are the right size for people.

working dogs; society does not recognize that there is expertise in animals and like us, expertise takes a long time to develop.

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Part II

Overview of Approaches to the Study of Expertise: Brief Historical Accounts of Theories and Methods

6 Studies of Expertise from Psychological Perspectives: Historical Foundations and Recurrent Themes

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Introduction

The study of expertise has a long history (see Ericsson, Chapter 1, this volume). In the first part of this chapter we emphasize a period of research roughly from the mid-1950s into the 1980s when empirical laboratory studies of expert reasoning were first combined with theoretical models of human thought processes that could reproduce the observable performance. In the second part of this chapter we will characterize some of the enduring insights about mechanisms and aspects of expertise that generalize across domains, reflecting on the original theoretical accounts but also considering more recent ones.

The Historical Development of Expertise Studies

While there was earlier important work related to scientific studies of complex thinking and expertise (e.g. Boden, 2006), in the period of focus (1950s–1980s) a number of trends came together to provide enough traction for the field of expertise studies to "take off." There were three main roots to this impetus: artificial intelligence, cognitive psychology, and education. We will overview these three roots briefly. If, to the reader, it may be confusing at times whether we are addressing artificial intelligence, cognitive psychology, cognitive science, or even education, the fact of the matter is that during a crucial long span of time in the development of expertise studies, it was hard to tell the difference.

Artificial Intelligence: Expertise in the Code

Early computer models developed by Herbert Simon and Allen Newell demonstrated that it is relatively easy for computational devices to do some things worthy of being considered intelligent. This breakthrough at Carnegie Mellon University (then Carnegie Institute of Technology) was based on the confluence of two key realizations that emerged from the intellectual milieu that was emerging between Carnegie and Rand at the time, curiously set within the context of a new business school (Augier & March, 2011; Augier & Prietula, 2009).

Allen Newell, Clifford Shaw, and Herbert Simon envisioned that computers could be used to process "symbols and symbol structures." To explore this, they developed what was to become the first list-processing computer language, namely the Information Processing Language (IPL), which

- Represent where your progress has brought you right now; and
- Try to find some currently available computational operator as a means that can decrease some aspect of the difference between these; or
- Try to represent and solve sub-goals to bridge the gap.

Strong methods are more heavily dependent on rich knowledge of the problem-solving area, and on understanding which operators are likely to be successful in encountered specific situations. They are domain specialists, not generalists. Consequently, there is a trade-off between the power of general search and the capabilities of task-relevant knowledge – more task-relevant knowledge reduces the need for search. Make the move-generator smarter; make the goals task-specific.

When early AI was being applied in relatively simple and well-structured areas, such as simple games like Samuel's checkers program, weak methods fared fairly well. As the field developed and researchers started to address richer, complex, and knowledge-laden task environments, such as medicine (Pauker, Gorry, Kassirer, & Schwartz, 1976; Shortliffe, 1976) and chemical spectral analysis (Buchanan & Feigenbaum, 1978), the need for ever-stronger methods became clear. Portability across task domains had to be sacrificed in favor of capability, but narrowly restricted capability. Over time, the development of computational models that did not aim at explicit representations of general psychological mechanisms emerged, but focused on capturing the methods and forms of exceptional performance on a problem in a particular task domain – expert systems (Buchanan, Davis, & Feigenbaum, 2006; Buchanan, Davis, Smith, & Feigenbaum, Chapter 7, this volume). Although the form and function of expert systems varied, the common goal was generally to "exhibit some of the characteristics of expertise in human problem-solving, most notably high levels of performance" (Buchanan et al., 2006, p. 87). Toward this end, the construction of these systems often relied on discerning the knowledge-based methods of human domain experts, and using that to inform an engineering process that yielded a coherent, functioning system capable of comparable or better performance. One extremely useful method brought to bear in understanding performance in general (for cognitive models) and skill in particular (for discerning expertise) was the method of instructing participants to "think aloud" (see Ericsson & Simon, 1993, for a description of a wide range of different instructions used to elicit thinking aloud).

The use of "think-aloud" instructions is perhaps best exemplified early on by Duncker's (1945) classic work on general problem-solving. Duncker (1945) took detailed notes on different thoughts generated by participants while they were thinking aloud while solving challenging problems that were drawn from everyday life. Later, during their research using think-aloud instructions to study logical reasoning, problem-solving, and chess playing, Newell and Simon (1972) discovered research that had used this method to study chess expertise by Adrian de Groot in a Dutch dissertation from 1946, which was translated into English (de Groot, 1946, 1965). Subsequent work by Ericsson and Simon (1980, 1993) refined this methodology for "think aloud" and developed standardized instructions based on theoretical analyses of the verbalization processes of thoughts and proposed rigorous analyses based on transcriptions of the participants' thoughts based on tape recordings of the sessions. When participants were instructed to remain focused on the task and merely verbalize their thoughts (as opposed to explaining their thoughts), reviews (Ericsson, Chapter 12, this volume; Ericsson & Simon, 1980, 1993; Fox, Ericsson, & Best, 2011) found no evidence for differences in performance accuracy between participants thinking aloud versus solving the same problems in silence.

Not surprisingly, groundbreaking progress in this regard came from the information processing camp in their studies of problem-solving that used this type of analysis (Newell & Simon, 1972), especially in their studies (following de Groot) of expertise in chess (Chase & Simon, 1973a, 1973b). This research demonstrated striking differences between experts and novices in their ability to perceive relevant information and their ability to think about and solve problems in their domain of expertise, such as chess (Charness, 1976, 1979, 1981; Chi, 1978), physics (Chi, Feltovich, & Glaser, 1981; Larkin, McDermott, Simon, & Simon, 1980), and medicine (Elstein, Shulman, & Sprafka, 1978). Furthermore, this (thinking aloud procedure) was to serve as a foundational method for some of the earliest computer programs, such as the GPS mentioned in the previous section:

> Working from the "protocol" recording the behavior of a test person solving a logic problem, a computer program called GPS (for General Problem Solver) is developed, which leads to a psychological theory of human problem solving. It is shown, how data giving the same results as derived from the protocol yields to an analysis in terms of a program characterized by a recursive structure of goals and subgoals. (Newell & Simon, 1961, p. 109)

It is interesting to think about whether a field of expertise studies could have emerged at all, and if so, what it could possibly have looked like, if alternatives to American neo-behaviorism had not emerged. Clark Hull's theory of linked habits was essentially an elaboration of Thorndike's behaviorism, but marshaling quantitative models to discern habit strength. B. F. Skinner disavowed causal explanation involving mental mechanisms, such as thoughts and memories, asserting that cognitive theories of learning are unnecessary (Hunt, 1993). Consequently, would we have discovered that experts do not just complete tasks and solve problems faster and better than novices, but often attain their solutions in qualitatively different ways? Would we have discovered that there are fundamental representational differences in how they see the problems? Would we have discovered that experts frequently spend a greater proportion of their time in initial problem evaluation compared to novices (e.g. Glaser & Chi, 1988, regarding "Experts spend a great deal of time analyzing a problem qualitatively"; Lesgold et al., 1988; see also Kellogg, Chapter 23, this volume, on planning by professional writers, and Noice & Noice, 2006, on the deep encoding by professional actors as they study their lines)?

Similar questions can be posited regarding the development of the cognitive science movement itself, which was highly influenced by the rise of the general-purpose computer, allowing programs to function as "mid-range" theoretical constructs in cognition mediating observable behavior (e.g. attention, plans, goals, concepts, aspiration levels, learning, and search) and "low-level" engineering efforts to mathematically model neuronal cell assemblies (e.g. Ashby, 1952; Hebb, 1949; McCulloch & Pitts, 1943; von Neumann, 1958). The rise of intermediate-level (i.e. above machine or assembler code), symbolic programming languages permitted cognitive science to "represent" constructs of novice and expert deliberations in forms amenable to discussion in the context of the concepts, functions, and associations (e.g. proximal, temporal) revealed empirically through behavioral studies. For example, both the Logic Theorist and the General Problem Solver were written using (albeit different versions of) a RAND–Carnegie Tech programming language, mentioned earlier, called IPL (Information Processing Language). IPL provided a necessary innovation (at the time) for non-numeric data types (symbols, lists) to allow important constructs (e.g. goals, sub-goals, generate-and-test methods, and heuristics) of the cognitive theory of task performance to be represented in the model (Ernst & Newell, 1969; Newell & Shaw, 1957). IPL was also engaged by other researchers, such as the early work on simulating concept formation (e.g. Hunt & Hovland, 1961). However, it is likely that these technological-methodological advances led to the emergence of the influential information processing approach in cognitive science (Newell & Simon, 1972; Reitman, 1965), which was itself to lay the foundations for expertise studies. Not every researcher could, or had to, build a computational model, but the successful construction of these computer models provided evidence of sufficiency in support of various cognitive constructs.

While modern views of expertise retain a criterion of superior (observable, repeatable) performance, as did behaviorism, there is also considerable interest and theorizing about mediating processes and structures that support and can be developed to produce these superior performances. Interestingly, current theorizing about the critical role of deliberate practice in the development of expertise embodies characteristics reminiscent of these earlier, neo-behaviorist approaches, such as the need for clear goals, repeated practice experiences, and the vital role of feedback about the quality of attempts (Ericsson, Chapter 38, this volume; Ericsson, Krampe, & Tesch-Römer, 1993). These insights into effective learning had an important impact on efforts to improve education and training.

Educational Psychology and Instructional Design: From Novice to Expert

The emergence of the cognitive science perspective in psychology also impacted educational psychology, with studies of expertise taking on a new role. Expert cognition was conceived as the "goal state" for education, the criterion for what the successful educational process should produce, as well as a measure by which to assess its progress, serving to inform pedagogical design and teacher evaluation (e.g. Berliner, 1988; Feldon, 2006). In this regard, advanced methods have now been developed for eliciting and representing the knowledge of experts (see Lintern, Moon, Klein, & Hoffman, Chapter 11, this volume). Novice cognition (as well as that of various levels of intermediates) could serve as "initial states," as models of the starting place for the educational process. In a sort of means–ends analysis, the job of education was to determine the kinds of operations that could transform the initial conditions into the desired more expert-like ones (Glaser, 1976). Although it is tempting to believe that upon knowing how the expert does something, one might be able to "teach" this to novices directly, this has not been the case (e.g. Klein & Hoffman, 1993); the achievement of expertise is the product of a long, complex process.

Expertise (as we are defining it) is a long-term developmental and adaptive process, resulting from rich instrumental experiences in the world and extensive and deliberate practice and feedback. (A current challenge for pertinent education and training is whether and how this experiential process, and the opportunity it provides for practice and feedback, can be compacted or accelerated, Hoffman et al., 2014). However, the kinds of experiences, practice, and feedback that are necessary depend on the characteristics of the task environment, and how individuals adapt to those characteristics within the constraints of their cognitive limitations. Simon's early descriptions of bounded rationality and the task environment are perhaps best reflected in the oft-quoted *The Sciences of the Artificial* (Simon, 1969, p. 25):

> A man, viewed as a behaving system, is quite simple. The apparent complexity of his behavior over time is largely a reflection of the complexity of the environment in which he finds himself.

Though perhaps an oversimplification, the statement does emphasize the important role of the task environment is shaping the observable behavior. This important role of the task environment was best articulated and exemplified by the detailed analyses, conducted by Newell and Simon, of task environments involved in human and computational problem-solving processes (Newell & Simon, 1972). Later, Simon (1990) would invoke a metaphor that would also serve to infuse the importance of the task environment into the theoretical apparatus of other theorists, noting "Human rational behavior (and the rational behavior of all physical symbol systems) is shaped by a scissors whose two blades are the structure of the task environments and the computational capabilities of the actor" (Simon, 1990, p. 7). The shaping of that behavior toward expertise over time, the developmental or educational process leading toward expertise, was a critical missing component of explaining expertise.

Consequently, some early expert–novice difference research led directly to the creation of new methods of instruction. This is particularly true in medical education where early expert–novice studies (Barrows, Feightner, Neufeld, & Norman, 1978; Elstein et al., 1978) led to the creation of "problem-based learning" (Barrows & Tamblyn, 1980). Over a long period of time, problem-based learning (and variants) has come to pervade medical education, as well as making significant inroads into all types of education, including K-12, university, and every sort of professional education (see Ward, Williams, & Hancock, 2006, for a review of the use of simulation in training).

Ongoing, and more recent, research in education in a particular domain at high levels of performance often involves attempts at explicating expertise in that domain to inform the design of the educational experiences in their task environments, such as emergency medicine (Pelaccia et al., 2016; Wears & Schuber, 2016), skills and standards for teachers (Anthony, Hunter, & Hunter, 2015; Kaub, Karbach, Spinath, & Brunken, 2016), and designing human–machine systems (Yu, Honda, Sharqawy, & Yang, 2016). Relatedly, the emergence of a focus on studying how individuals and groups make decisions in real-world task environments (as opposed to replicating elements of the task environment in a controlled context), generally referred to as "naturalistic decision making" (see Klein, 2008; Mosier, Fischer, Hoffman, & Klein, Chapter 25, this volume) has led to insights and innovations regarding training and education based on expertise (Keller, Cokely, Katsikopoulos, & Wegwarth, 2010; Klein, 2016; Klein, Woods, Klein, & Perry, 2016). We now briefly recapitulate historical roots discussed so far and offer some follow-on developments.

Recapitulation and Extensions

The modern study of expertise started with analyses of expert chess playing and other types of games, and domains with formal structures and rules, as we have already described. This was followed by extensions into more knowledge-intensive fields, emphasizing the critical role of knowledge, knowledge organization, knowledge access, and so forth. In an influential book, Bloom (1985) reported how individuals attained an international level of performance in six very different domains. In addition, the first conference explicitly using the word "expertise" in its title was focused primarily on domains of expertise where knowledge is critical, including physics, medicine, and computer programming (Chi, Glaser, & Farr, 1988), but also research on high levels of practical skills. A subsequent conference attempted to broaden the evidence to include other domains of expertise, such as sports, music, writing, and decision making (Ericsson & Smith, 1991a).

This was followed by several edited and authored books on topics including the relations of the psychology of expertise to the field of Artificial Intelligence (Hoffman, 1992), sports and motor expertise (Starkes & Allard, 1993; Starkes & Ericsson, 2003), as well as covering a wide range of research on human and computer expertise (Ericsson, 1996; Ericsson & Smith, 1991a; Feltovich, Ford, & Hoffman, 1997). The first edition of this handbook appeared in

2006 (Ericsson, Charness, Hoffman, & Feltovich, 2006) which integrated what was known about the structure and acquisition of expertise and expert performance, and books were written about particular domains, such as sports (Baker & Farrow, 2015; Farrow & Baker, 2013). General books on the topics of expertise and expert performance have been published, focusing on professional development (Ericsson, 2009), accelerating the development of expertise (Hoffman et al., 2014), as noted earlier, and expertise in professional decision making (Hoffman, 2007).

