Edited by
Marie-Line Germain · Robin S. Grenier

Expertise at Work

Current and Emerging Trends

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Expertise at Work

"True organizational value lies in the expertise that resides in the skills, experience, and behaviors of employees. Yet, not enough has been known about how to identify, develop and measure employee expertise… Until now. This comprehensive review brings together leading researchers and practitioners from around the world, offering new insights, perspectives, and advice on how to make the best of the expertise that resides across a range of organizational settings."

—Dr. David McGuire, Reader in Human Resource Development, *Glasgow Caledonian University, Scotland*

"This book provides a much-needed volume that elucidates and provides substantive guidance about the complex construct of expertise. It is a 'must read' to help professionals committed to workplace learning move towards a more strategic approach to expertise development."

—Dr. Wendy E. A. Ruona, *University of Georgia*. Former President of Academy of Human Resource Development

"This book packs a lot into its pages. It's both an invaluable education in problem solving, and a riveting perspective on using contemporary human dimension ideas with emerging technology to help solve nagging organizational issues. I could have used this in my military career!"

—Ross Guieb, COL. USA(ret), Executive Director of the Bush Combat Development Complex, *Texas A&M University System*

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Le temps est un juge bien plus précis qu'un expert. —Marie-Line Germain
For Gram. She was a pie making expert. —Robin S. Grenier

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Contents

1 An Introduction to *Expertise at Work: Current and Emerging Trends* 1
Robin S. Grenier and Marie-Line Germain

Part I Expertise: Definitions and Concepts 15

2 The Changing Concepts of Expertise and Expertise Development 17
Yujin Kim

3 Routine Expertise, Adaptive Expertise, and Task and Environmental Influences 39
Katerina Bohle Carbonell and Amber Dailey-Hebert

4 Identifying and Measuring Expertise in Organizations 57
Robin S. Grenier

Part II Expertise in Organizational Settings 71

5 **Veteran Experts: Transitioning Military Expertise into Civilian Work** 73
Sarah E. Minnis and Michael Kirchner

6 **Expertise in Sports: What Is the Secret Behind World-Class Athletic Success?** 99
Gabija Liutkutė, Florentina J. Hettinga, and Marije Elferink-Gemser

7 **An Assemblage of Knowledge: Novices, Experts, and Expertise in Universities** 129
Zachery Spire

Part III Emerging Concepts of Expertise in Organizations 147

8 **A Brief History of the Relationship Between Expertise and Artificial Intelligence** 149
Jan Maarten Schraagen and Jurriaan van Diggelen

9 **The Impact of Changing Workforce Demographics and Dependency on Technology on Employers' Need for Expert Skills** 177
Marie-Line Germain

10 **Preparing for the Future of Work and the Development of Expertise** 197
Jason Moats

11 **Conclusion** 225
Marie-Line Germain and Robin S. Grenier

Index 233

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List of Tables

Table 2.1	Definitions of experts	20
Table 7.1	Five-stage model of the mental activities involved in directed skill acquisition	134
Table 8.1	Phases of artificial intelligence (AI)	152
Table 9.1	Work values and skills by generation	179
Table 9.2	Employability skills in for-profit and nonprofit organizations	183
Table 9.3	Changes in expertise	186
Table 9.4	Comparison of artificial intelligence and human expertise	189

1

An Introduction to *Expertise at Work:* *Current and Emerging Trends*

Robin S. Grenier and Marie-Line Germain

Sustained organizational success is largely built on expertise, which is commonly defined as a combination of knowledge, years of experience in one domain, problem-solving skills, and behavioral traits (Germain, 2006; Germain & Tejeda, 2012; Grenier, 2005, 2009). Knowledge is a fundamental component of any organization, and according to Greer and Egan (2019), it is vital to organizational survival. This is because what an individual learns and knows has consequences for the organization in which they work (Simon, 1991). As Nonaka (1991) contends, "successful companies are those that consistently create new knowledge, disseminate it widely throughout the organization and quickly embody it in new technologies and products" (p. 162).

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To ensure survival and enhance organizational success, it is critical that leaders, managers, and human resource development professionals know how to not only define expertise, but also how to identify and nurture it in others. For instance, a strong understanding of employee expertise can aid an organization in making the best allocations of labor, while also improving organizational performance and flexibility (van der Heijde & van der Heijden, 2006). At the same time, organizations who have a strong grasp of expertise and value it in employees can effectively address what De Cuyper and De Witte (2011) call the management paradox. This occurs when organizations want to retain employees with high levels of expertise, but are confronted with an investment in the development of expertise that is at odds with the possibility of losing those employees to competitors once occupational expertise is achieved and before seeing a return on the training and development investment.

Furthermore, since expertise is local or trans-situated (Nicolini, Mørk, Masovic, & Hanseth, 2017), it exists in many places simultaneously with each having a unique history and path to it. This local conceptualization, according to Nicolini et al. (2017), means it is "not only relational and socio-material but is also inherently situated in multiple connected locales" (p. 28). A deeper understanding of expertise such as this is vital for organizations seeking to create and foster a culture where expertise is appreciated and rewarded. Organizations that embrace expertise as part of their organizational culture, ensure that the shared values, beliefs, and understandings that guide decision making and engagement foster learning and instill the growth mindset (Grossman, 2015) necessary for expertise to flourish. Grossman (2015) notes that in such a culture, employees are compelled to help their organization and are also then motivated to share their expertise with others. Conversely, organizations that ignore the important role of expertise in their structures and culture face a number of repercussions. For instance, an organization may unintentionally create an environment where sharing knowledge and expertise is devalued, resulting in knowledge hoarding (Bender & Fish, 2000), which is where employees are not willing to communicate or share their expertise with others. Or expertise may be constrained or underutilized in an organization or field of practice when processes, routines, and incentives that reward creative action are not attended to or when there is an unwillingness to be flexible and reconfigure in response to changing needs, technologies, or markets.

Equal to the importance of an organization's understanding and commitment to expertise is an individual's awareness of their own expertise. With such an understanding an individual can seek out organizations that recognize expertise in all its forms and identify opportunities that provide supportive processes that move them from competency to expertise or to redevelop expertise. It can also be helpful in understanding the value of one's expertise. Today, the job market is filled with people constantly looking for their next better job opportunity and that is influenced by organizations looking to operate on small budgets and with fewer employees. Individuals new to the workforce must quickly identify what sets them apart from other job seekers, while those already employed may want to capitalize on their expertise to retain a position, move up in the organization, or secure a more challenging or rewarding job somewhere else (De Vos, Forrier, Van der Heijden, & De Cuyper, 2017). And for those already working, the importance of movement capital (Wei-Ming, 2004) is critical. The combination of education, special prior experience, transferable skills, and cognitive ability, as well as their occupational expertise (Forrier, Verbruggen, & De Cuyper, 2015) shape an individual's perception of their contributions to their current organization, as well as influencing their sense of potential marketability to other employers.