One thing these contributions bring out is the deep entanglement of expertise studies with the history and evolution of basic and applied cognitive science, broadly, across the 1980s and 1990s (see Hoffman & Deffenbacher, 1992; Hoffman & Militello, 2008). This brings us to the second major section of this chapter.

Toward Generalizable Characteristics of Expertise and Expert Performance

We now attempt to crystallize the enduring findings from the study of expertise. We will draw upon generalizable characteristics of expertise identified in earlier reviews (Glaser & Chi, 1988) and describe how these characteristics have been refined and developed in light of studies of reproducibly superior performance. In doing so we contrast two general approaches to expertise studies, what we call the "expert–novice" and "expert performance" approaches. The approaches differ most in how people are selected to be studied at various levels of relative expertise. In the, mostly earlier, expert–novice tradition, experts (and novices and various intermediates) were identified by such factors as experience and educational levels. In the expert performance scheme, experts (and novices, etc.) are selected for their relative superior performance on representative tasks from their domain. We will also discuss the original theoretical accounts for the findings presented, as well as more recent findings and theoretical treatments reviewed in the chapters of this handbook.

Expertise is Limited to a Domain of Knowledge, and Elite Performance is Mediated by Domain-Specific Skills and Adaptations

In their pioneering review Glaser and Chi (1988, p. xvii) stated that the first characteristic of expertise is that "Experts excel mainly in their own domain." They argued that the superiority of experts could be related to their organized, relevant knowledge rather than some global superiority, such as intelligence or better "reasoning." (Recall our earlier discussion of "strong methods" in artificial intelligence.) They cited Voss and Post's (1988) research, in the expert–novice tradition, on problem-solving in political science by experts and novices. Novices, such as college students, were thinking about the presented problems at a very concrete level, whereas the experts (their professors) thought about the same problems in more abstract ways. Glaser and Chi (1988) also cited earlier research on taxi drivers' knowledge about how to take a passenger between two points in a city and found that the more experienced drivers were able to generate a larger number of possible routes (Chase, 1983). Similarly they pointed to expert physicians' more differentiated knowledge of diseases into numerous more specific disease variants (Johnson et al., 1981). Several of the other characteristics differentiating more experienced and knowledgeable individuals (experts) from less experienced individuals (novices) concerned the experts' "larger patterns" and "deeper (more principled)" encoding of domain-related information.

A different approach to studying expertise was introduced by Ericsson and Smith (1991b). According to this approach, the expert performance approach, the focus should not be on identifying experts based on their more extensive

The original explanation by Chase and Simon (1973a, 1973b; Simon & Chase, 1973) for expert superiority involved "chunking" in perception and memory. With experience, experts acquire a large "vocabulary" or memory store of *board patterns involving groups of pieces*, or what were called chunks. A chunk is a perceptual or memory structure that bonds a number of more elementary units into a larger organization (e.g. the individual letters "c", "a," and "r" into the word "car"). When experts see a chess position from a real game, they are able to recognize such familiar patterns. They can then associate these patterns with moves stored in memory that have proven to be good moves in the past. Novices do not have enough exposure to game configurations to have developed many of these kinds of patterns. Hence they deal with the board in a piece-by-piece manner. Similarly, when experts are presented with chess boards composed of randomly placed pieces that do not enable the experts to take advantage of established patterns, their advantage over novices for random configurations amounts to only a few additional pieces.

These basic phenomena attributed to chunking were replicated many times, in chess but also in other domains, such as GO, bridge, electronics diagrams, and football play sketches (see also, Ericsson, Chapter 36, this volume; Gobet & Charness, Chapter 31, this volume). The identified chunks were not only larger but also reflected a deeper meaningful structure. For example, one chunk of chess pieces for an expert might be a "king defense configuration," composed of a number of individual chess pieces. In many domains experts develop abilities to encode perceptual characteristics of objects and scenes to facilitate rapid judgment and the generation of appropriate actions (Landy, Chapter 10, this volume).

Expertise Involves Deeper and More Functional Representations of Tasks

Influential findings came from the early work in physics (Chi et al., 1981) and medicine (Feltovich, Johnson, Moller, & Swanson, 1984; Johnson et al., 1981). In the basic task from the physics study, problems from chapters in an introductory physics text were placed on individual cards. Expert (professors and advanced graduate students) and novice (college students after their first mechanics course) physics problem-solvers sorted the cards into groups of problems they would "solve in a similar manner." The finding was that experts created groups based on the major physics principles (e.g. conservation and force laws) applicable in the problems' solutions. Novice groupings were organized by salient objects (e.g. springs, inclined planes) and features contained in the problem statement itself. Similarly, in studies of expert and novice diagnoses within a sub-specialty of medicine, expert diagnosticians organized diagnostic hypotheses according to the major pathophysiological issue relevant in a case (e.g. constituting the "Logical Competitor Set" for the case; e.g. "lesions involving right-sided heart volume overload"), while novice hypotheses were more isolated and more dependent on particular patient cues.

Similar results have been shown from yet other fields, using somewhat different methods that compared the performance of groups of adults who differ in their knowledge about a given domain. For example, Voss and co-workers (Spilich et al., 1979) studied ardent baseball fans and more casual baseball observers. Participants were presented with a colorful description of a half-inning of baseball and were then to recall the half-inning. Expert recall was structured by major goal-related sequences of the game, such as advancing runners, scoring runs, and preventing scoring. Novices' recall contained less integral components, for example, observations about the weather and the crowd mood. Novice recall did not capture basic game-advancing, sequential activity nearly as well. More recent research on fans who differ in their knowledge about soccer and baseball has found that comprehension and memory for texts describing games from these sports is more influenced by relevant knowledge than by general verbal abilities (see also Hambrich & Engle, 2002).

In sum, individuals with more knowledge and experience have a more complex and appropriate structure of their knowledge, which allows them to think and reason in a deeper and more functional manner.

Mechanisms Underlying Expert Performance

When knowledge is viewed as the primary source of difference associated with expertise, as was the primary focus in the expert–novice approach, it makes sense to study the structure of individuals' knowledge. If, on the other hand, we are interested in studying the individual differences in objective performance that define expertise in a domain, such as winning chess games in tournaments, and having superior outcomes for patients after cancer surgery, a different approach is needed.

In the expert performance approach to expertise (Ericsson & Smith, 1991b; Ericsson & Ward, 2007), researchers attempt to identify those tasks that best capture the essence of expert performance in the corresponding domain, and then standardize representative tasks that can be presented to individuals with different amounts of experience. For example, medical doctors and residents differ in their ability to diagnose diseases based on X-rays. It is possible to present many participants with the same X-rays and ask them to think aloud as they diagnose the X-rays. By having experts repeatedly perform the diagnoses, experimenters can identify differences in the thought processes associated with superior accuracy in diagnosis (Ericsson, 2015). Hypothesized mechanisms can then be evaluated by designed experiments (Ericsson, Chapters 12 and 36, this volume). The superior performance on tasks related to the associated domain of expertise has been successfully described by different psychometric factors (e.g. expert reasoning and expert working memory) than those general ability factors that describe the performance of individuals with lower levels of performance, such as beginners and novices (Ericsson, 2014; Horn & Masunaga, 2006; and see Ackerman & Beier, Chapter 13, this volume, for a review of individual differences as function of level of expertise).

From Short-Term to Long-Term Working Memory in Expertise

The once-popular hypothesis that all cognitive processes, including those of individuals with higher levels of performance and experts, were uniformly constrained by a severely limited short-term memory (STM), was questioned in the mid-1970s. If working memory capacity could be expanded then there were many different possibilities for experts to improve their performance beyond developing larger chunks. In a dissertation supervised by William Chase, Charness (1976) showed that expert chess players do not rely on a transient short-term memory for storage of briefly presented chess positions. In fact, they are able to recall positions, even after the contents of their short-term memory have been completely disrupted by an interfering activity. Subsequent research has shown that chess experts have acquired memory skills that enable them to encode chess positions in long-term working memory (LTWM, Ericsson & Kintsch, 1995). The encoding and storage of the chess positions in LTWM allow experts to recall presented chess positions after disruptions of STM, as well as being able to recall multiple chess boards presented in rapid succession (see Ericsson, Chapter 36, this volume, and Gobet & Charness, Chapter 31, this volume, for an extended discussion of new theoretical mechanisms accounting for the experts' expanded working memory). Experts' superior ability to encode representative information from their domain of expertise and store it in long-term memory, such that they can efficiently retrieve meaningful relations, provides an alternative to the original account of superior memory in terms of larger chunks stored in STM (see Ericsson, Chapter 36, this volume, for a discussion of experts' superior working memory).

Experts' Usability of Their Knowledge

Being able to recall knowledge when explicitly asked does not necessarily mean that the individual will always be able to retrieve that knowledge when it is relevant. Pioneering investigators (e.g. Feltovich et al., 1984; Jeffries, Turner, Polson, & Atwood, 1981) have suggested that a major limitation of novices is their inability to access knowledge in relevant situations, even when they can retrieve the same knowledge when explicitly cued by the experimenter. Problems in knowledge usability may be associated with overload or inefficiency in using working (or short-term) memory.

An alternative proposal about usability of knowledge was subsequently put forward by Ericsson and Kintsch (1995). They postulated that experts acquire memory skills that are designed to encode relevant information in long-term memory (LTM) in a manner that allows automatic retrieval from LTM when later needed, as indicated by subsequent activation of certain combinations of cues in attention. They argued that experts acquire LTWM memory skills that enable them, when they encounter new information (such as a new symptom during an interview with a patient), to encode the relevant associations such that when yet other related information is encountered (such as subsequent information reported by the patient), the expert will automatically access relevant aspects of the earlier information to guide encoding and reasoning. The key constraint for skilled encoding in LTM is that the expert be able to anticipate potential future contexts where the encountered information might become relevant. Only then will the expert be able to encode encountered information in LTWM in such a way that its future relevance is anticipated and the relevant pieces of information can be automatically activated when the subsequent relevant contexts are encountered. In this model of the experts' working memory storage in LTM, the large capacity of LTM allows the expert to preserve access to a large body of relevant information without any need to actively maintain the information in a limited general capacity STM (Ericsson, Chapter 36, this volume; Gobet & Charness, Chapter 31, this volume; Noice & Noice, 2006; Wilding & Valentine, 2006).

Functionality of Expert Representations Extends to Entire Activities, Processes

The functional nature of experts' task representations that we mentioned earlier extends to entire activities or events. Ericsson and Kintsch (1995) proposed that experts acquire skills for encoding new relevant information in LTWM to allow direct access when it is relevant and to support the continual updating of a mental model of the current situation – akin to the situational models created by readers when they read books (see Endsley, Chapter 37, this volume, on the expert's superior ability to monitor the current situation – "situational awareness"). This general theoretical framework can account for the slow acquisition of abstract representations that support planning, reasoning, monitoring, and evaluation (Ericsson, Patel, & Kintsch, 2000). For example, studies of expert firefighters have shown that experts interpret any scene of a fire dynamically, in terms of what likely preceded it and how it will likely evolve. This kind of understanding supports efforts to intervene in the fire. Novices interpret these scenes in terms of perceptually salient characteristics, for example, color and intensity (Klein, 1998; see also Mosier et al., Chapter 25, this volume). In similar manner, expert physicians represent diseases as an extended process involving enabling conditions (conditions that incline a patient toward a disease), faults (the actual pathophysiological or abnormal anatomical features involved in the disease), and consequences (the observable signs and symptoms spawned by the fault/s) – a so-called "Illness Script" (Feltovich & Barrows, 1984; Charlin, Boshuizen, Custers, & Feltovich, 2007). Studies of expert surgeons have shown that some actions within a surgery have no value for immediate purposes, but are made in order to make some later move more efficient or effective (Koschmann, LeBaron, Goodwin, & Feltovich, 2001). The research on expert chess players shows consistent evidence for extensive planning and evaluation of consequences of alternative move sequences (see Ericsson, Chapter 36, this volume, and Gobet & Charness, Chapter 31, this volume). Furthermore, there is considerable evidence pertaining to experts' elaborated encoding of the current situation, such as in situational awareness (Endsley, Chapter 37, this volume), mental models (Durso, Dattel, & Pop, Chapter 20, this volume), and LTWM (Noice & Noice, 2006).

Analyzing Superior Performance

Once one has accepted that experts can acquire, build, and modify the structure of their cognitive processes, it becomes a question of how their superior performance is mediated and how the associated mechanisms are either acquired or reflect innate differences. In the expert performance approach the first step, as we have noted, involves identifying representative tasks and reproducing the experts' consistent superior performance in a controlled laboratory situation (see Ericsson, Chapters 12, 36, and 38, this volume). A good example is to have athletes or other individuals generate actions in a simulator or respond immediately to a video sequence. In the second step, investigators record observable information on the experts' and less skilled participants' processes by collecting think-aloud protocols and patterns of eye fixations. For example, an elite tennis player can anticipate (better than chance) where a tennis ball will land *before* the server has made ball contact; this implies an ability to anticipate based on cues in the server's preparatory movements. Such studies and analyses have shown that the structure of knowledge is but one of many different types of mental representations and skills, and different types of physiological adaptations, that account for the observed expert performance.

Reflection and Mental Representations Mediate Expertise during Execution, Evaluation, and Learning

Another challenge to the traditional information processing view, with its severe constraints on cognitive capacity, concerns the experts' ability not just to perform effectively but also to be able to reflect on their thought processes and methods (Glaser & Chi, 1988). The traditional account of reflection within the information processing model is that abstract descriptions of plans and procedures enable an individual to operate on or manipulate problem-solving operations, for example, to modify and adjust them to the current situation and context. In addition to abstraction in control and planning, there must also be mechanisms for maintaining information to allow efficient back-tracking or starting over when lines of reasoning need to be modified or abandoned.

The traditional view, especially given severe STM constraints, has difficulties in accounting for the possibility that experts might be disrupted or otherwise forced to restart their planning. More recent research has shown that experts are far more able to maintain large amounts of information in working memory. For example, chess masters are able to play chess games with a quality that approaches that of normal chess playing under blindfolded conditions in which perceptual access to chess positions is withheld. (For a review see Ericsson et al., 2000; Ericsson & Kintsch, 2000.) Chess masters are able to follow multiple games when they are presented move by move and can recall the locations of all pieces with high levels of accuracy. Chess masters are also able to recall a series of different chess positions when they are briefly presented (5 seconds per position).

Reasoning and Self-Monitoring in Expertise

In studies of expert physicians (e.g. Feltovich, Spiro, & Coulson, 1997), we have found that when experts do not know the correct diagnosis for a patient, they often can give a plausible description of the underlying pathophysiology of a disease; that is, they are able to reason at levels which are more fundamental and defensible in terms of the symptoms presented. When medical students fail to reach a diagnosis for a patient, their rationale for possible alternatives is generally incompatible with the symptoms presented. Experts fail gracefully; but when medical students fail their mistakes can be major. Vimla Patel and her colleagues (Groen & Patel, 1988; Patel & Groen, 1991) have found that medical experts are able to explain their diagnoses by showing how the presented symptoms are all explained by the proposed integrated disease state, whereas less advanced medical students have a more piecemeal representation that is less well integrated.

Research in education has consistently demonstrated the value of self-monitoring and regulation in learning (for reviews, see Hacker, Dunlosky, & Graesser, 2009; Winne & Nesbit, 2009; Zimmerman, 2008). It is also important for experts to test their own understanding and evaluate partial solutions to a problem. This kind of planning prevents blind alleys, errors, and the need for extensive backup and retraction, thus ensuring overall progress to a goal. In addition, these same kinds of self-monitoring and self-regulation behaviors are critical throughout the process of acquiring knowledge and skills on which expertise depends (MacIntyre, Igour, Campbell, Moran, & Matthews, 2014). For example, one study of elite endurance runners revealed a detailed specification of their self-regulatory planning, monitoring, and adjustment processes, and how they contributed to their success (Brick, MacIntyre, & Campbell, 2015). Another study demonstrated that inducing self-monitoring of learning during acquisition of surgical skills led to higher performance levels (Gardner, Jabbour, Williams, & Huerta, 2015).

Thus, the mental representations developed by aspiring experts have multiple functions. They need to allow efficient and rapid reactions to critical situations, and they need to allow modifiability. This includes, for example, mechanisms by which a skilled performer adjusts his/her performance to changed weather conditions, such as a tennis player dealing with rain and/or wind, or adjusts to unique characteristics of the place of performance, such as musicians adjusting their performance to the acoustics of the music hall. Furthermore, these representations need to be amenable to change so aspiring expert performers can improve aspects and gradually refine their skills and their monitoring representations.

Routine versus Controlled Processing in Expertise

Experts, for the most part, work in the realm of the familiar (for them, not for people in general) and are often able to generate adequate actions by rapid recognition-based problem-solving, perhaps followed by more effortful reasoning (Chi et al., 1981; Hatano & Inagaki, 1986; Klein, Calderwood, & Clinton-Cirocco, 1986; Simon, 1990). In their early work with chess experts, Chase and Simon (1973a) conjectured that “the most important processes underlying chess mastery are these visual-perceptual processes rather than the subsequent logical-deductive thinking processes” (p. 215). With respect to expertise, the recognition-based components of skill are sometimes referred to as intuitive or routinized while the subsequent forms are called controlled, adaptations in the structure and acquisition of expert performance across different domains. The theory of Simon and Chase (1973) proposed that the invariant limits on information processing and STM severely constrained how expert skill is acquired. They proposed a theory based on the accumulation through experience of increasingly complex chunks and pattern–action associations. This theory emphasized the acquired nature of expertise and focused on the long time required to reach elite levels and the learning processes sufficient to gradually accumulate the large body of prerequisite patterns and knowledge. This view of expertise offered the hope that it would be possible to extract the accumulated knowledge and rules of experts and then use this knowledge to more efficiently train future experts and, thus, reduce the decade or more of experience and training required for elite performance (Buchanan et al., Chapter 7, this volume). Efforts were even made to encode the extracted knowledge in computer models and to build expert systems that could duplicate the performance of the experts.

Subsequent research on extended training revealed that it is possible to acquire skills that effectively alter or, at least, circumvent the processing limits of attention and working memory. Studies of expertise focused initially on the expert's representation and memory for knowledge. As research started to examine and model experts' superior performance on representative tasks, it became clear that their mediating complex representations and mechanisms could not be acquired by mere experience – living in a cave does not make one a geologist (Ericsson, Prietula, & Cokely, 2007). Research to determine how individuals achieve expert performance, rather than mere mediocre achievement, revealed that expert and elite performers seek out teachers and engage in specially designed training activities (deliberate practice). The future expert performers need to acquire representations and mechanisms that allow them to monitor, control, and evaluate their own performance, so they can gradually modify their own mechanisms while engaging in training tasks that provide feedback on performance, as well as opportunities for repetition and gradual refinement.

The discovery of the complex structure of the mechanisms that execute expert performance and mediate its continued improvement has had positive and negative implications. On the negative side, it has pretty much dispelled the hope that expert performance can easily be captured and that the decade-long training to become an expert can be dramatically reduced (but see Hoffman et al., 2014, for examples that do demonstrate acceleration and the conditions for acceleration, on the developmental path toward expertise). With regard to acceleration, all the paths to expert performance appear to require substantial extended effortful practice, but can benefit from technologies and training programs that compact or accelerate effortful representative experience (e.g. with representative cases) and that provide appropriate feedback and guidance. Effortless mastery of expertise, for example just teaching learners "expert ways," is just a myth. This myth cannot explain the gradual acquisition, through adaptation, of the mechanisms and adaptations that mediate skilled and expert performance. Even more importantly, the insufficiency of the traditional school system is becoming apparent. It is not reasonable to teach students knowledge and rules about a domain, such as programming, medicine, and economics, and then expect them to be able to convert their knowledge into effective professional skills by additional mere experience in the pertinent domain. Schools need to help students acquire the skills and mechanisms for proficient performance in the domain under the supervision of teachers. They also need help to acquire mental representations that allow them to monitor and correct their performance, and that will allow them gradually to take over control of the learning of their professional skills and enable them to design deliberate practice activities that produce continued improvement.

On the positive side, the discovery of effective training methods for acquiring complex cognitive mechanisms has allowed investigators to propose types of training that appear to allow individuals to acquire levels of performance that were previously thought to be unobtainable, except for the elite group of the innately talented. The study of the development of expert performers provides evidence on how they modified or circumvented different types of psychological and physiological constraints. It should be possible for one type of expert in one domain, such as surgery, to learn from how other experts in music or sports, for instance, have designed successful training procedures for mastering various aspects of perceptual-motor procedures, and to learn the amount of practice needed to reach specified levels of mastery. If someone is interested, for instance, in whether a certain type of perceptual discrimination can ever be made reliably, and how much and what type of training would be required to achieve this, then one should in the future be able to turn to a body of knowledge of documented expert performance. Our vision is that the study of expert performance will become a science of learning and the human adaptations that are possible in response to specialized extended training. At the same time, as our understanding of the constraints on acquiring high levels of performance in any domain becomes clearer, and the similarities of those constraints across many different domains are identified, the study of the acquisition of expert performance will offer a microcosm for how various types of training can improve human performance and provide insights into the potential for human achievement.

The study of expert performance is not merely concerned with the ultimate limits of performance, but also with earlier stages of development through which every future performer needs to pass. There is now research emerging on how future expert performers will acquire initial and intermediate levels of performance. Attaining these intermediate levels may be an appropriate goal for people in general and for systems of general education (e.g. recreational athletes, patrons of the arts). However, knowing how to achieve certain goals is no guarantee that people will be successful, as we know from studies of dieting and exercise. On the other hand, when the goal is truly elite achievement, the study of expert performance offers a unique source of data that is likely to help us understand the necessary factors for success, including the social and motivational factors that push and pull people to engage in the requisite daunting regimes of training.

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7 Expert Systems: A Perspective from Computer Science

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AI and Expert Systems: Foundational Ideas

Artificial Intelligence (AI) sprang from the startling idea that computers could be intelligent and has pursued as its fundamental scientific goal understanding the mechanisms of intelligent behavior, whether in machines or people.

One branch of that exploration – variously called expert systems, or knowledge-based systems – has focused on constructing programs intended to embody a robust model of human expertise in a domain, using a particular set of architectural choices and construction techniques. The first element of this – the goal of a model of expertise – means these systems are focused on getting the answer right. Other research seeks to model cognition more broadly (e.g. Newell & Simon, 1972), which includes in its models aspects of human cognition that produce errors in performance, such as limited short-term memory, forgetting, and biases. Models that produce the same sort of mistakes that people do can provide useful insight into human thinking, but the focus in knowledge-based systems is on accuracy.

It is likewise important that these programs are intended to be models of *human* expertise, i.e. they are designed to use the same sort of concepts and reasoning techniques that people do. This is in some ways limiting: even a brief glance at the long list of techniques used in scheduling, optimization, planning, and other fields reveals how many powerful (and not necessarily intuitive) problem-solving and inference methods there are. But the focus on human expertise makes it enormously more easy to create systems that are *transparent*, i.e. able to explain their reasoning. If the system's concepts and reasoning techniques are familiar to people, transparency can arise in part from having the system recount its actions. Also, transparency results in easier maintenance and improvement over time.

One of the key architectural properties of these systems is the separation of their two key components: the knowledge base and reasoning or inference engine (Buchanan & Smith, 1988). The *inference engine* of an expert system is the machinery that applies that knowledge to the task at hand. The *knowledge base* of an expert system contains both factual and heuristic knowledge.

- *Factual knowledge* is that knowledge of the task and the domain that is widely shared, typically found in textbooks or journals, and commonly agreed upon by those knowledgeable in the particular field.

- *Heuristic knowledge* is the less rigorous, more experiential, more judgmental knowledge of performance. In contrast to factual knowledge, heuristic knowledge is rarely discussed, and is largely individualistic. It is the knowledge of good practice, good judgment, and plausible reasoning in the domain. It is the knowledge that underlies the art of good guessing (Polya, 1954). Although Polanyi (1958) and others have asserted that much expertise relies on tacit knowledge that cannot be articulated, the knowledge engineering view of expert systems is that tacit knowledge is explicable.

Keeping these two factors distinct can make it far easier to augment what the system knows, and emphasizes capturing domain knowledge in terms of what to know, distinct from how to employ it. The knowledge base also typically contains explicit representations of knowledge (Davis, Shrobe, & Szolovits, 1993), i.e. knowledge captured in a form that makes it easier to examine and modify. One variety of representation widely used in the early systems was simple IF/THEN rules that specified a precondition and an action that could justifiably be carried out if the precondition was met. This simple form is another element in establishing transparency, and facilitates knowledge acquisition.

The emphasis on extensive amounts of domain-specific knowledge and relatively modest inference methods is characteristic of these systems. It reflects in part the shift to the view that the wellspring of high levels of performance is specialized knowledge, not general inference methods. This has been called the knowledge-based paradigm in AI (Goldstein & Papert, 1977). It is also the origin of the term *knowledge based*, which reflects the belief that the performance of these systems is based primarily on knowledge, rather than on the inference or problem-solving methods they use.

Expert systems are a subclass of knowledge-based systems, notably those that seek to deliver expert-level performance. Historically, expert systems were the starting place for much of this work, as some of the earliest efforts aimed at real-world problems that required substantial amounts of knowledge and aimed at achieving truly expert-level performance, e.g. determining chemical structures from analytic data (Lindsay, Buchanan, Feigenbaum, & Lederberg, 1980) or diagnosing causes and recommending therapies for infectious diseases (Buchanan & Shortliffe, 1984). It soon became clear that the knowledge-based paradigm held even at less expert levels of performance, leading to the notion of knowledge-based systems in general.

These systems are also characterized by their construction technique. As models of human expertise, they are often developed by debriefing a subject matter expert ("SME"), whose knowledge is then represented in an explicit form amenable to being examined and modified as the system is tuned. The routine use of human experts as the source of knowledge for the systems was another factor contributing to calling them expert systems. In the language of Kahneman's *Thinking, fast and slow* (Kahneman, 2011), the SME articulates knowledge in the explicit form that is taught to beginners – the way a careful student *should* proceed – not the abbreviated form that allows fast thinking which may include shortcuts not sanctioned by the textbook, "slow" version.

While many AI programs use substantial amounts of knowledge, e.g. about chess or mathematics, expert systems rely on symbolic knowledge acquired from sources other than a programmer's own knowledge or introspection, thus forcing a level of perspicuity beyond clever algorithmic encoding.

In the language of knowledge-based systems, *task* refers to some goal-oriented, problem-solving activity; *domain* refers to the subject area within which the task is being performed. Typical tasks include diagnosis, planning, scheduling, configuration, design, and advice-giving. The application of task-specific methods within a domain of expertise, then, will blend general knowledge about how to solve a particular *type* of problem, e.g. diagnosis or planning, with specific knowledge about the *instantiation* of the problem in a domain, e.g. troubleshooting (or diagnosing) failures in automobile engines or scheduling (planning) aircraft crew assignments.

As with human experts whose expertise is based on cognitive skills, rather than perceptual or motor skills, a knowledge-based system is expected to exhibit several important properties (Berg & Sternberg, 1992; Shanteau, 1988):

- Problem-solving at high levels of ability, well above the performance levels of competent practitioners and novices, even in the face of incomplete or incorrect descriptions of problems.
- An architecture that separates facts about the subject matter domain from procedures and strategies that use those facts.
- A capacity to explain the relevant factors in solving a problem and to explain items in its knowledge base.
- A capacity to modify its knowledge base and to integrate new knowledge into the knowledge base.

One of the most important contributions of knowledge-based systems to the study of expertise has been to provide tools for building testable models and thus determining characteristics of expert problem-solvers (e.g. Elstein, Shulman, & Sprafka, 1978; Larkin, McDermott, Simon, & Simon, 1980; Pauker & Szolovits, 1977). With a computer program that can be run repeatedly under varying conditions, questions and claims about the importance of different parts of the model can be examined without trying to manipulate human subjects (Buchanan, 1994). For example, are there measurable differences in performance when goal-driven and data-driven strategies are used for problem-solving?

More generally, computer programs provide not just proofs of concept but a means to experiment with variations on the mechanisms that would be impossible, or unethical, with human subjects (Buchanan, 1994).

Knowledge-based systems have also brought new methods and new questions into the study of expertise, and into the science and engineering of AI. For instance, is performance alone sufficient to call a system, or a person, an expert? The DeepBlue chess program (DeepBlue, 2005) is a case in point. Although it won a celebrated match against the reigning world champion, its success was probably due more to the number of possibilities it could consider at each move than to its knowledge of chess strategy and tactics. How much does the speed of performance matter in the definition of expertise (Anderson, 1982; Arocha & Patel, 1995)? How does one measure the *amount* of knowledge used by a person or a program?