Furthermore, expertise is equally important to those working independent of any organization. The growth of the gig economy sees emerging digital platforms and structures that rely on dispersed and unorganized workers (Kneese & Rosenblat, 2014) who need the career competencies of: knowing how, knowing whom, and knowing why (Arthur, Inkson, & Pringle, 1999; DeFillippi & Arthur, 1996). This means that contingent workers, including independent contractors, temps or freelancers, or others with no specific organizational ties like artists, athletes, or writers all have the need for developing, retaining, and communicating expertise in a response to the importance of employability, rather than job security, for long-term success.

Given the importance of expertise in the workplace and for individuals who work, and the need for those preparing to study organizations to have a strong grasp of its definition, application, and development, we assembled a group of authors to contribute to *Expertise at Work*. This book is designed as both a stand-alone collection for professionals who want to survey the current thinking on occupational expertise and a text that covers a broad array of issues, ideas, and domains of expertise to study and critique in undergraduate or graduate classes in human resource development, adult learning, leadership, and business and management.

Overview of the Content

There are numerous texts about expertise, but books focusing on expertise in the context of work and in organizations are largely absent, so we wanted to bring together a collection of authors who together could help readers to see the diverse picture of occupational expertise. This book offers scholars and scholar-practitioners a comprehensive look at the development of human expertise in organizations, as well as a glimpse into the future of occupational expertise. Using contemporary perspectives across a broad range of domains, readers are introduced to expertise within the context of various professional perspectives that when taken together provide a more holistic understanding of what defines expertise in different environments and how organizations influence expert development. The book also describes how researchers and practitioners can address practical problems related to the development, redevelopment, and sustainability of expertise in light of current and future organizational needs. To do this the book puts specific emphasis on the emerging trends in the study and practice of expertise in organizations, including the use of artificial intelligence (AI).

Chapter 2 begins this exploration by providing a foundation of expertise in the workplace. Yujin Kim introduces and discusses the theoretical and conceptual underpinnings of expertise. This is an excellent entry point, not only because many of the chapters that follow build of the concepts she introduces, but because such defining is important since expertise is a word "rooted in ordinary language" that often becomes murky when we try to explain what makes one individual an expert and not another (Watson, 2020, ix). Drawing from the extensive literature on expertise that spans across numerous disciplines, Kim covers: a review of definitions of expert and expertise, psychological and sociological perspectives of expertise, concepts of flexpertise and adaptive expertise, and emerging theories of expertise development in the workplace. In her chapter, she posits that the fundamental dimension of expertise is social processes to operationalize experts and expertise in terms of social roles and functions. Based on these foundations, Kim offers two conclusions. First, a traditional concept of expertise as a set of structured and decontextualized knowledge and skills tends to overlook subtle and other critical, but lesser-known aspects of expertise in dynamic environments. Second, an understanding of adaptive expertise and flexible expertise is valuable in Human Resource Development (HRD) and for organizations more broadly since the core dimensions of expertise in the modern workplace are related to solving unpredictable and atypical problems, as well as the continuous transformation of expertise.

In Chap. 3, "Routine Expertise, Adaptive Expertise, and Task and Environmental Influences," Katerina Bohle Carbonell and Amber Dailey-Hebert maintain that organizations operating in increasingly dynamic environments must focus on the importance of adaptive expertise, as well understanding the usefulness of informal learning in developing such expertise. Building off of Kim's introduction to adaptive expertise in Chap. 2, Bohle Carbonell and Dailey-Hebert offer a deeper dive into the phenomenon through their review of relevant literature that addresses important aspects of adaptive expertise in organizations. First, they describe adaptive expertise as the result of switching from fully or semi-automated processes to fully conscious and manual behaviors. Then they explore the notion that environmental conditions affect an individual's ability to deal with unfamiliar problems and thus develop adaptive expertise. This idea of environment and culture is one that is repeated by other authors in this book because it is central to understanding expertise. Environments are filled with resources and objects, people, stressors, environmental conditions, and distractors (Hambrick, Burgoyne, & Araujo, 2020) and all of these come into play with cognition and expertise. Bohle Carbonell and Dailey-Hebert conclude the chapter with ideas for supporting adaptive expertise development. They suggest that places where individuals work need to be encouraging and create space necessary for flexibility to adjust to unexpected situations. They also emphasize the need for organizations to design and facilitate employee engagement in a variety of tasks in dynamic environments that provide individuals with an array of organizational problems to work through.

Identifying and Measuring Expertise in Organizations written by Robin S. Grenier is the final foundational chapter. She notes that while there is clear evidence that expertise is important for workers and the overall success of an organization, many individuals responsible for hiring or those in human resource development still struggle to clearly identify and measure expertise in employees or volunteers. Taking what is presented in the preceding chapters, Grenier begins Chap. 4 with an explanation of the term competence in relation to expertise in order for readers to compare that definition to definitions of expertise presented throughout this text. Defining competence also provides an entrance into an introduction to competency models that are useful for organizations' attempts to identify expertise in their workforce. Next, she presents six approaches designed to measure expertise across a variety of fields. These measures are the *Professional Expertise Scale* (Johanna & van der Heijden, 2000), the *Cochran-Weiss-Shanteau Index of Performance* (Weiss & Shanteau, 2003), the *Expertise Measurement* (Mieg, 2009), the *Generalized Expertise Measure* (Germain, 2006), the Employee Expertise Development Scale (Kim, 2015), and the *Adaptive Expertise Inventory* (Bohle Carbonell, Könings, Segers, & van Merriënboer, 2016). Methods such as these can help improve organizational understanding of the behavioral and attitudinal correlates of verifiable, objective and subjective expertise, and the management of employees' expertise. In their book, Klein, Shneiderman, Hoffman, and Ford (2017) state that we depend "on experts for mission-critical, complex technical guidance for high-stakes decision making…Experts are the people the team turns to when faced with difficult tasks" (p. 67), and in doing so they highlight the imperative need for organizations to be able to identify and assess expertise. As such, Grenier's chapter concludes with a call to action for organizations to take up methods for assessing expertise.