A Brief History of AI and Knowledge-Based Systems

Knowledge-based systems are based on the computational techniques of AI. From its beginnings as a working science in 1956, AI has been a growing collection of ideas about how to build computers that exhibit intelligence. As mentioned, one major branch of AI, the psychology branch, sought to understand and faithfully simulate the problem-solving methods of humans. A second major branch of AI, the engineering branch, sought to invent methods that computers could use for intelligent problem-solving, whether or not used by humans (Feigenbaum & Feldman, 1963). In both branches, an important source of data and inspiration was the human problem-solver, and both have contributed to the study of expert systems.

In the earliest phase of AI, roughly 1950–65, there was much emphasis on defining efficient symbol manipulation techniques, finding efficient means to search a problem space, and defining general-purpose heuristics for pruning and evaluating branches of a search tree. The early programs were demonstrations of these core ideas in problem areas that were acknowledged to require intelligence. For example, in 1956–57, Newell, Shaw, and Simon's Logic Theory Program found two novel and interesting proofs to theorems in Whitehead and Russell's *Principia Mathematica*; in 1957–58, Gelernter's Geometry Theorem Proving Program showed superb performance in the New York State Regents Examination in Plane Geometry; and by 1963 Samuel's Checker Playing Program had beaten one of the best checker players in the USA (Samuel, 1959). Samuel's work is especially interesting, given the expert systems work that was to come, because he chose the components of the feature vector used to evaluate the goodness of a board position by extensively interviewing master checker players.

Theorem proving within formal logic was also a major focus in AI in the 1960s. It appeared to be a universal method for solving problems in any task domain and was especially attractive after Robinson invented an efficient method for proof-by-contradiction, called the Resolution Method (Robinson, 1968). To some, it seemed that the main problem of creating intelligent computers had been solved (Nilsson, 1995), because in all of this early work, intelligence was considered to be due more to the *methods* than to the *knowledge*, including the methods of search, means–end analysis, backtracking, and analogical reasoning.

Others in AI experimented with *knowledge-rich* programs in a quest for powerful behavior. With knowledge-rich programs, expertise is seen to lie in the domain-specific and common-sense facts, assumptions, and heuristics in a program's knowledge base, implementing a computational form of Francis Bacon's assertion (1597) that in knowledge lies power.

A program's *knowledge representation* formalizes and organizes the program's knowledge. One widely used representation in expert systems, is the conditional rule, "IF A THEN B," sometimes knows as a *production rule*, or simply *rule*. Expert systems whose knowledge is represented in rule form are called *rule-based systems* (Buchanan and Shortliffe, 1984). The antecedent lists a set of conditions in some logical combination. The consequent may name a complex action, and when the conditions are satisfied, the consequent can be concluded, or its problem-solving action taken. A surprising result of this work has been that reasoning methods in programs achieving high levels of expertise can be quite simple, often little more than modus ponens (i.e. if A, and A implies B, then B).

The Emergence of the Expert Systems Focus in AI Research, 1965–1975

Beginning in the mid-1960s, in particular with the DENDRAL research project (Lindsay et al., 1980) at Stanford University, AI research began to shift to exploring the power of knowledge in problem-solving. Questions for AI arose that were framed in terms of the knowledge required for expert-level performance. For example:

- *How could the methods-based approach of earlier AI work be augmented by domain-specific knowledge to model human expertise in difficult tasks of hypothesis induction?* The specific task for DENDRAL was to hypothesize organic chemical structures from spectral data. Because the task was performed by chemists with doctoral degrees, it required expertise that had to be specified and represented. And because the experts' knowledge had to be translated into computer-readable representations, the programmers not only had to elicit the knowledge from experts, they had to interpret it and represent it in ways that would allow easy examination and change. Representing it directly in computer code would render it opaque and subject to misinterpretation when translated, so it was written in straightforward conditional rules, with meaningful predicate

There is More to Expertise than is Captured in the Oversimplified Model of Knowledge Base + Inference Engine

The simple two-compartment model did highlight the importance of separation so that the relative simplicity of the inference engine could be demonstrated. And it also highlighted the important issues of representing and acquiring expertise in declarative knowledge structures. IF-THEN rules, for example, seem "natural" for stating the inferential knowledge needed to diagnose the causes of many medical problems or for classifying borrowers into levels of credit risk.

It was clear, however, that other important kinds of knowledge structures are used by experts in addition to simple inference rules. In the decades after the successful demonstration of MYCIN, and even within that program, much work has focused on the use of spatial, temporal, taxonomic, and causal relationships among types of objects and events in the domain. Diagrams are known to be useful for human problem-solving (Chang & Forbus, 2014; Forbus et al., 2011; Polya, 1954), but their use by computers is still only partially understood (Hammond & Davis, 2004; Lindsay, 2012). Experts also use knowledge of mechanisms to account for causal relationships, side effects, and anomalies when observed facts are at odds with the accepted wisdom.

Lacking this kind of richness, knowledge-based systems do not perform well in the face of unanticipated contingencies; human experts do much better. The first generation of knowledge-based systems exhibited only a little flexibility. Within the sphere of "known unknowns" they performed admirably; but outside of their restricted scope they were brittle. That is, when the details of a specific problem crossed a boundary of a system's knowledge, the system's behavior went from extremely competent to incompetent very quickly (Davis, 1989). To overcome such brittleness and deal with unanticipated situations, researchers have focused on reasoning from models, principles, and causal mechanisms (Davis, 1984).

Meta-Level Knowledge about the Strategies, Contextual Cues, and Appropriateness for Using Specific Items of Knowledge is an Important Part of Expertise

Strategic knowledge is important because of its power: experts use more efficient problem-solving strategies than novices. Not only do we expect experts' answers to be better than those of novices, we expect their chain of reasoning to be more focused and more efficient.

This capability is replicated to some extent in expert systems through meta-level knowledge. For example, MYCIN's diagnostic strategy was predominantly backward chaining: starting with the goal of recommending therapy for a patient with an infection, MYCIN works backward at what it needs to know to do that – recursively until the answers to what it needs to know can be found by asking a doctor or nurse. This conveys a sense of purpose to the doctor or nurse using the program. However, MYCIN was also given meta-knowledge to direct the lines of reasoning even further, e.g. to indicate the order in which to pursue different goals. Meta-knowledge in the program, as with experts, also told MYCIN whether enough information was available on a case to warrant a conclusion or whether it had enough knowledge relevant to a case to attempt solving it at all (Davis, 1980).

Expertise Requires Dealing with Facts about People and Things in the World that are Almost Always Incomplete and Uncertain

Work on knowledge-based systems made it abundantly clear that any model of expertise must deal with facts that are uncertain or missing altogether. Observational reports, for example, frequently contain errors and partial truths. An expert, or an expert system, may fill in reasonable defaults by looking at prototypes or by inferring plausible features from others that are known. Or it may be possible to ignore the missing information and deal just with available data. In real-world problems, the evidence is rarely certain and it becomes important to accumulate support from several pieces of data. The set of methods for using uncertain knowledge in combination with uncertain data in the reasoning process is called *reasoning with uncertainty*. Knowing how to treat incomplete descriptions is a small, but important, part of high performance (Moskowitz, Kuipers, & Kassirer, 1988).

Expertise Also Requires Dealing with the Uncertainty of the Knowledge and Assumptions on which Inferences Are Based

The accepted textbook knowledge and best practices used by experts are incomplete in many domains. In medicine, for example, effective treatments may be associated with sets of symptoms before their mechanisms are known. Moreover, the amount of experiential evidence supporting these associations may range from "used for centuries" to "seemed to work in a similar case." In real-world problems, the available problem-solving knowledge is often uncertain, and it is important to account for the credibility of the associations or the degree to which they can be believed. To deal with uncertain inference, a rule may have associated with it a *confidence factor* or a weight indicating how much evidential support the condition provides for inferring the conclusion. The set of methods for reasoning with uncertainty, then, must take into account both uncertain knowledge and uncertain data in the reasoning process.

One important method for reasoning with uncertainty combines probability statements using Bayes' Theorem to infer the probabilities associated with events or outcomes of interest. Tversky and Kahneman (1974) have shown that even expert decision-makers fail to combine probability statements rationally, according to Bayes' Theorem and other laws of probability. By contrast, a Bayesian program makes no such calculation errors. This helps emphasize the point that expert systems are models of human expertise as it ought to be applied, not computational models of human performance with all of its shortcomings.

Several other methods have been introduced for assessing the strength of evidence and of the conclusions it supports within expert systems (Buchanan & Shortliffe, 1984; Gordon & Shortliffe, 1985; Pearl, 2001; Weiss, Kulikowski, Amarel, & Safir, 1978; Zadeh, 1965). One of the lessons learned from these investigations is that rough estimates of uncertainty often support expert-level performance. Moreover, rough estimates avoid the illusion of knowing more precise facts than are actually known and serve as reminders that the data may support alternative conclusions.

Eliciting Expert Knowledge is not Necessarily the Same as Eliciting Tacit Knowledge

The process of transferring knowledge to a computer program from an expert came to be seen as a much-discussed "bottleneck" because it is difficult and time consuming. The first systems were constructed by programmers, who came to be known as "knowledge engineers," interviewing experts and transforming what they understood into a machine-usable form. Not surprisingly, it became obvious that knowledge engineers with social skills were more adept at this than others. However, they also needed to be very skilled at thinking through the complexity of finding efficient representations and computational procedures to using the knowledge. Eliciting knowledge from experts and representing it for use in a knowledge-based system is a skill in its own right worthy of investigation (Motta, 2013; Scott, Clayton, & Gibson, 1991; Shadbolt & Burton, 1989), but it can be accomplished with careful and skilled knowledge engineering (Shaw & Gaines, 1987; Tecuci, Marcu, Boicu, & Schum, 2015).

However, in spite of early reservations about the impossibility of eliciting tacit knowledge, it became obvious that for many applications, experts did not need to articulate how they *actually reasoned*, only how they believed a careful, rational person or program *should reason.*

Iterative refinement of a knowledge base using case presentations has been found to be a successful method for eliciting knowledge from an expert that might otherwise appear to be inexplicable. Interviewing alone is not as successful as interactive discussions of specific problems. However, insofar as the knowledge transfer process requires social interaction between knowledge engineers and experts (Forsythe & Buchanan, 1992), there will be non-technical difficulties that interfere with success.

Numerous approaches have been taken to ameliorate the difficulties of eliciting and translating an expert's knowledge for use by a computer program. Interactive tools have been developed to assist in conceptualizing and encoding expertise (Boose, 1989) and to assist in the process of knowledge base refinement (Davis, 1979; Pazanni & Brunk, 1991; Tecuci et al., 2015; Wilkins, Clancey, & Buchanan, 1987).

Polanyi's concept of tacit knowledge (Polanyi, 1958) was thought in the 1960s to provide a stumbling block, if not an impossibility argument, for encoding expertise. We now know this is not the case. Although experts may still perform with learned knowledge that has become tacit with use and often elided into shortcuts, they can often articulate the knowledge underneath their thinking using the kinds of rules and principles that are learned from textbooks and that can model their faster-thinking performance. In other words, what is often referred to as "intuition" is not a mystery: it is knowledge that is unexamined.

Continued Maintenance of a Knowledge Base is a Key to Continuing Success

Since most interesting tasks requiring expertise are not static, the knowledge base requires frequent updating. Organizing a body of knowledge within a conceptual framework (called an "ontology") that is familiar to an expert makes it easier to manage and easier to maintain (Chandrasekeran, Josephson, & Benjamins, 1999).

As the knowledge base grows, however, the number of interactions among its elements grows with it. Limiting the scope of the problem being addressed is key to successful maintenance efforts. In some cases, as with medical diagnosis in any sub-specialty area, the relevant knowledge grows in spite of a constant scope. Subject area domains with rapidly expanding knowledge have proven to be extremely difficult for both expert systems and human experts to master and maintain their mastery.

With expert systems and other computer programs relying on large amounts of knowledge, there is some progress in automating the maintenance of the knowledge bases. Machine learning has matured to the point that knowledge bases for expert systems can sometimes be learned from stored descriptions of prior cases (Buchanan & Wilkins, 1993; Pazzani & Brunk, 1991; Rulequest, 2017). However, performance and understandability are improved after an expert reviews and modifies the learned information (Ambrosino & Buchanan, 1999; Davis, 1979; Richards & Compton, 1998). In any case, the vocabulary and conceptual framework in which the experiential data are described are critical to the success of automated systems that search for associations in the data, just as they are when experts are looking for patterns in data.

Learning by reading is becoming a possible route for knowledge acquisition, now largely limited to Google-style statistical learning from massive amounts of text available on the Web. A substantial international effort is under way to define, and later distribute, semantic markup languages that would empower those who create Web or database entries to give some meaning to their text or graphics. The flow of research communications about the so-called semantic web (Berners-Lee, Hendler, & Lassila, 2001) are on the website www.semanticweb.org. The technology for traversing the Web to infer knowledge from the semantic markups is complex, in part because it involves semantic structures (ontologies), and needs human assistance, at least for the foreseeable future (Hendler & Feigenbaum, 2001). As a result, progress has been limited to date.

Expertise Serves Many Purposes and Can be Categorized Along at Least Two Dimensions: Formal vs. Informal Knowledge and Public vs. Private

As described by Forsythe, Osheroff, Buchanan, and Miller (1991), knowledge encoded in textbooks and journals is formal and public. It is the stuff we usually think of when we think of knowledge acquisition for expert systems. But other forms of knowledge, such as heuristics shared among members of a lab, tend to be informal and private. This form of expertise can be difficult to elicit in part because it is not written down and may not be recalled until needed in practice, e.g. who to ask about a specific problem. Insofar as expert systems codify knowledge from experts as well as from textbooks and journal articles, they are formalizing some informal heuristics and moving some privately held knowledge into a more public form, available to an enterprise-wide community of practice. This is analogous to the “knowledge sharing” that is central to all current knowledge management efforts (O’Dell & Hubert, 2011; Smith & Farquhar, 2000). Paradoxically, making private knowledge public may destroy its value, as might be the case with knowledge about people who are willing to “bend the rules” to expedite a process.

Human Expertise is Not Always Necessary for High Performance Problem-Solving

Although problems involving perceptual or motor skills are difficult to rationalize, computers have achieved high, and increasingly more expert, levels of performance in some task areas with a variety of computational procedures that may have little correspondence with human thinking in these tasks. These include both sophisticated mathematics based on detailed physical and control models as well as statistical learning from large collections of examples. For example, through various mixes of control theory, machine learning, perception, and robotics, computers can land a jumbo-jet, play ping-pong, and drive a car, truck, or lunar explorer (see, for example, Urmson et al., 2009).

Purely statistical methods work well for perceptual and motor tasks – and even for some cognitive tasks like translating among languages – when there are very large databases from which to learn (Halevy, Norvig, & Pereira, 2009). Building neural networks from massive amounts of data, known as “deep learning,” has decoupled human expertise and high performance. For example, the 2016 victory of the AlphaGo program over a champion GO player demonstrates the power of machine learning (Byford, 2016), although the learned strategies and tactics are not of use to humans learning to play the game. With expert systems, the rationalization for an expert’s cognitive performance does not capture the exact path of synapses of his or her actual thought, but that level of detail is considered to be uninformative for training human novices.

Expertise in Knowledge-Based Systems, and in Many Humans, is Limited to a Circumscribed Frame of Reference

As with human problem-solving, the knowledge and problem-solving methods are embedded within a larger conceptual framework that carries basic assumptions about the world. To the extent that the context can be articulated, knowledge-based systems can be given an ability to determine when they are operating at the boundaries of their expertise. Even human experts are sometimes blind-sided by making invalid, often implicit, assumptions about context. For example, computer and human diagnosticians, such as physicians and automobile mechanics, frequently assume that a single causal explanation for all the symptoms is preferable to an explanation with multiple causes (Occam's Razor).

It is apparent that cognition is situated in a much larger world of experience than can now be given to knowledge-based systems. There are numerous assumptions we all make based on the context of the moment. Moreover, an expert's own experience certainly colors his or her articulation of knowledge, with a blurring between the facts that are generally true and the facts that are based more on personal experience. A big advantage of using computational systems to study expertise is that assumptions such as these can be made explicit and changed, while with human experts they may remain unexamined for a long time.

The Specialized Knowledge of Experts Often Rests on a Base of Everyday Knowledge

Although it is possible for people to exhibit extraordinary ability in just one area that is largely decoupled from everyday experience, such as chess or music, many experts need to interact with people and the world within their areas of expertise as well as outside of it. In medicine, for example, experts cannot be isolated from what their patients take for granted. Because "everyone knows" that a human fetus develops only in human females, it is a sign of ignorance for a medical diagnosis program, or a medical student, to ask whether a male patient has recently undergone a test for abnormal fetal development.

The task of encoding millions of such facts about the everyday world is daunting, but conceivable (Lenat & Feigenbaum, 1987), and at least one large project, CYC, is encoding common-sense knowledge. Expert systems have been able to finesse the problem of encoding all that knowledge, however, by making the assumption that persons using those programs themselves have enough common sense to avoid making stupid inferences. To a large extent, the circumscribed scope of an application makes this assumption workable in practice.

Expertise is Partly Defined by Experts' Ability to Explain Their Reasoning

Experts may leap to a conclusion without consciously stepping through a chain of inferences. However, we have found that they can, after the fact, explain where their conclusions come from, a requirement Plato believed was necessary for distinguishing knowledge from mere belief. We expect them to be able to teach apprentices how to reason about hard cases and critique their own and others' use of knowledge. We expect knowledge-based systems to have some of the same capabilities (Rennels, Shortliffe, & Miller, 1987). After all, in order to commit significant resources to a recommended action we want to know the justification for it, and our legal system demands that decision-makers be able to justify those actions. A person who merely carries out the orders of a "black box" cannot lay claim to being an expert – but neither can the box.

Expert systems have demonstrated the ability to show how they reach a conclusion by showing the rules that connect inferential steps linking primary facts about a case with the program's conclusions, e.g. its recommendations for how to fix a problem, as in the MYCIN program (Buchanan & Shortliffe, 1984). They can also explain why some facts and inference rules were longest-running commercial expert systems (since the 1980s) monitors the operations of 1,200 gas turbines, steam turbines, and generators (Thompson et al., 2015). Other examples of real-time systems that actively monitor processes can be found in steel making, oil refining, and even the control of space probes for space exploration (Muratore, Heindel, Murphy, Rasmussen, & McFarland, 1989; Nayak & Williams, 1998).

Synthesis Tasks: Planning and Scheduling

Systems that fall into this class analyze a set of one or more potentially complex and interacting goals in order to determine a set of actions to achieve those goals, and/or provide a detailed temporal ordering of those actions, taking into account personnel, materials, and other constraints. This class has great commercial impact. Maintenance of rapid transit subway, airport express, and commuter rail lines in Hong Kong, for example, is scheduled by an expert system to avoid disruptions and delays as much as possible – a "mission critical" application (Chun & Suen, 2014). A system developed for Ford Motor Company manages the automobile manufacturing process planning at Ford's vehicle assembly plants (Rychtyckyj, 1999). Other valuable examples involve airline scheduling of flights, personnel, and gates; manufacturing job-shop scheduling; and manufacturing process planning.

Configuration of Manufactured Objects from Subassemblies

Configuration is historically one of the most important of expert system applications, and involves synthesizing a solution to a problem from a set of elements related by a set of constraints. Configuration applications were pioneered by computer companies as a means of facilitating the manufacture of semi-custom minicomputers (McDermott, 1982). Expert systems have found similar uses in many different industries, e.g. modular home building, telecommunications, circuit design, manufacturing, and other areas involving complex engineering design and manufacturing. Another long-running expert system (built as a case-based reasoning system; Cheetham, 2004) configures a color formula at GE Plastics (later SABIC) to match customers' very specific requests for colors of their plastic products.

Decision Making and Advice-Giving Tasks: Financial Decision Making

The financial services industry has been a vigorous user of expert system techniques. Advisory programs have been created to assist bankers in determining whether to make loans to businesses and individuals. Insurance companies have used expert systems to assess the risk presented by the customer and to determine a price for the insurance. An important early application for MetLife (Glasgow, Mandell, Binney, Ghemri, & Fisher, 1997) analyzes thousands of insurance applications per month. In the financial markets foreign exchange trading is an important expert system application.

Fraud Detection

Some of the earliest commercial applications were in fraud detection software for credit card transactions (Dzierzanowski, Chrisman, MacKinnon, & Klahr, 1989) developed for American Express. Another landmark use of expert systems was monitoring the huge volume of stock market transactions for the National Association of Stock Dealers to detect fraudulent activity (Kirkland et al., 1999). Criminals make use of the fact that fraudulent activity will be lost among the millions of financial transactions conducted daily. Knowledge-based systems review these transactions to separate the abnormal, anomalous activities from the overwhelming number that are normal and routine.

Procedure and Regulation Compliance

Another important function of an expert system is to apply relevant knowledge of regulations and procedures to a user's problem, in the context in which the specific problem arises. Some are designed to be used by a diverse set of people, others by a small, restricted set. Two widely distributed expert systems in the former category are an advisor that counsels a user on appropriate grammatical usage in a text, and a tax advisor that accompanies a tax preparation program and advises the user on tax strategy, tactics, and individual tax policy. Note that in both cases the role of the system is to find and then present the user with knowledge relevant to a decision the user has to make.

Personalized Recommendations of Products and Services

With the growth of Internet shopping, major suppliers of goods and services have gathered data about shoppers' individual preferences in order to recommend items that are likely to appeal to them. These systems are embedded within much larger shopping and ordering websites but are at work whenever the well-known "more like this" button appears.

Many other examples of knowledge-based systems in actual use, and expert systems in particular, can be found in three decades of Proceedings of the Innovative Applications of Artificial Intelligence (IAAI) conference along with many other successful applications. The major tasks addressed by these systems have remained much the same over the years, at least at the high level of the three classes above. As new applications are featured in the conference, however, they frequently involve new domains of application, as shown in Figure 7.1, with interesting technical challenges. The first systems for fraud detection, for example, involved finding small variations in patterns within huge volumes of transaction data. A summary of technical developments, with additional summaries of examples, appears in Smith and Eckroth (2016).

Some Variations in the Implementation of Expert Systems

One common but powerful paradigm involves chaining IF-THEN rules to form a line of

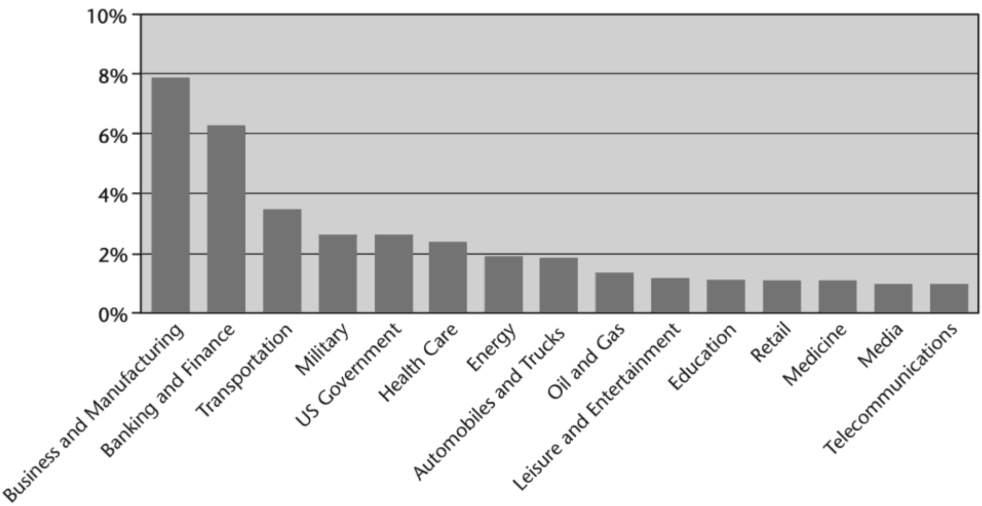

Figure 7.1 Distribution of domains in IAAI papers 1989–2016.

reasoning. If the chaining starts from a set of conditions and moves toward some conclusion, the method is called *forward chaining*. If the conclusion is known as, say, a goal to be achieved, but the path to that conclusion is not known, then reasoning backwards is called for, and the method is *backward chaining*. Data-directed problem-solving is forward chaining; goal-directed reasoning is backward chaining. Some combination of forward and backward chaining is often a better strategy than either one alone. As mentioned, a set of explicit meta-rules can direct the selection of rules to be invoked depending on dynamic characteristics of each problem or a fixed strategy.

In addition to the rule-based paradigm, another widely used representation, called the *structured object* (also known as *frame*, *unit*, *schema*, or *list structure*) is based upon a more passive view of knowledge. Such a unit is an assemblage of associated symbolic knowledge about an entity to be represented (Minsky, 1981). Typically, an object in these systems consists of a list of properties of the entity, associated values for those properties, and relationships of the entity to others; e.g. in an "IS-A" or "PART-OF" hierarchy.

Since every application of a task to a domain consists of many entities that stand in various relations, the properties can also be used to specify relations, and the values of these properties are the names of other units that are linked according to the relations. One unit can also represent knowledge that is a special case of another unit, or some units can be parts of another unit. Structured objects are especially convenient for representing taxonomic knowledge and knowledge of prototypical cases. An orca, for instance, is a marine mammal which, in turn, is a mammal; thus orcas and all other species of mammals can be found to share the characteristics of mammals without having to duplicate the representation of those characteristics.

The *problem-solving model* (or framework, problem-solving architecture, or paradigm) organizes and controls the steps taken to solve the problem. These problem-solving methods are built into program modules we earlier referred to as *inference engines* (or *inference procedures*) that use knowledge in the knowledge base to form a line of reasoning. While human experts probably use combinations of these, and more, expert systems have been successful following each of these strategies singly.

The *blackboard model* of reasoning (Engelmore & Morgan, 1988; Erman, Hayes-Roth, Lesser, & Reddy, 1980) is effectively a dynamic mix of reasoning forward from available data as well as backward from overall goals. It is said to be opportunistic in the sense that the order of inferences in problem-solving is dictated by the items that seem most relevant in the problem description, in the partial solution, or in the knowledge base. This model can be used effectively to combine the judgments of multiple expert systems with specialized knowledge in different parts of the problem.

Still another paradigm, which emphasizes the power of experiential knowledge, is *case-based* or *analogical reasoning* (Kolodner, 1993; Leake, 1996). In a case-based reasoning system, a new problem is matched against previously solved cases. The closest matches are retrieved to suggest analogous solutions for the new problem.

Conclusion

Using computers to model the expertise of recognized experts has brought new issues into focus and has provided new experimental tools for the study of expertise. Each successful application confirms the adequacy of both the representation and inference methods for capturing the expertise needed to perform a specific task in a specific domain. Representing expertise about diagnostic problems in rules, for example, has been confirmed enough times that it makes sense to consider using this representation for a new troubleshooting problem.

On the other hand, there can be valuable information gained when a new task or a new domain requires more than one of the "standard" paradigms – if we only collect and review these data. In one of the experiments using the MYCIN program for tutoring, for example, Clancey (1985) found that rules alone did not provide sufficient justification for their inferences. Medical students need to know more about the underlying reasons why a condition warrants an action than MYCIN's explanations provided.

Computational methods have added significant expressive power to the field of cognitive science. Mathematics is often overly precise and awkward; descriptions in English are often vague. Computer programming forces precision but also allows describing procedures within the context of complex situations. Expert systems, in addition, require explicit, declarative statements of an expert's knowledge and allow manipulation of that expertise.

Just as human experts frequently exhibit exceptional performance in only one area (e.g. chess), knowledge-based systems are constrained in the scope of their high performance, but even more so than humans. As Davis (1984) and others have noted, when expert systems are given problems outside their assumed scope they frequently fail miserably, while human experts are more likely to recognize the boundaries of what they know and don't know; i.e. they possess relevant meta-level knowledge (Davis, 1980). The resulting brittleness of knowledge-based systems makes the differences between the knowledge of human experts and computer programs fruitful areas of research in both AI and cognitive psychology.

On the applied side, within the bounds of what expert systems do well, applications have been abundant and have been proliferating greatly in this era of ubiquitous small applications, Web apps, and smartphone or tablet apps. Expert knowledge has value to the millions of users of these apps and the consequent commercial value is driving the proliferation. They provide abundant data to cognitive scientists about the representation and use of expertise (Patel & Groen, 1991).

Finally, one consequence of the ubiquity and value of knowledge-based systems, and the success of AI generally, has been societal discussion about the changing nature of work, the displacement of workers, and the ethics of letting machines make decisions for us. One pair of authors speculates whether the proliferation of "AI expertise" will result in a hollowing out of the middle class of professional workers (Brynjolfsson & McAfee, 2014). On a more positive side, another speculates about "a world without work" (Thompson, 2015) and its benefits to humankind.