These first chapters set the stage for defining and situating expertise within an organizational and work context. In the next three chapters, authors take up this framing to explore expertise within the specific contexts of veteran's transition to non-military employment, the world of professional cycling, and the organizational structures of higher education. Military expertise has been described "as an expansive and evolving concept that overlaps with knowledge in a variety of civilian sectors" (Crosbie & Kleykamp, 2020, p. 129). Looking at the military as a workplace where a vast array of expertise is developed, Chap. 5 from Sarah E. Minnis and Michael Kirchner focuses on the unique, yet applicable, expertise service members develop while serving in the US Armed Forces while highlighting the importance of expertise redeveloped for veterans as they transition to non-military employment. Chapter 5 begins with an explanation of what military veterans' expertise is and the importance of both soft skills and technical skills to defining the concept. Minnis and Kirchner then suggest that veterans need a new language for communicating their expertise; one that effectively translates their military expertise into the soft and technical skills sought after in civilian employment. They go on to address this by explaining how the definition and understanding of expertise can differ between veterans and non-military employers, and why that incongruity threatens the employability of veterans. Then Minnis and Kirchner introduce the need for expertise redevelopment as veterans transition to non-military employment. After summarizing the Model of Expertise Redevelopment (Grenier & Kerhahn, 2008), they use a case study that highlights this transition and expertise redevelopment for a military motor transport operator. Minnis and Kirchner conclude the chapter by addressing how both organizations and veterans have a role in ensuring the value of military veterans' expertise for civilian employment is valued.

In Chap. 6, expertise is explored in the context of professional sports. Straying outside traditional notions of work, Gabija Liutkutė, Florentina J. Hettinga, and Marije Elferink-Gemsera use competitive cycling as a case for examining the elite athlete's expertise. Central to their chapter is the concept of self-regulation as the ultimate determinant for attainment and execution of expert performance in athletes. Self-regulatory mechanisms are constantly engaged during sport performance, meaning that elite athletes are proactive and committed learners who use reflection, goal setting, planning, monitoring, and evaluation of their performance to achieve exceptional performance. Developing such self-regulation demands effort, focus, and self-awareness by an athlete if they are going to be able to effectively respond to changes in performance (Zimmerman, 2002). As Liutkutė, Hettinga, and Elferink-Gemsera point out, sport presents a multitude of psychological challenges to overcome during expertise development, including anxiety, affect, mood, pain, and fatigue. They contend that if these challenges are managed correctly, the resulting self-regulation will enable successful deliberate practice—a process central to expertise development. Those athletes who master self-regulatory skills and overcome the psychological and physical challenges are more likely to achieve an elite level of performance.

In the final exploration of expertise in an organizational context, Zachery Spires asks readers to consider what it means to have expertise in a university. In Chap. 7, he uses the lens of assemblage theory (Bacevic, 2018) to consider how expertise serves to illuminate tensions about and create possibilities of the forms, functions, and stated purpose of universities. To begin, Spire addresses the way universities act as sites of expertise and what it means to be an expert in higher education. He then presents cases from university programs: Stanford University's Institutional Research and Decision Making Support (Stanford IR&DS), and the University College London (UCL) Arena Centre for Research Based Education (UCL Arena). These provide a way for the reader to situate Spires' broader discussion about the potential of expertise, experts, and novices in universities that can turn these organizations into assemblages of knowledge. The chapter concludes with the potential for universities as emergent and complex places of educational possibility; spaces for experts and novices to develop individual and social knowledge, awareness, ability, and capacity and where individuals can serve themselves, as well as the public and society as a whole.

After establishing the concept of expertise in organizations and seeing how those notions are applied in some specific contexts, the authors of the final chapters of the book invite readers to look ahead at how what we know about expertise can change in the future. Many like Fulbright and Walters (2020) believe that humans and artificial intelligence (AI) will soon be working together and in doing so compensate for each others' weaknesses. The authors of Chap. 8, Jan Maarten Schraagen and Jurriaan van Diggelen focus on helping readers understand artificial intelligence

(AI) from this joint cognitive systems viewpoint in relation to expertise. Through their presentation of the relationship between expertise and artificial intelligence, they posit that expertise is currently viewed as a skilled adaptation to complexity and novelty and that artificial intelligence, when restricted to machine learning systems, results in brittle systems that cannot cope with unanticipated variability. This creates a poor match with human experts' competencies. Schraagen and van Diggelen argue that from a joint cognitive systems perspective, we can see the intricacies of the mutual dependencies between humans and AI, and the constantly evolving distribution of skill sets required from an organizational perspective. Through a case study in radiology, they illustrate these general principles. Specifically, in order to effectively collaborate with human experts, AI requires collaborative skills, such as being able to explain itself, and the introduction of AI results in a series of new skills, or fusion skills (Daugherty & Wilson, 2018), that human experts need to develop in order to deal with AI.

Chapter 9 is written by Marie-Line Germain. She begins a conversation about how the future of work might challenge the assumptions of traditional notions of expertise by examining the impact of workforce demographics and technology on how human expertise is perceived and defined. This is important to the future of organizations since evolving changes influence traditional approaches to work, as well as effect labor demands (Acemoglu & Restrepo, 2018). Germain presents a look at the changing composition of the US workforce, which is increasingly more diverse compared to previous decades (in educational attainment, age, gender, and race). She then addresses how this diversity has changed the typical profile of today's CEOs and entrepreneurs, especially in the tech industry. Next, the chapter includes an explanation of how the digital revolution and the exponential use of artificial intelligence in the workplace have created new demands in labor needs and employee skills in for-profit and nonprofit organizations. In her conclusion, Germain posits that the combination of these three areas of change is reshaping how human expertise is perceived and defined, especially in technology fields.

In Chap. 10, Jason Moats combines much of the thought on expertise that is contributed by others at this point in the book and uses it to invite readers to look into the near future. He does this through an imaginative and very plausible case study that helps us to see what likely "could be" a worker's experience in a durable goods plant. In doing so he is able to then explore opportunities to enhance what he calls the necessary and valuable deliberate practice needed to develop expertise at an expedited pace. His emphasis on speed is critical given that, as Kodden (2020) notes, although change is not new, the speed of change is; this is due in large part to innovations in technology that "are not linear, but rather exponential" (p. 26). Moats posits that in a future where organizations will be challenged to swiftly and continually transform and adapt (even more so than today), employees will need to redefine their expertise—learning knowledge and skills in ways that are both rapid in response and uncompromising in the level of mastery. He concludes the chapter by calling on human resource development professionals and organizational leaders to question the current methods for developing expertise, which may be incongruent for establishing and/or maintaining a competitive advantage in an excellerative environment driven by technology and innovation. Jason Moats' chapter delves into the ubiquitous nature and the rapid evolution of workplace technology, the ever-present transformation of the workplace, and the unrelenting fast pace of innovation, which, he posits, will continue to disrupt the competitive landscape which subsequently challenges organizations' performance.