The applications of knowledge-based systems over several decades provide an important model for working *with* automation, in which AI intelligent assistants make human work safer, less tedious, and usually better. Mistakes caused by human fatigue, lack of training, or carelessness can be avoided when a watchful partner corrects us. Our work becomes qualitatively better with an intelligent assistant but it is still our work.

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8 Developing Occupational Expertise through Everyday Work Activities and Interactions

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Prolegomenon

Occupational expertise comprises the ability to generate goods or provide services with high levels of performance in both routine and non-routine work tasks. Such performance arises when both intra-individual (i.e. intra-psychological – internal capacities) and inter-individual (i.e. inter-psychological – between individuals and the world beyond them) preconditions are met. Often, these two areas are analyzed separately, and from diverse theoretical standpoints. In research on expertise, the intra-individual view has been privileged, with the perspective of cognitive science focusing on the acquisition of mental structures and processes that underlie outstanding performance. Research that privileges contributions from outside the individual may focus on supra-individual entities such as teams, groups, communities, or even societies, or on artifacts like workplaces, professions, and occupations, or on situational contexts impacting how individuals are expected to perform and how they actually perform (Baartman & de Bruijn, 2011; Bloor & Dawson, 1994; Dalton, Thompson, & Price, 1977). The most widely acknowledged approach is the one that is well represented in this handbook: the superior performance approach as developed by Ericsson and colleagues (Ericsson, Charness, Hoffman, & Feltovich, 2006). The first edition of this handbook gives an excellent overview of the main achievements of this approach and reflects the first perspective. Quite deliberately, a focus is set on cognitive analyses of structures and processes that underlie reliable outstanding performance, measured through relevant domain-specific tasks. Research contributing to this approach has uncovered many facets of the memory and knowledge of experts who achieve high-level performance. Strong evidence exists that such cognitive correlates of expertise result from extended deliberate practice (Ericsson, 2014; Ericsson, Krampe, & Tesch-Römer, 1993).

Approaches that focus on contributions outside the individual (e.g. on professions or occupations) aim to understand, describe, and analyze the successful development of such capacities in workplaces and professional networks. Among the constructs that may play an important role in such approaches are social acceptance, power, and so on. Thus, those approaches address whether and in what ways excellence or expert performance is constructed: how individuals come to learn and participate in workplace roles and occupational groupings.

Of course, the underlying theoretical concepts that best describe these two sets of respective preconditions are not necessarily compatible. Our attempt here is to align and reconcile these perspectives when engaging with a grounded, significant, and important field of human practice: occupations. Too often, representatives of such research approaches are not well informed about – not to mention appreciative of – other approaches. Taking together the requirements that individuals and organizations (or groups, teams, workplaces, societies, etc.) have to meet to be professionally successful, we refer here to occupational expertise and its development. Processes associated with the development and maintenance of occupational expertise, in contrast to the "usual" acquisition of expertise, tend to happen in everyday work activities and interactions rather than in planned, deliberately designed learning and training situations (Guile & Griffiths, 2001). Nevertheless, those everyday or practice-based processes can also be augmented and made more efficacious if they are planned and supported. This relates the issues of occupational expertise and of deliberate practice as both are skeptical about institutionalized, "schooled" activities, and stress the relevance of practice-based learning processes. Many issues related to practice-based instructional support recently have been addressed in an international handbook of research in professional and practice-based learning (Billett, Harteis, & Gruber, 2014).

In this chapter, we develop a framework to understand and analyze occupational expertise. We are conscious of risks associated with aligning different research traditions, each with their own preferred methodologies, scientific references, examples, and methods to assure quality of research and generalizability of results, and that such an alignment may not fully meet every single side's expectations. Yet, the article entitled "Situated learning: Bridging sociocultural and cognitive theorising" (Billett, 1996) identified many commonalities in conceptions, focuses, and concerns, suggesting such an alignment was possible and worthwhile. Numerous recent attempts to bridge this gap have come to similar conclusions and some are referred to in this chapter. One bridging example is the concept of "personal professional theories" (Schaap, de Bruijn, van der Schaaf, & Kirschner, 2009). This concept is derived from the perspective of cognitivism, and is related to schema-based theories and models of expertise development such as encapsulation theory (Boshuizen & Schmidt, 1992; Schmidt & Boshuizen, 1992) or knowledge restructuring (Boshuizen, Schmidt, Custers, & van de Wiel, 1995). It uses ideas such as procedural knowledge and compiled knowledge, and is thus consonant with a cognitive perspective. It can also be applied situationally and used in quite different theoretical contexts. The results of research on personal professional theories can, for example (we deliberately chose a quite controversial example), also be discussed in the light of cultural-historic activity theory (Engeström & Sannino, 2010). This theory offers a distinct view on the role of theory and practice and the interdependences of individuals and their environments, in terms both of organizations and of situational contexts. Activity systems, in this approach, are considered to be structures formed by individual practitioners, their communities, occupational actions, available tools and instruments, activities, and so forth. Many of these impacting factors help to describe the nature of workplaces and how they influence individuals and the relations between individuals. An approach that has the potential to bridge such seemingly irreconcilable perspectives of research as expertise theory and cultural-historic activity theory might be that of Social Network Analysis or "networked expertise" (Hakkarainen, Palonen, Paavola, & Lehtinen, 2004). In research about networked expertise, important relations among individuals and their roles in the development of expertise have also been investigated (Rehrl, Palonen, Lehtinen, & Gruber, 2014). These analyses of relations with third parties help in understanding the mechanisms that initiate and maintain deliberate practice activities. These mechanisms are salient when the attention is directed to the relation amongst individuals, co-workers, their trainers, coaches, and the like. Thus, more generally, the role of "persons-in-the-shadow" (Gruber, Lehtinen, Palonen, & Degner, 2008) has been analyzed to secure a broader understanding of deliberate practice and intra-individual cognitive development (Lehmann & Kristensen, 2014).

Other examples of this bridging refer to the different usages of the concept "knowledge" itself, including the knowledge about what is not known or should not be done (negative knowledge: Gartmeier, Bauer, Gruber, & Heid, 2008). In their taxonomy, de Jong and Ferguson-Hessler (1996) proposed differentiating a large number of different types and qualities of knowledge, depending on their academic origins. In relation to occupational expertise, the distinction between explicit and implicit knowledge (Nonaka & Takeuchi, 1995) is often stressed, as is the importance of tacit knowledge (Eraut, 2000), particularly where a crucial quality of expert performance is unconscious, intuitive acting (Dreyfus & Dreyfus, 1986; Harteis & Billett, 2013). Delineating different modes of knowledge in order to do justice to the complexity of workplace activities has been suggested. While often in research "mode-1 knowledge" is investigated (which is based on the canonical underlying of knowledge in relevant academic disciplines), workplace analyses frequently show that "mode-2 knowledge" is more viable in real-work contexts (knowledge derived from research in a context of application). We consider both modes of knowledge as legitimate, because they both indicate success factors for occupational expertise and for improved professional performance. It is our long-term and sustained attempt to understand the requirements for occupational performance and its development that has led to these attempts to both draw upon and reconcile contributions from concepts and research traditions that variously privilege either the intra-individual or inter-individual contributions. These are elaborated here in consideration of developing and sustaining occupational expertise.

Developing and Sustaining Occupational Expertise through Work Activities and Interactions

Occupational expertise is central to achieving many societal and economic needs. These include providing the services and goods required for human existence and contemporary standards of living, sustenance, healthcare, education, and shelter, to name a few. Developing and maintaining this expertise is, therefore, an essential societal goal. This expertise is essential for individuals to secure and sustain employability across lengthening working lives that are increasingly subject to changing occupational and workplace-specific requirements. As indicated in the prolegomenon, this chapter aims to augment existing conceptions of expertise by elaborating the social, situational, and personal bases of occupational expertise and its development through everyday work experiences. Drawing on the heritage laid down through studies of expertise, it proposes that occupations have social geneses, are transformed by changing societal needs, yet have goals, practices, and outcomes that are manifested situationally. What constitutes expert occupational performance is held to be shaped by situational factors that comprise the kinds of occupational tasks, goals, and practices that are afforded in circumstances of the occupational practice. They reflect societal and situational bases that need to be mediated by and integrated into individuals' personal domains of occupational knowledge by workers when addressing occupational tasks.

This conception of occupational expertise and its development draws upon and complements conceptions that have arisen through cognitive science and the quest to understand what constitutes expertise within a domain of human practice and how this might best be developed, as proposed above. The premise for much of what is proposed here draws upon the assumption that the requirements for performance in the same occupation, whilst canonical, are also highly situated, that is, localized goals and situationally appropriate solutions. The consideration and emphasis of person-specific domains of occupational knowledge complement the more general account of research on expertise as advanced by cognitive science (Ericsson & Smith, 1991). We propose, ultimately, that beyond the canonical and situational, occupational knowledge is something constructed, represented, and enacted in person-dependent, impossible-to-codify ways by individuals, albeit shaped by canonical and situational premises. Hence, we take forward the concept of domains of knowledge and suggest that these exist in three ways: the canonical, situational, and personal.

We also focus on experiences in workplaces and across working life as key sources of initial and ongoing development of occupational expertise. Certainly, there has been much and long-term interest in young people's development of occupational capacities through schooling, vocational and tertiary education programs. Whilst experiences in educational settings are the subject of much research, the intentional focus here is on experiences in work settings and across working lives, as these are key but under-theorized and legitimized circumstances for learning occupational knowledge. Part of much contemporary occupational preparation and most of its ongoing development is premised on individuals' learning through engagement in work activities and interactions as students or workers, not by being taught in educational programs (Billett et al., 2014). Such primacy of practice-based learning resembles the concept of deliberate practice because it requires intentional and considered activities aimed at the improvement of performance within the professional activity, regardless of its monitoring by institutions or the persona. Although variously explained in anthropological literature, through models such as knowledge encapsulation (Schmidt & Rikers, 2007) and acknowledged in workplace contributions to individuals' cognitive adaptation and learning in those settings (Dornan & Teunissen, 2014; Herbig & Müller, 2014; Lehmann & Gruber, 2006), the role and contributions of everyday learning activities are not fully understood, acknowledged, or legitimated. Within contemporary "schooled societies" there is a tendency either to overlook or to minimize the educational worth of experiences outside of those in educational institutions. Here, a central concern is to redress that tendency. This includes offering informed accounts to counter those suggesting experiences are referred to as "informal" learning as a residual category to describe learning whose legacies are quite concrete and restricted to circumstances where they were learnt (Skule, 2004).

Indeed, what constitutes occupational expertise and the contributions of workplace experiences to its development also questions some orthodoxies of educational discourses. Evidence suggests these settings support learning that is as rich and adaptable as any other (e.g. classrooms) (Eraut, 2004a). Work settings afford occupational experiences, as they require the enactment of activities and interactions in specific work settings (Breckwoldt, Gruber, & Wittmann, 2014). Hence, they can promote depth of understanding and honing of specific procedures, and can generate strategic procedures required for occupational competence (Tigelaar & van der Vleuten, 2014). The personal dispositions and epistemologies of individuals engaging in those work activities are essential here as these direct, monitor, and appraise their work and learning efforts (Thornton Moore, 2004). This last point is important as the knowledge, knowing, and performances be able to respond to the particular requirements of those workplaces. That is, responding to routine and non-routine occupational tasks was, in part, a product of situational factors (Billett, 2001). They comprise the situated domain of practice that shapes and constrains the actual practice of hairdressing (i.e. "what we do here is") and the problem space in which the hairdressers performed their occupation.

To take another example, doctors' roles in large metropolitan teaching hospitals may be quite different from those required for a nearby general practice, or those in hospitals in regional or remote communities. Motor mechanics working in roadside recovery, regular maintenance, major overhaul, or car racing roles require capacities to respond to the distinct tasks and to realize quite different outcomes (e.g. prevent a holiday from being ruined, recondition a vehicle, secure high levels of vehicle performance). In these instances, occupational performance is not only dependent on the canons of the occupation, but on situationally relevant capacities and appropriate actions. So, whereas canonical occupational knowledge informs actions and performance, what constitutes effective occupational performance is situation dependent and rendered more or less appropriate and efficacious by situational factors.

It follows that as occupational performance requirements are situated and not uniform, expertise has to be developed and demonstrated in particular circumstances of practice (Billett, 2001). Hence, there is no such entity as an occupational expert: no expert doctor, nurse, physiotherapist, or car mechanic per se. Instead, the occupational expertise of doctors, nurses, physiotherapists, and car mechanics is premised in the circumstances of where they practice. Avoiding limiting occupational performance to particular circumstances necessitates extensive episodes of experiences that promote adaptability based on the canonical (i.e. the informed principles and practices referred to above). So, the canonical domain both grounds and provides the platform of concepts, practices, and dispositions that assist in adapting occupational knowledge to the multifold manifestations of its enactment. What comprises these situated practices, however, is not easily expressed through national occupational standards or assessed through standardized tests or examinations. Instead, measures of performance, judgments about them, and their learning are likely accessible through experiences in and across those settings.

The two domains of occupational expertise referred to here and their attendant problem spaces are manifested in the social world, one abstracted from actual practice (i.e. occupational) and the other shaped by particular instances of practice (i.e. situational). These domains of occupational knowledge are what is encountered, mediated, and appropriated by individuals and comes to constitute their personal domains of knowledge comprising what individuals construct, represent, exercise, and develop arising from their engagement with both these canonical and situational bases.

Personal Domains of Occupational Knowledge

Individuals' personal domains of occupational knowledge are understood in the widest sense as the individual and personal representation of occupational expertise intra-individually. They comprise conceptual, procedural, and dispositional occupational elements (i.e. what individuals know, can do, and value) that have been learnt through their experiencing, and utilized and developed further through their enactment. These domains are personally shaped and arise through and across individuals' personal histories: their ontogenetic development (Scribner, 1985). They arise as a product of engaging with the canonical and situational bases of occupational knowledge but also affective and emotional bases that go beyond cognitive and codified aspects of knowledge. These personal domains arise from how individuals engage with and mediate experiences across working lives through micro-genetic development (moment-by-moment learning) as they think, act, and feel at work (Rogoff, 1990; Scribner, 1985). A highly honed form of this development is intuition (Harteis & Billett, 2013) arising through extensive experiencing, conscious consideration, and rehearsed procedures. These experiences shape the learning and adaptability of their occupational knowledge through the exercise of intentionality and agency (Goller & Billett, 2014) that shapes how work activities are encountered, including changes to work requirements. For instance, one hairdressing apprentice had a particular interest in hair coloring and this became important for her work, as one of the senior hairdressers in the salon was partially color blind. This led to her engaging far earlier and with greater responsibility for hair coloring than would be usual for apprentices (Billett, 2001). Coloring became an important aspect of her conception of hairdressing and identity as a hairdresser, and how she engaged in responding to clients' requests for hairdressing. All of this shaped how she negotiated the problem space of assessing clients and responding to their requests, as framed by canonical practices and situational factors to generate problem solutions. Another hairdresser had an allergic reaction to the powder used in hair setting solutions and developed a strong disaffection for using chemicals in his hairdressing practice. This, likewise, led to his practice being shaped in a particular way and his consideration of canonical practices and situational requirements rendering problem solutions shaped by his personal domain of preferences and practices.