Chapter 11, the concluding chapter, is a reflection on the complexity of the construct of expertise, both from a theoretical perspective and from practical perspective. The editors charge the readers with staying abreast of the ever-evolving nature of expertise, pointing out that the swift changes most organizations have to embrace, like those resulting from the COVID-19 pandemic, necessitate preparation and anticipation to ensure that expertise is maintained. Using the work of the authors' chapters, the editors offer implications and considerations for scholars and scholar-practitioners as they seek ways to support experts and expertise at work.

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Part I

Expertise: Definitions and Concepts

2

The Changing Concepts of Expertise and Expertise Development

Yujin Kim

Now more than ever, individuals must constantly develop expertise so that their knowledge and skills are not just growing to meet the needs of their current job, but is also transferable across their entire career (Arthur, Khapova, & Wilderom, 2005; Tams & Arthur, 2010). Moreover, organizations must grasp the realization that continuous learning and innovative adaptation to change characterizes the development of employee expertise (Herling, 2000), thus requiring employees and organizations to be proactive and innovative in (re)defining and (re)developing their expertise (Grenier & Kehrhahn, 2008). Thus, this chapter may be helpful to organizations and those working within HRD as they seek to not only define what it means to be an expert, but understand the psychological and sociological perspectives of expertise.

This is accomplished by first addressing the more traditional and long-held concept of expertise as a set of structured and decontextualized knowledge and skills. While important and helpful in understanding deliberate practice, this thinking is limiting. It overlooks subtle and other

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critical, but lesser-known aspects of expertise found in today's dynamic organizations. Next, concepts that challenge the traditional notions of expertise in the workplace, including the role of adaptive expertise and flexible expertise for solving unpredictable and atypical problems are presented. These offer organizations and HRD professionals a means of recognizing and encouraging the continuous transformation of expertise. Finally, this chapter ends with emerging ideas of expertise and expertise development in the workplace that can serve HRD scholars and practitioners as they continue to understand, nurture, and honor employee expertise.

Defining Expertise

The study of expertise is generally based on two different approaches: absolute approach and relative approach (Chi, 2006). Each has different implications for studying and understanding expertise development. The absolute approach to expertise focuses on the impact of genetic inheritance in cognitive or physical abilities. The underlying assumption is that innate talent or ability leads to exceptional performance, thus, only a small number of people can reach the greatest level of performance (Ackerman, 2014; Chi, 2006; Kaufman, 2007). That means a person's general intelligence (Hambrick et al., 2014), working memory (e.g., Hambrick & Meinz, 2011), or other innate physical abilities (e.g., absolute pitch in music, Ruthsatz, 2014) influence expertise and leads to some individuals gaining more benefit from practice or some requiring more practice than others (Campitelli & Gobet, 2008, 2011). This is supported with evidence of the great differences in developmental trajectory between individuals (Campitelli & Gobet, 2008). For instance, the variability in the number of hours of intense practice a person needs to achieve a master level in chess, from a minimum of 3,000 hours to a maximum of 23,600 in total practice hours (Gobet & Campitelli, 2007). In contrast to the absolute approach, the relative approach to expertise views experts on a continuum of proficiency levels by comparing experts to relatively less experienced people (i.e., novice or intermediate). This approach assumes that a majority of people can attain expertise through learning (Ericsson, 1998, 2006). The relative approach sees expertise attained through a developmental process shaped by context where a less skilled person becomes more skilled (Chi, 2006).

Both approaches are informed by, or are the basis for, numerous and varied definitions and descriptions of expertise from an array of disciplines. Despite the plethora of sources, the definitions are likely framed in exceptional performance by addressing "superior performance," "optimal performance," or "exceeding the requirements". A collection of definitions is presented in Table 2.1.

Although general definitions of expertise are a useful starting point for those responsible for developing human resources in organizations, a more complex and nuanced look at expertise may become necessary. For that, we turn to the psychological and sociological perspectives on expertise that are used to shape conceptual understandings of experts and expertise and practices that encourage development of expertise in the workplace.

Psychological Perspective of Expertise

More classical views of understanding and identifying expertise are rooted in a psychological perspective, which establishes an expert as having an extensive knowledge base that is represented and organized in qualitatively different ways from a novice. As such an expert can efficiently apply relevant domain knowledge and strategies to problem-solving situations (Chi, 2006; Feltovich, Prietula, & Ericsson, 2018; Herling, 2000). Domain-specific knowledge is what an individual knows about the specific domain (e.g., history) and topics in the domain (e.g., the Boston Tea Party) in order to function as an expert (Alexander, 2003; Grenier & Kehrhahn, 2008) and is considered a critical dimension of expertise. Having a deeper and richer base of domain-specific knowledge provides an individual "unique cognitive architecture" (Dane, 2010), where an expert's domain-specific knowledge is drawn upon for cognitive processing, like solving problems quickly and efficiently. Central to the psychological perspective is the notion that the superior information processing mechanism of expertise is domain specific and cannot be transferred to

Table 2.1 Definitions of experts

Citation	Definition of experts or expertise
Chi, Feltovich, and Glaser (1981); Chi, Glaser, and Rees (1982)	Expertise is the possession of a large body of knowledge and procedural skill (Chi et al., 1981); experts organize knowledge in terms of a deeper, more fundamental conceptual structure (Chi et al., 1982)
Schvaneveldt, Durso, Goldsmith, Breen, and Cooke (1985)	Expertise refers to performance in a particular domain, such as chess, physics, or medical diagnosis that is superior to the performance of a number of other people within that same domain
Hatano and Inagaki (1986)	Adaptive experts are those who not only perform procedural skills efficiently but also understand the meaning of the skills and nature of their object
Bereiter and Scardamalia (1993)	Expertise is a process of progressive problem solving in which people continuously rethink and redefine their tasks
Swanson (1994)	Expertise is defined as the optimal level at which a person is able and/or expected to perform within a specialized realm of human activity
Jacobs (1997)	One who has the knowledge and experience to meet and often exceed the requirements of performing a task
Kuchinke (1997)	Expertise is an ability to rapidly organize and process small bits of information into meaningful and creative solutions to specific problems
Herling (2000)	Human expertise is defined as displayed behavior within a specialized domain and/or related domain in the form of consistently demonstrated actions of an individual that are both optimally efficient in their execution and effective in their results
Ericsson (2006)	Expertise refers to the characteristics, skills, and knowledge that distinguish experts from novices and less experienced people who are consistently able to exhibit superior performance for representative tasks in a domain
Germain and Ruiz (2009); Germain and Tejeda (2012)	Expertise is the combination of knowledge, experience, and skills held by a person in a specific domain

other expertise domains (Glaser, Chi, & Farr, 1988). Since expertise from this approach is likely based on assessing expertise in a context-free performance that is quite typical in the context of the given domain, for example, selecting equations to solve a physics problem, this view of expertise is of limited use for practitioners identifying expertise in a complex organization.

Sociological Perspectives of Expertise

The other view of expertise, the sociological perspective, emphasizes social and attributional aspects and the dynamic alteration of the boundaries of an expert's domain knowledge. Unlike the classic view of expertise from a psychological perspective, researchers like Mieg (2006) view expertise through a sociological lens of expertise that is based on the expert's relationship to the audience and the expert's social functions in a particular context. Important to the sociological perspective is the concept of relative expertise, a term coined by Mieg (2006). Relative expertise reflects the idea that the knowledge and skill level "differs in our society, as well as the level of knowledge and skill necessary to serve a function in a context" (p. 745). Thus, for instance, if you are a sociology student and in trouble with a basic statistics assignment, you turn to a friend who majors in statistics. In this context, your friend functions as an expert not because of absolute superiority in defining expert performance (Ericsson, 2018), but because the major gives some notion of expertise in the topic.

Furthermore, a sociological perspective views expert knowledge as composed of context-dependent, functional, and imperfect abstractions (Agnew, Ford, & Hayes, 1994). Not all knowledge claims have endured rational-empirical tests against the real world. Social selection process (e.g., mass opinions) and personal interpretation on experience play roles to construct expert knowledge in the specific cultural context. This is particularly true for the modern knowledge-based economy characterized by an increase of knowledge and information. Supporting this contention is evidence (e.g., Bullough & Baughman, 1995; Orland-Barak & Yinon, 2005) indicating the existence of contextual fluctuations in experts' performances as they move from novice to expert level, as well as periodic alternation of the roles of experienced experts and novices in workplaces (e.g., Fuller, Hodkinson, Hodkinson, & Unwin, 2005). Such fluctuations are particularly important for organizations to acknowledge, since experts must be supported as they consistently redefine their roles and identities against the demands of society, their organization, or career field to which they belong.

Expertise in the Workplace

The psychological and sociological perspectives are useful for looking more closely at expertise and how it is developed in the workplace. For instance, psychological perspectives of expertise are the basis for older competency models. These models explain domain-specific expertise development based on repetition and the practice of skills, often through deliberate practice. On the other hand, the sociological perspective of expertise is useful in explaining flexible and adaptive forms of expertise and for understanding the concept of the boundaryless career.

Expertise Development Through Skill Acquisition

There are numerous skill acquisition models that are useful for understanding expertise development including Fitts's (1964) stages of skill learning, Schmidt's (1975) schema theory, and Benner's (1982) stages of clinical competence. Most are similar with a move in stages of skill from initial cognitive representation of the skill to a point where a person can correctly perform the action with a minimal amount of effort. This is the case with the classic competency model of linear skill development from Dreyfus and Dreyfus (1980). This model of skill acquisition focuses on four binary qualities of mental activities in skill acquisition: recollection (non-situational or situational), recognition (decomposed or holistic), decision (analytical or intuitive), and awareness (monitoring or absorbed). As mental function matures through practice, the individual's level of expertise moves across five consecutive stages: novice, competent, proficient, expert, and master.

Due to its functional focus on behavior objectives, Dreyfus' (1980) model of skill acquisition has been widely used as a theoretical foundation for workplace training and vocational education. However, the narrow focus on observable skills and performance, as well as a lack of clarity about developmental processes of cognitive abilities (e.g., conceptual forms of knowledge) (Dall'Alba, & Sandberg, 2006; Hodge, 2016) make them less than ideal. Moreover, models of skills acquisition indicate a time when experience no longer contributes to further development of the skill or expertise; people simply retain/maintain a satisfactory level of performance. Those who aim to become an expert need to counteract automaticity by developing more complex mental representations and maintaining conscious control on their performance (Ericsson, 1998, 2006). As such, it is problematic for HRD professionals to rely on competency-based training because the goal of every day skill acquisition is to reach the autonomous stage as rapidly as possible, but that does not assure attainment of expertise.

The limitations of learning and development that largely ignore the development of the problem-solving skills required for both practical and nuanced conceptual forms of knowledge (Hodge, 2016) is countered through deliberate practice. Combining the model of skill acquisition with cognitive psychology, Ericsson (1998, 2006) suggests that deliberate practice is a necessary mechanism to superior performance and expertise. This intentional practice maintains cognitive and associative states that facilitate continuous breakthroughs to improve performance and develop expertise (Ericsson, 1998, 2006). So, rather than conforming to a routine sequence of actions and mere experience, an extensive amount of deliberate practice leads to the superior performance of an expert. But it should be noted that deliberate practice is a separate construct from a work activity (e.g., participating in a competition or a performance) or expertise relevant, but playful activity (e.g., listening music for a classic musician) (Ericsson, Krampe, & Tesch-Römer, 1993). However, in a study of jazz musicians (Gruber, Degner, & Lehmann, 2004) participants exhibited strong enjoyment in taking part in many deliberate practice activities, blurring the boundary between deliberate practice and playful activity.

Deliberate practice in this case seemed indistinguishable from enjoyment (i.e., playful activity) and professional reward (i.e., work-related activity; Gruber et al., 2004).

Since Ericsson, Krampe, and Tesch-Römer (1993) introduced the concept of deliberate practice and its effect on expertise development in music (i.e., violinists and pianists), numerous other researchers have examined the effect of deliberate practice in diverse fields (e.g., professional writing, music, sports, chess; for a review see Ericsson, 2006). Recently, authors of some meta-analysis studies argue that deliberate practice leaves the majority of variance in performance unexplained, indicating that deliberate practice is necessary, but not sufficient, in developing expertise (Hambrick et al., 2014). Even in traditional skill-based domains of expertise like chess or music, deliberate practice explained only about 30–34% of variance. Furthermore, the explained variance plummeted in the unpredictable fields of expertise such as educations (4%) and other professions (less than 1% e.g., computer programming, piloting, soccer refereeing, and insurance selling; Macnamara, Hambrick, & Oswald, 2014).