So, the construction, engagement, and utilization of both the canonical knowledge and situational domains of knowledge both shape and are shaped by the personal domain of what workers know, can do, and value, and how confident they feel. That domain comprises the extent and diversity of their previous experiences (e.g. in work) that has legacies in how workers come to adapt their knowledge to new circumstances. This includes developing the kinds of informed principles and practices that underpin that adaptation, and the dispositions assisting in responding to those situations. Hence, individuals' domains of occupational knowledge arise from what they have experienced across the instances of situated practice in which they have engaged, not just the canonical knowledge they possess (Mandl, Gruber, & Renkl, 1996).

A comprehensive understanding of occupational capacities and occupational expertise requires the consideration of these three foundational domains of occupational practice, their distinct qualities and interrelationships. These domains have distinct epistemological dimensions that are central to how individuals engage in and remake occupational practices as work requirements change. Yet, it is individuals who ultimately shape their progression and the remaking of their occupational practices. This occurs through the moment-by-moment and day-by-day decision making by occupational practitioners, including engaging in the kinds of non-routine problem-solving tasks which are seen as the hallmark of occupational expertise. Hence, occupational expertise is represented in an individual way as a product of personal history of experiences. As learning and development at work vary across individuals, the individual representations of expertise also vary. What constitutes occupational expertise is, thus, difficult – if not impossible – to codify. This consideration of a personal domain of occupational expertise explains some of the inter-individual differences also found in cognitive approaches to investigating expertise that applied think-aloud protocols to investigate experts' problem-solving (Schmidt, Norman, & Boshuizen, 1990).

Having set out bases for what comprises occupational expertise, it is necessary to consider how practice-based experiences contribute to the development of individuals' securing and sustaining that expertise.

Development of Occupational Expertise through Work Activities

This section discusses the process of individuals' development of their personal domains of occupational knowledge that permits expertise and adaptability. Emphasized here are how individuals mediate what they experience in their everyday work activities and interactions. The discussion is approached, first, from a historical perspective of the development of occupational capacities. Then, how work activities are aligned with learning processes is discussed, before advancing theoretical concepts describing personal dimensions of knowledge as intra-mental structures and their learning and development that arise through everyday work activities, inter-mentally or inter-psychologically (i.e. between the person and the social and brute world beyond them).

The Importance of Experiencing and Practice

The task of developing occupational expertise significantly predates provisions of education and training programs, such as those provided contemporaneously by universities and technical colleges. Before the advent of mass education, structured programs and instruction in educational institutions were accessible to only a tiny minority of the population, and for a limited range of occupations. Across human history, the vast majority of occupational capacities have been learnt through participating in them. Up until modern times, that participation usually occurred in families or small local workplaces (Greinert, 2004), through active engagement in everyday work activities, observing and remaking what others do, experiencing success and failure, and extending established practices (Billett, 2014). This learning was largely mediated by individuals' efforts and agency with learners variously being expected to steal (Marchand, 2008), apprehend (Goody, 1989), or secure the knowledge through unobtrusive observation (Singleton, 1989). Teaching or direct guidance by more experienced workers appears to have been a rarity. The former appears to be largely a product of schooling and the latter, it seems, only used when learning through discovery was not possible (Gowlland, 2012). So, across the majority of human history, occupations were learnt, not taught, which appears to be the case for sustaining occupational practices across working lives (Billett, 2014). Yet, many of those family businesses and cottage industries were subsequently displaced by industrialization. The loss of these local sites of learning led, in part, to the formation of mass educational provisions to meet the needs of industrialized economies, including preparing for new occupations required in newly industrial societies, and also aligning individuals' interests to those of the nation state.

There is nothing particularly novel here, as learning sciences, through various theoretical accounts, have long considered individuals' learning and development arising mainly through their mediation of daily life experiences (Baldwin, 1894; Valsiner & van der Veer, 2000) rather than being taught. Yet, currently, much educational research and educational practice and policy privileges the provision of instruction, education, and training. As such, they risk ignoring the contributions of individuals' engagements in practice-based activities and interactions. Resnick (1987) criticized the emphasis on instruction in ways that prompted a reconsideration of engagement in practice within scientific deliberations about learning and instruction. This led to fresh considerations of how learning in working life could inform making schooling experiences more effective, through processes such as reciprocal teaching and learning (Palincsar & Brown, 1984) and cognitive apprenticeship (Collins, Brown, &

Newman, 1989) that emphasized positioning students as active learners, rather than being taught. Moreover, through government mandate, industry insistence, and community need, it has become almost obligatory for tertiary education provisions preparing students for specific occupations to include practice-based experiences in their curriculum. Importantly, these experiences are also helpful for maintaining occupational capacities across working lives. The Programme of International Assessment of Adult Competence data (OECD, 2013) indicates that workers' engagement in both routine and non-routine problem-solving tasks is generative of new learning as well as refining what they know, and this learning arises as much through workers' personally mediated actions as through guidance by supervisors and more experienced co-workers (Billett, 2015).

Hence, appraising the contributions of workplace experience and practice is central to elaborating how developing occupational expertise might arise through accessing and exercising occupational knowledge in work settings.

Work Activities and Learning

Each individual engagement in goal-directed activities is inevitably related with learning. The inference from the evidence is that engagement in familiar activities leads to the refining and honing of what they know, whereas engaging in novel activities and interactions is generative of new learning that is potentially adaptable to other purposes. Experiencing failure can also initiate learning from mistakes. The key premise of learning through and for work is, thus, developing knowledge by accessing workplace activities and interactions. This applies to individuals' learning of both canonical and situational dimensions of occupational knowledge.

Accounts of goal-directed action imply that individuals' goal setting, planning and executing actions, and monitoring and evaluating their outcomes are central to the change or learning they encounter. These processes are not uniform or comprised of set sequences. Individuals may, for instance, define their goal after having started to act or they may modify a goal during acting. It is, instead, a general pattern of acting at work through which learning arises in personally distinct ways. Workers act on bases of goal-directed accomplishments, as defined and coordinated by sub-goals and sub-actions, through which they regulate their actions and learning (Hofmann, Schmeichel, & Baddeley, 2012). Multi-parted tasks might be broken into smaller sub-tasks that are accomplished sequentially. Yet, it is individuals who need to do this sequencing. Action regulation (Hacker, 2003) delineates various levels of mental coordination of these sub-goals and sub-tasks comprising (a) conscious application of declarative knowledge, (b) flexible action patterns (i.e. rule-based action and knowledge compilation), and (c) two non-conscious levels of physical skills that become automated (i.e. highly learnt and not requiring conscious recall) and represented in procedural knowledge and metacognitively as tacit or intuitive knowledge. Some exceptional performances (e.g. sports players and musicians) rely on these well-honed procedures being applied without requiring conscious recall (Greenwood, Davids, & Renshaw, 2012; Harteis & Billett, 2013); however, more conscious considered recall and monitoring of performance may be required for other and specific aspects of occupational practices (e.g. surgery, architecture, hairdressing).

As noted, experiences in workplaces have provided essential learning opportunities through action (i.e. observing, imitation, and practice) and regulation across human history. Through observation, novices can come to understand and form goal states toward which their efforts and learning are directed. Through explanations and descriptions by co-workers, individuals develop declarative knowledge and approximate work tasks (Rohbanfard & Proteau, 2011; Rosenthal & Zimmerman, 2014). They also monitor their increasingly mature approximations of achieving those goal states and classifying declarative or procedural learning as being either positive or negative in terms of goal accomplishment (Gott, 1989). Positive knowledge is that which assists to effectively achieve those goals, whereas negative knowledge is that which assists to effectively avoid obstacles to achieving goals. Both kinds of knowledge contribute to work-related learning and practice-based occupational development (Gartmeier et al., 2008). Even when engaging in routine work activities, individuals refine and hone what they know and can do (Goodnow, 1986; Scribner, 1984), build links or associations with what they know (Groen & Patel, 1988; Wagner & Sternberg, 1986), and reinforce or nuance what is valued (Guberman & Greenfield, 1991; Perkins, Jay, & Tishman, 1993). So, even routine work activities and interactions provide learning experiences, making procedures more effective, building causal links and associations amongst concepts, and variously reinforcing or questioning interests and values associated with how and what we do (Chan, 2013; Eraut, 2004b; Kolodner, 1983; Tynjälä, 2008).

In these ways, when engaging in everyday goal-directed activities, workers have to decide how to act, monitor their actions, make adjustments or modify response, and evaluate outcomes. All of these develop their personal domains of occupational knowledge through situated engagement. What is afforded by work activities is analogous to the kinds of intentional experiences that teachers and educational institutions seek to enact to secure rich learning (Kirschner, 2002; Roth, 2001). Yet, work experiences arise every day across working life and are experienced by workers as variously being routine or novel, and together provide opportunities for generating new knowledge and reinforcing and refining what they already know, can do, and value. So as workers deploy their knowledge in everyday work activities, learning arises incrementally and is shaped by and contributes to their personal domains of occupational knowledge and, therefore, their competence and expertise (Billett, 2003). What is proposed here is not hybrid or sitting outside of existing explanatory accounts of learning or the development of expert performance. Indeed, a consideration of these learning processes is helpful in challenging some of the perhaps undeserved privileging of schooling processes in the development of expertise.

Conceptualizations of Learning Processes

Processes of skill formation have been the subject of extensive empirical work and theorizations. Building on Fitts (1964), Anderson (1982) proposes three phases of skill acquisition comprising a declarative, a compilation, and a tuning phase. The premise for this model is that individuals first require declarative knowledge (e.g. explanation from colleagues or supervisors) which is later proceduralized and recognized as patterns with associated action patterns, and finally automatized and transformed through practice to skilled performance, possibly supported by social partners' environment through feedback and hints. With increasing levels and extent of skill development, progressively greater elements of this knowledge become proceduralized, and can be enacted without recourse to conscious regulation and control (Gott, 1989; Sun, Merrill, & Peterson, 2001). This is sometimes referred to as embodied knowledge (Reber, 1992). Ackerman (2005) offers an analogous account of developing skilled performance that progresses from controlled processing through to automatized processing as captured in a hierarchical three-phase model comprising a cognitive phase, an associative phase, and an autonomous phase of skill acquisition. Learning in the cognitive phase is premised on individuals' awareness or engagement when engaging in novel activities and interactions. They need to make sense of the situation or instruction, identify and construe relevant goals, being immersed in the practice of tailoring, and progressing through a sequence of tasks. This sequencing and progression was based on apprentices' learning, unaccompanied by any direct guidance. The apprentices observed tailors and their working and used artifacts, such as completed garments or those under construction, to guide their own approximations of achieving observed performances. They gradually progressed along a pathway of tailoring activities on the garments being made in the workshops. This pathway involved initially engaging in tasks in which errors could be tolerated, and progressed by engaging incrementally in more demanding tasks that were commensurate with their developing tailoring competence (i.e. where their errors would not jeopardize the garments they were making). Billett (2006) identified analogous sequencing of activities in the example of hairdressing salons mentioned earlier, in which hairdressers also progressively engaged in tasks commensurate with their developing occupational competence, but founded on experiences that progressively developed capacities, such as learning to communicate and negotiate with clients, washing hair, shaping and then learning to cut it – tasks that are canonical to hairdressing. Similar patterns of progression were also identified in food manufacturing and for hotel room attendants (Billett, 2011). In essence, there were courses to follow – tracks to progress along shaped by workplaces' productive requirements – and through participating in their enactment, learning arose. The kinds of opportunities afforded in such settings shape the learning of occupational practice through the learners' engagement with and mediation of it. Whilst permitting participation and providing opportunities for observation, imitation, feedback, and practice, they are also shaped by particular work requirements. So, more than developing canonical occupational knowledge, they can lead to developing situational expertise. While this is very helpful, these experiences and learning need to be augmented so that adaptable learning also arises.

Providing access to knowledge that might not otherwise be learnt. Work activities can provide access to knowledge that might not otherwise be accessible or learnt through the lived experience of workplaces. For instance, Marchand (2008) refers to apprentice minaret builders engaging in intentional structured learning experiences, commencing in mixing mortar and fashioning stones prior to supplying stone masons with these materials in ways that permitted them to observe and, ultimately, practice stone-laying on the inside of a minaret being built from the inside out. Only when they had honed these skills were apprentices permitted to place stones on its outside: a critical task and one crucial to the finished appearance of the minaret. Singleton (1989) also identified stages through which apprentices progress in a Japanese pottery workshop, premised on access to the potter's wheel. The stages are: (a) pre-practice observation with apprentices engaged in menial work and household tasks, (b) tentative experiments at the wheel outside of work time, (c) assigned regular practice at the wheel, (d) assigned production at the wheel, and (e) a period of subsequent work in the shop to repay the training. So, these occupations have requirements that need to be met through structured engagement in work activities that also have inherent pedagogic potential, including making the knowledge required for performance accessible.

Such curricula or pathways as means of organizing learning are not restricted to occupations that are held to be low status and of relatively low skills. Junior doctors also have a set of experiences through which they progress in hospitals in learning to practice medicine effectively (Sinclair, 1997). Initially, they might engage in the admission and examination of new patients, sometimes repeating what has been done by the admitting doctor. Having learnt and honed these skills, they progress to other kinds of activities, building upon foundational capacities of understanding patients and diagnosing their conditions.

Similarly, Jordan (1989) identified the ordering of skill acquisition of Mexican birth attendants. They moved through phases of practice associated with developments within the prenatal phase, then on to the birthing process and postnatal support, each of which has crucial elements. It is noteworthy that across these various models of practice curricula (i.e. the lived experience and intentionally organized ones), the nature and ordering of experiences provide opportunities to engage progressively with and learn in a specific instance of occupational practice. This includes gaining access to the occupational goal states: what has to be achieved for effective practice in that particular setting.