There is indication that not only does the relative importance of deliberate practice vary depending on the domains, but also the best types of deliberate practice vary depending on domains (Charness, Tuffiash, Krampe, Reingold, & Vasyukova, 2005; Ward, Hodges, Starkes, & Williams, 2007). For an example, researchers found that there are considerable differences in deliberate practice across areas of music (Gruber et al., 2004). Expert jazz guitarists highly valued hearing and analyzing the recordings of famous musicians and had doubts about the value of formal training. Jazz musicians' expertise development was enhanced by exposure to a community of experts, in contrast to classical musicians who benefitted from direct instruction from a teacher.

Due to the intentionality of learning, engagement in deliberate practice can uniquely contribute to employee expertise development. Besides acquiring advanced skills and knowledge beyond immediate needs, individuals can develop a general and conceptual foundation of expertise (Billett, 1999; Grenier, 2009; Paloniemi, 2006). Individuals can critically reflect and link their learning from/through work to broader contexts by involving explicit learning activity to focus on concepts, ideas, research outcomes, and theories inside and outside the profession (Simons & Ruijters, 2001). Although an understanding of skill acquisition for expertise through deliberate practice is in some ways helpful, unresolved issues remain, including the blurring of what experiences are integral parts of expertise and expertise development (Billett, 2004; 2008; Hodge, 2016) and the defining of deliberate practice in an organization so as to reflect the specific natures and contexts of the domain of expertise. Additionally, despite the fact that deliberate practice may aid in the transfer of expertise to other contexts (Mieg, 2009), the construct largely ignores context. The limited concept of deliberate practice remains insufficient for explaining the variety in expertise development across different domains, which means that other factors play important roles in expertise development. Recognizing this shortcoming, in particular, is important in understanding employee expertise development.

Adaptation and Flexibility

For those in HRD, taking the existing definitions generated from both psychological and sociological perspective of expertise (see Herling, 2000; Kuchinke, 1997), as well as the unique dimensions of expertise in the context of an organization's dynamic environmental changes is critical. This means that the concepts of adaptability and flexibility are useful to HRD professionals in expanding how expertise might be identified and developed in organizational contexts. Adaptive expertise is depicted as a transferable form of expertise that can be shifted and applied to new problems or situations (Hatano & Inagaki, 1986). It is expertise where knowledge is represented on a more abstract and structural level (Kimball & Holyoak, 2000) thus enabling application of knowledge to complex and novel problems that have different characteristics from typical tasks.

To explain, consider a programmer who is very efficient at applying their knowledge and skills rapidly and accurately to solve a coding problem. They gained that efficiency through repetition and practicing the tasks needed to correct the program and in doing so they accumulate the knowledge and experience needed to address problems, making the process routine. They have developed routine expertise. Yet the programmer's routine expertise doesn't always work since they may face novel situations that require non-routine adaptation. Those situations call for adaptive expertise—where efficiency is important, but so is innovation (Schwartz, Bransford, & Sears, 2005). Addressing novel situations requires innovation that moves the programmer away from the most efficient approach. To be optimally adaptive the programmer instead fluently uses their well-organized knowledge and skills to rearrange the novel environment and their thinking style, thus demonstrating adaptive expertise (Schwartz et al., 2005). Those, like the programmer, who exhibit adaptive expertise have higher self-efficacy for adaptable behaviors (Griffin & Hesketh, 2003) and perform better in the face of changes in complex situations (Chen, Thomas, & Wallace, 2005) or when encountering exceptions to the rule (Neal et al., 2006).

Adaptive expertise as introduced by Hatano and Inagaki (1986) is in many ways similar to flexibility for gaining expertise. Adaptive expertise highlights creation of new knowledge and methods in the atypical situation (Carbonell, Könings, Segers, & van Merriënboer, 2016), while flexible expertise explicitly suggests the transfer of expertise "across different domains and problem types smoothly and appropriately" (Birney, Beckmann, & Wood, 2012, p. 573). This is contrasted with the psychological perspectives of expertise that emphasize domain specificity. Flexible expertise differs qualitatively from routine expertise in that routine expertise relies on previously acquired domain-specific knowledge and skills, while flexible expertise involves domain-general metacognitive and self-regulatory processes (Birney et al., 2012).

Flexible expertise can be likened to van der Heijden's (2000) term flexpert. This is an individual who is "capable of acquiring more than one area of expertise within adjacent or radically different fields" (p. 12) or someone able to acquire a means for mastering a new area of expertise or expert performance in a completely different territory (Frie, Potting, Sjoer, Van der Heijden, & Korzilius, 2019). Frie et al. (2019) qualitatively explored the experiences of recognized flexperts and demonstrated that becoming a flexpert begins with a new idea and follows a deliberate process to materialize the idea in the working context (e.g., new products or service). This study implied that flexpertise is closely related to significant innovation in performance, as well as the creation of new areas of expertise.

Taken together, adaptive expertise and flexpertise can, in many ways, be found in the concept—the boundaryless career. In the early 1990s, the concept of the boundaryless career (Arthur, 1994) emerged in response to the changing career landscape characterized by an increase of transient employment relationships, career pursuit as reputation-building, employability in industry fields, and the increasing prominence of the subjective over the objective career. Boundaryless career is defined as a sequence of career paths "that go beyond the boundaries of single employment settings" (DeFillippi & Arthur, 1994, p. 307), yet they are not context independent; rather they are constructed under wide contextual constraints and boundaries (Tams & Arthur, 2010). For example, IT contractors build their own communities or networks that provide technical and non-technical support in order to supplement the limited availability of institutionalized resources (e.g., repository of skills accumulated in an organization; Barley & Kunda, 2006). These careers lie outside the bounds of an organization. The work demands frequent evaluations in the market (Barley & Kunda, 2006), meaning that these professionals have to rely on their individual resources for job continuity and security, including self-directedness and recontextualizing.

Self-directedness in career and expertise development is a marked characteristic of boundaryless workers (Inkson, Heising, & Rousseau, 2001) who, unlike many of their professional counterparts, must engage in continual learning and use intensive and sustained effort to stay up-to-date and competitive. Knowledge and experience, accumulated through completing diverse assignments for different organizations, are the primary source of expertise development for boundaryless workers (Inkson et al., 2001). Moreover, since the trajectory of individuals' careers become a "credentialing process", these workers carefully arrange their learning opportunities to enhance their reputation and expertise (Barley & Kunda, 2006, p. 52; Inkson et al., 2001). By using the concept of recontextualizing, Guile (2012) explained the process by which professionals in boundaryless careers reorient themselves through inter-professional work. In collaborative practices, these professionals are required to make their domain-specific knowledge and insights explicit to others whom they are working with at the time in order to develop collective inferences in a team. This process of collective inference results in recontextualizing of domain-specific knowledge and perspectives. By hearing explicit explanations and interpretations from members of diverse fields, individuals can infer the implications of new suggestions in relation to their own and others' professional forms of knowledge and perceiving.

Emerging Ideas of Expertise Development

New ideas continue to emerge as the definition of expert and expertise evolve. The limits of skills acquisition models have been identified and a sociological perspective of expertise that underscores flexibility and adaptability has been expanded. Empirical studies have repeatedly reported that learning through/from work experience is a key mechanism of employee expertise development (e.g, Cheetham & Chivers, 2001; Dragoni, Oh, Vankatwyk, & Tesluk, 2011; Enos, Kehrhahn, & Bell, 2003; Grenier, 2009; Paloniemi, 2006). As such, looking at a person's professional networks and work experiences through the concept of situated learning (Lave & Wenger, 1991) in the workplace is being investigated as a promising element for explaining employee expertise development. This includes investigating what happens when employees participate in individualized interactions and practice across various professional networks to enhance their career and expertise (e.g., networks of practice, Brown & Duguid, 2001).

Furthermore, assessing growth of social networks in organizations is an indicator of an individual's expertise development (Gruber, Lehtinen, Palonen, & Degner, 2008). Researchers (Eraut, 2004; Grenier, 2009; van Winkelen & McDermott, 2010) in the field of workplace learning confirm the prominent, developmental values of participation in social contexts through individuals' professional networks both inside and outside the workplace. For example, Eraut (2004) described participation in group activities, working alongside others, and working with clients, while a study from van Winkelen and McDermott (2010), found experts from various fields emphasized the critical roles of being mentored or working with well-regarded experts in the process of being an expert.

Another emerging dimension for understanding expertise in the workplace is the type of work experiences that have formative value in developing expertise. Like deliberate practice, which is especially designed to enhance expertise, developmental work experience may enhance expertise development (Cheetham & Chivers, 2001; Goldman, 2008) as it pushes individuals to move out of their comfort zone (van Winkelen & McDermott, 2010, p. 564). Learning in this way is a byproduct of work and often implicit in nature (Marsick & Watkins, 2001). For instance, Goldman (2008) found that significance in size and complexity, proactivity, newness, regularity, and intensity of focus were the common characteristics of valuable experiences in developing strategic competence among ten CEOs in the healthcare industry. Despite the differences in fields of expertise, other researchers also report similar findings, including: variety in experience (Paloniemi, 2006), taking on valuable and challenging tasks (Eraut et al., 2004), dealing with abnormal work situations (Billett, 2008), and exploring new strategies to solve imminent problems in business (O'Shea & Buckley, 2010). Through developmental work experiences employees can enhance contents of expertise territory and better adapt to the environment in the territory (Grenier & Kehrhahn, 2008) by learning situated knowledge. Also, work experience can guide individuals to focus on more relevant information and better understand theoretical knowledge that they learned through formal education (Paloniemi, 2006). In other words, this emerging line of inquiry points to the newness, variability, and challenges in experience as key characteristics of developmental work experience that leads to a means for optimizing one's expertise in the workplace and directing further advances in expertise development.

A third emerging consideration for studying and understanding workplace expertise comes from a sociological perspective and Mieg's (2006) work on relative experts that was presented earlier in this chapter. The idea of relative expert emphasized not the absolute level of expertise belonged to an individual, but the functional roles of an individual in certain circumstances (Mieg, 2006). Evidence supports this premise with findings that demonstrate a contextual fluctuation in experts' performances between the expert and novice level (e.g., Bullough & Baughman, 1995; Orland-Barak & Yinon, 2005) and a periodic alternation of the roles of experienced experts and novices in workplaces (Fuller et al., 2005; Grenier & Kehrhahn, 2008). This is because professionalism reflects a perceived social recognition of expertise; thus, expertise operates as professionalism (Mieg, 2009).

Mieg (2009) suggests professionalism is a core dimension of professional expertise development in the society, accompanied by a person's professional engagement and commitment to a profession (e.g., taking on responsibility for our discipline), which is based on socio-cognitive competence (e.g., communicative and organizational skills; Mieg & Evetts, 2018). As such, professionalism is an activity for developing the profession *and* professional excellence, both of which consequently (re) define and guide the development of individual expertise. Thus, this dimension can be particularly important in new, budding professions for which sets of performance criteria have yet to be established.

A final emerging area of exploration is from scholars attempting to explain transfer, transition, or fusion of expertise. For instance, Frie et al. (2019) present the Model of Expertise Renewal that depicts a process by which individuals create a new field of expertise and integrate new expertise with their existing one. This process consisted of three distinct groups of activities. The first of these is exploring a new expertise domain requiring a circulated process that begins with generating new ideas, then moving to testing the value of the ideas, and then focusing on a limited set of ideas to acquire new knowledge and skills. Next is creating stimulating context that involves claiming the idea or new expertise, creating networks of ambassadors (i.e., a group of people who support and help the development of an idea and new expertise), and creating space (e.g., gaining access to resources such as finance and time). Finally, materializing ideas and new expertise involves activities in which the idea and new expertise is realized by the process of fine-tuning the product with other experts and embedding the products in routine ways of working.

Others are also exploring this idea of expertise transition. Gegenfurtner (2013) contends that a horizontal transition of expertise should be contrasted with vertical development of expertise from novice to expert. As Gegenfurtner (2013) points out, while vertical transitions of expertise are typical in the relatively stable domains that has reached full maturity, horizontal transitions often occur in dynamic contexts such as technology-rich environment in which information and knowledge from diverse domains of expertise intermingle and fuse with each other. Thus, not only does social process lead to transfer and generalizability of expertise, but so does cognitive process. More recently, Boshuizen, Gruber, and Strasser (2020) suggest that knowledge restructuring through case processing (KR-CP) theory is applicable to various domains of expertise. Having reviewed evidences from four different domains of expertise (i.e., medicine, counseling and psychotherapy, business management, and law), they argued that handling complex cases plays a key role in developing expertise in many professions and results in cognitive adaptations (i.e., knowledge restructuring) to both routine and non-routine situations. All these studies offer promising new directions for understanding expertise in the workplace.