In summary, developing canonical occupational competence and situated expertise requires, first, engagement in the lived experience of work over time and through authentic work activities; second, progressing along a pathway of activities exposing individuals to goals for effective work, and progressively accessing experiences that incrementally develop understanding, values, and procedures required for effective work performance; third, providing access to particular kinds of experiences to develop capacities that will not be learnt through engaging in the lived experience of the workplace alone; and, fourth, ordering and sequencing of experiences to most effectively support individuals' learning. Yet, as foreshadowed, it is necessary to enrich those experiences so they can be more pedagogically effective, and also to develop adaptable understandings and procedures. Indeed, progression along these pathways is also premised on two additional factors. The first is the provision of experiences that augment the workplace experiences; the second, how learners engage in and mediate what they experience.

Practice Pedagogies

Practice pedagogies are means by which learning through everyday work activities and interactions can be supported and/or augmented. These include making accessible the occupational knowledge needing to be learnt for canonical competence, and situated expertise which includes developing adaptable capacities that might not be learnt through individuals' mediation of those experiences alone, that is, learning through discovery. As occupational knowledge arises in the social world, means of accessing that knowledge can be essential. The augmentation extends to assistance in making links, propositions, and causal associations amongst concepts that characterize depth of knowledge that is central to occupational expertise; and also means for promoting procedural and dispositional occupational knowledge and its application to new circumstances and problems.

Practice pedagogies are usually distinct from those enacted in classrooms. They primarily are deployed whilst engaging in work tasks. They can comprise particular kinds of engagements with others, but also with artifacts, objects, and interactions and guidance with others. As noted, Pelissier (1991) identified where artifacts and guidance were used intentionally to assist learning. Importantly, some activities are potentially pedagogically rich, because of inherent qualities in promoting learning through coming to know (i.e. construal of what is experienced), engaging in, and evaluating actions and responses (i.e. constructing knowledge micro-genetically). Nurses' handovers can provide opportunities for developing deep understanding about patient care, as they engage nurses in verbalizing their understandings and involve discussing (a) the patients, (b) their condition(s), (c) their treatment, (d) their progress with that treatment, and (e) formulation of prognoses (Newton, Billett, Jolly, & Ockerby, 2011). These five interrelated considerations afford contextually rich bases for learning about patient care, including securing factual knowledge, enriching concepts, and building of causal links and propositional associations amongst concepts through these discussions that also assist the formation of goals for nursing activities. Doctors' mortality and morbidity meetings perform similar roles, with a particular emphasis on diagnosing problems arising through particular critical medical cases. In both examples, those participating in these work activities have to engage in, follow, and evaluate what is being presented and discussed, and make judgments about the processes and outcomes. These experiences support learning of robust (i.e. adaptable) procedural knowledge and depth of propositional knowledge of the kinds required for expert performance.

The same applies for close or proximal interactions with more experienced interlocutors (Rogoff, 1990, 1995) and forms of close or interpersonal guidance, such as scaffolding, modeling, coaching (Collins et al., 1989), and guided learning (Billett, 2000). These practice pedagogies exemplify learning being guided by more expert partners who can assist the development of less-experienced individuals through joint problem-solving. More experienced workers can advise about tricks of the trade or heuristics, and assist novices develop schemas for undertaking work tasks, including heuristics and mnemonics (Rice, 2010). Mnemonics can comprise letters to remind doctors about a series of interrelated conditions (e.g. the causes of the distended abdomen can be remembered as the Five Fs – fat, fluid, flatus, faeces, and foetus). Junior doctors are advised to remember particular illnesses or diseases by referencing to patients in which they first identified them (e.g. remember Mr. Taylor), as this assists recalling characteristics of the disease for later diagnoses (Sinclair, 1997) and developing "illness scripts" (Schmidt & Boshuizen, 1993). These pedagogies require learners' engagement and rehearsal to prompt their recall. These qualities are generative of what Barsalou (2003) refers to as simulation: the multimodal and sensory representation of knowledge that permits recall and applicability. They are also the kinds of development that permit adaptability to new circumstances.

In sum, practice pedagogies play particular and salient roles in augmenting workplace learning experiences. These include: (a) making accessible knowledge that otherwise might not be accessed or learnt; (b) identifying and providing opportunities to practice and be guided in honing and refining what is being learnt; (c) supporting the development of knowledge through indexing it to practices that have implications for adapting it to new circumstances and tasks; (d) promoting recall or utilization through specific strategies and processes; and (e) providing access to artifacts and activities that support individuals' learning.

Personal Epistemologies

Across this chapter, personal epistemologies and epistemological acts have been emphasized as key mediating means and contributors to individuals' process of experiencing and construction of their personal dimension of occupational competence and situated expertise (e.g. observing and imitation, listening, engaging in tasks, and deliberate practice progresses) (Billett, 2009a). Key premises for developing occupational competence and expertise associated with these epistemologies include (a) individuals indicating an interest and willingness to learn occupations (Bunn, 1999; Singleton, 1989); (b) learning to engage effectively in developing occupational capacities (Gowlland, 2012; Marchand, 2008); and (c) actively engaging in learning through work (Rice, 2010). Therefore, these epistemologies both assist and direct individuals' capacities and embodied knowledge, their sense of self (i.e. subjectivity) and gaze (i.e. how they view the world and how they believe the world is viewing them) (Davies, 2000), and reciprocally shape the direction and intentionality of their efforts (Zimmerman, 2006). All of these premises are particularly relevant for constructing the "hard-to-learn" knowledge necessary for both occupational competence and situational expertise as it requires learners' effortful and intentional participation and willingness to engage interdependently with others and artifacts.

As discussed above, through such activities arises important embodied knowledge (Jordan, 1989; Lakoff & Johnson, 1999; Reber, 1992) or processes of proceduralization (Anderson, 1982) comprising the compilation and automatization of knowledge. This is the case whether referring to haptic or other sensory forms of knowing, for example, somatic markers (Damasio, 2012) that all contribute to expert performance. Personal epistemological practices are, therefore, central to how learning progresses in and through occupational practice. For example, it is impossible to learn bicycling without practicing and experiencing the problem of balancing. Ultimately, the active engagement and construction of knowledge identified widely across this literature (Marchand, 2008; Singleton, 1989; Webb, 1999) is the key premise which, as Kosslyn, Thompson, and Ganis (2006) note, includes individuals having to assent to engage in and learn the occupational practice. Specific epistemological processes, such as ontogenetic ritualization (Tomasello, 2004) – negotiating with a social partner to secure access – are necessary to gain access to the knowledge required for work. These all assist in explaining the person-dependent process of learning and developing domains of occupational knowledge comprising both its canonical and situational manifestations, albeit largely through mediating experiences.

In summary, individuals' personal epistemologies are central to learning through practice and essential for rich learning from practice-based experiences and pedagogic practices. They include (a) an active interest and engagement in work-related learning; (b) readiness in terms of interest and knowing how to be positioned as effective learners; (c) engaging and learning interdependently in practice settings and through activities and interactions; (d) developing capacities to come to know, including haptic, auditory, sensory, and procedural capacities; and (e) engaging with others and artifacts to actively access understandings, values, and procedures; (f) and in ways that can adapt to other circumstances.

Developing Occupational Expertise through Everyday Work Activities and Interactions

The approach advanced in this chapter offers a view on occupational expertise that acknowledges the well-established cognitive accounts on the one hand, but also complements this perspective, on the other hand, by exploring accounts that consider the contributions of the social and cultural environment for the development and exercise of occupational expertise. Hence, this chapter merges two distinct academic perspectives that are more or less isolated from each other. The chapter has elaborated how the social and cultural world shapes the kind of activities humans engage in, how they engage and the consequences of that engagement in terms of their learning and development. Such a perspective reveals that many of the requirements for occupational expertise, including adapting occupational capacities to new circumstances and tasks, arise through everyday workplace activities and interactions. There is no contradiction between cognitive and socio-cultural accounts of occupational expertise that are adopted here. Instead, they differ in their focuses on individuals or on the socio-cultural environments.

Differences arise, however, in conclusions about how best to support the development of expertise. A cognitive perspective may lead to a focus on instruction whereas the socio-cultural perspective emphasizes the importance of social negotiations and practices for development. A view into the past reveals that learning through practice has been the basis through which most occupational capacities have been developed across human history and, likely, across working lives. Yet, to more effectively secure those capacities and contemporary occupational expertise, the organization of workplace experiences (i.e. practice curriculum) and their augmentation through practice pedagogies are required. The chapter discussed the central role of learners' personal epistemologies and how they mediate the creation and exercise of personal domains of occupational knowledge. A core argument is that they are shaped by what comprises canonical occupational knowledge and situated requirements for performance. Importantly and inevitably, learning as described here is informed and shaped by the social and material work environment. However, this kind of learning through work cannot be taken for granted, because that learning sometimes may come at a cost to immediate production or provision of services. But in many ways, learning through work is essential for the workplace, its efficacy and continuity. Indeed, to deny the contributions of work activities to learning risks inhibiting workplace developments and erecting barriers to learning. Workers may come to perceive their learning as being unappreciated with the potential consequence that they will not seek out learning opportunities or engage in intentional learning activities. Hence, optimizing learning through everyday work activities is far from a given as these activities usually have to follow the imperative of efficiency – and learning efforts may impede efficiency.

By drawing upon accounts from cognitive science, and historical and anthropological studies, what has been proposed here aims to offer explanatory accounts of both occupational competence and situated, yet adaptable, expert performance and also how these arise through practice settings. In doing so, this chapter has sought to align and reconcile contributions across a number of disciplinary fields to inform the important task of identifying qualities of expert occupational practice and how it might be developed. That alignment and reconciliation stands to contribute to the work over the past two decades by those who are interested in integrating these contributions in addressing important societal issues rather than seeking to differentiate on the basis of the disciplinary origins of their contributions.

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9 Professionalism, Science, and Expert Roles: A Social Perspective

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Introduction

From a social perspective, the "expert" is an ascription. The kernel or expected value attached to this ascription is the specific knowledge we might share, or specific service we might receive, from the expert. The criteria for considering someone an "expert" vary, from qualifications (e.g. "certified public accountant"), proven experience (e.g. "10 years' experience in turnaround management"), or demonstrated performance (e.g. "one of the top-ten tennis players in the world") to roles within an organization (e.g. "responsible for our business in Asia"). Depending on the context, we speak of "expert drivers" as well as "court-appointed experts" or simply "the experts." Thus, expert status might refer to an "elite" and indicate something exclusive (e.g. Nobel Laureates); it can be relative, as in the case of the expert driver; and might even be transitory, such as in the case of some "experts" on TV game shows.

From a historical point of view, we see various predecessors of modern experts. For instance, we can conceive of priests or shamans as an extreme, undifferentiated version of "experts" in pre-modern societies, encompassing the roles of counsel, physician, and medium. In the rising empires of antiquity we see the growing importance of scholar-officials – experts with literacy skills – such as the Chinese mandarins, often charged with extended official duties in astronomy, architecture, or bureaucratic planning. Schools were founded to systematically prepare these scholars. In medieval times, merchants and artisans (bakers, shoemakers, carpenters, etc.) formed trade guilds that controlled quality standards, prices, and the rules for apprenticeship, thereby organizing the work and markets for craftsmanship in European cities. The historical view shows two trends: differentiation and (self-) organization. Guilds were self-organized and can be considered the predecessors of today's professions. Knowledge and services also became more specific: in medieval Nuremberg, we see more than a dozen guilds solely for metalworking (cf. Braudel, 1992), and today there remain more than 100 ancient and modern guilds ("livery companies") listed by the City of London (City of London, 2016).

Our chapter consists of three parts that draw from different disciplines. From a sociological point of view, expertise has long been professionalized, thus experts are professionals: "Professionalism has been the main way of institutionalizing expertise in industrialized countries" (Abbott, 1988, p. 323). Consequently, the first and main part of this chapter introduces professionalism as an organized and differentiated form of knowledge-based work in current societies. In the second part, we focus on science as the main reference system for knowledge, e.g. for professional knowledge, accepted in current societies. Drawing from the history of science, we depict the evolution of the role of scientists, which itself became professionalized in the twentieth century. In the third part, we abstract from professionals and scientists, and reflect on expert roles in general, based on research from social psychology. This results in thinking about relative – even everyday – experts (beyond professions and science), as well as rethinking expertise as a professionalized competence in differentiated domains that display more or less (self-)organization of experts and their communities.

Professionalism: The Sociology of Professional Groups

One way of operationalizing and analyzing the concept of expertise sociologically is by means of its formation and utilization in different professional occupational groups. Consequently, this first part of the chapter focuses on the history, concepts, and theories of the sociology of professional groups. This intellectual field has a long and complex history. It is clearly linked – and closely associated with – the sociologies of work and occupation, where initially Anglo-American sociologists began to differentiate particular occupations (such as law and medicine) in terms of their aspects of service orientation and "moral community" and hence their contribution to the stability and civility of social systems.

The concept of *profession* is much disputed (Adams, 2015; Evetts, 2013; Sciulli, 2005). During the 1950s and 1960s, researchers shifted the focus of analysis to the concept of profession as a particular kind of occupation, or an institution with special characteristics. The difficulties of defining the special characteristics and clarifying the differences among professions and other (expert) occupations troubled analysts and researchers during this period (such as Etzioni, 1969; Wilensky, 1964). It is generally the case, however, that precision about what is a profession is now regarded more as a diversion in that it did nothing to assist understanding of the power of particular occupational groups (such as law and medicine, historically) or of the contemporary appeal of the discourse of professionalism in all occupations.

In the following subsections, we will provide a historical account of the sociology of professional groups. We then expand on the current "discourse of professionalism" that pervades occupational work contexts. The third subsection discusses how the discourse of professionalism is used to control work. The final subsection builds a bridge to psychology, and discusses the epistemology of professional work.

The Early Years: From Professions to Professionalization

The earliest analyses and interpretations of professional groups tended to focus on and utilize the concept of professionalism. For the most part these analyses referred to professionalism as providing a normative value and emphasized its meanings and functions for the stability and civility of social systems. Durkheim (1992) assessed professionalism as a form of moral community based on occupational membership. Tawney (1921) conceived professionalism as a force capable of subjecting individuals to the needs of the community. Carr-Saunders and Wilson (1933) saw professionalism as a force for stability and freedom against the threat of encroaching industrial and governmental bureaucracies. Marshall (1950) emphasized altruism or the "service" orientation of professionalism and how professionalism might form a bulwark against threats to stable democratic processes.

The best known, though perhaps the most frequently misquoted, attempt to clarify the special characteristics of professionalism and its central normative and functional values was that of Parsons (1951). Parsons was one of the first theorists to show how the capitalist economy, the rational-legal social order (cf. Weber, 1979), and the modern professions were all interrelated and mutually balancing in the maintenance and