Conclusion

At the outset of this chapter, a review of diverse definitions of expertise affirmed that experts pursue "exceptional performance" and the developmental processes to expert status are applicable to almost all individuals. Next, through a comparison of psychological and sociological perspectives of expertise, fundamental dimensions of expertise in the workplace were presented. The first was a traditional concept of expertise as a set of structured and decontextualized knowledge and skills that has long been held by HRD scholars. While important and helpful in understanding deliberate practice, this skills acquisition thinking is limiting because it overlooks subtle and other critical, but less known aspects of expertise found in today's dynamic organizations. The second included concepts that challenge the traditional notions of workplace expertise. Considering the role of adaptive expertise and flexible expertise for solving unpredictable and atypical problems means that organizations recognize and encourage the continuous transformation of expertise. This chapter concludes with emerging ideas that can serve Human Resource Development scholars and practitioners as they continue to understand, nurture, and honor employee expertise.

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3

Routine Expertise, Adaptive Expertise, and Task and Environmental Influences

Katerina Bohle Carbonell and Amber Dailey-Hebert

Organizations seek employees who can deliver high performance in dynamic environments. This means finding individuals who can deal with external forces. According to Moore's Law, technological capacities double every year (Brynjolfsson & Mcafee, 2014) so organizations must face increases in computing power, the growth of artificial intelligence, and further technological changes yet to be defined. In addition to technology as an external force, organizations have to expect changes in other areas, such as globalized competition and the changing mind-sets, which together can result in destabilized operating environments (Schreyögg & Sydow, 2010; Wiggins & Ruefli, 2005). These factors can create dynamic environments, which are more difficult to navigate for individuals. This

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is because it requires simultaneously maintaining efficiency-focused processes, that is, processes that enable them to operate in the known environment, while also possessing flexibility-focused processes, which are processes that allow them to respond to the changes in the environment (Eisenhardt & Martin, 2000).

Dynamic environments mean that individuals need to be efficient, while also being flexible. One of the hallmarks of expert performance is efficiency with task execution, through automatization of processes (Arts, Gijselaers, & Boshuizen, 2006; Ericsson & Lehmann, 1996). This automatization is context specific, as experts take time to learn and internalize procedures for a specific domain (Ericsson, Krampe, & Tesch-Römer, 1993; Macnamara & Maitra, 2019). However, while this automatization leads to performance gains under routine situations, it results in a breakdown of performance when changes are made to the environment and individuals fail to develop adaptive expertise (Hatano & Inagaki, 1986; Schwartz, Bransford, & Sears, 2005). To develop adaptive expertise, opportunities to recognize changes in the environment and develop new solutions is needed, as well as opportunities to become proficient in certain tasks to free cognitive resources necessary to scan the environment for change.

In this chapter, we focus on the importance of adaptive expertise for succeeding in dynamic environments. We begin by explaining what adaptive expertise is, and how environmental and task characteristics influence its development. The link between dynamic environments and performance levels rests on adaptive experts' ability to recognize changes and opportunities for adapting procedures. Based on our discussion of adaptive expertise, we conclude with a list of practical implications for organizations seeking to develop adaptive expertise in their employees.

What Is Adaptive Expertise?

Adaptive expertise is the ability to maintain an expert level of performance in novel situations (Hatano & Inagaki, 1986). Hatano and Inagaki (1986) originally applied the concept to children, explaining how different factors influence their knowledge acquisition. The authors' main premise is that expertise performance can be achieved through a procedural or conceptual understanding of the domain. Through a procedural understanding, individuals can execute a skill at the level of an expert. However, there is a lack of understanding as to why the skill needed to be executed in a certain way. To attain adaptive expertise, Hatano and Inagaki (1986) posit that an individual needs not only procedural understanding by conceptual too. Conceptual understanding leads to a more deeply developed and fine-grained knowledge base gained through repeated practice of a skill in a variety of environments. Because the different environments provide new information about when and how to execute the skill, individuals are able to determine why a certain skill has to be executed in a specific way.

Hatano and Inagaki (1986) describe three factors that support or hinder the development of adaptive expertise: build-in systematic randomness, the risk of performance, and the reward of gaining conceptual knowledge. The first factor refers to systematic and naturally occurring variations in the environment. This factor asks if a situation is novel or random or if the variability of the situation means there's little chance for learning or exploration. For example, growing plants, when done outside, provides natural variations due to changes in sunlight and rain. This helps a gardner to build a deep and fine-grained understanding of the various conditions different plants require in order to grow. The second factor describes what is at stake for an individual if they deviate from the known and established procedures to try out something new. If the stakes for performance are high, individuals may be reluctant to try out new ways to perform a procedure. Thus, individuals shy away from playful behaviors and instead continually perform the skill in the same way to avoid a risk of failure and the associated consequences. Novelty avoidance does not lead to a deep and fine-grained understanding of the skill as variations are avoided and the status quo is maintained. The third factor, reward of gaining conceptual knowledge, refers to the societal norms regarding a desire for speedy performance or understanding. Due to the deeper processing it requires, developing conceptual knowledge is more time consuming than developing procedural knowledge. Individuals seeking conceptual knowledge spend more effort understanding why a skill is performed, instead of simply focusing on performing a skill at an expert level in the quickest possible way. If the societal norm places a high value on quickly performing, individuals may be reluctant to spend the necessary time to achieve a conceptual understanding.

Also helpful in defining adaptive expertise are individual characteristics in adults described by Bohle Carbonell, Stalmeijer, Könings, Segers, and Van Merriënboer (2014). First, is an individual's knowledge representation that is decontextualized and abstract. This form of mental knowledge representation is aided by analogical problem-solving skills and abstract reasoning skills. Hence, the ability to deconstruct a problem to develop similarities between situations aids the development of a fine-grained and detailed representation of domain knowledge. These skills are supported by self-efficacy and goal setting. Self-efficacy and goal-setting help individuals to create the right reward structure for engaging in a variety of practices, which Hatano and Inagaki (1986) argue is important for the development of adaptive expertise.

Adaptive expertise is often, in simplistic terms, compared to routine expertise (Hatano & Inagaki, 1986; Mylopoulos & Scardamalia, 2008). Individuals with high levels of adaptive expertise demonstrate flexibility, creativity, and innovation in the use of their knowledge structure and skills (Bransford, Brown, & Cocking, 2000; Hatano & Oura, 2003). On the other hand, individuals with routine expertise do not demonstrate these characteristics. Common between adaptive and routine expertise is a highly structured knowledge base that experts develop to help them perceive meaningful patterns in their work environment, mental models which drive the selection of task strategies, efficient problem-solving, and faster retrieval of domain-specific information from memory (Lajoie, 2009).

The tendency to juxtapose adaptive expertise with routine expertise is an oversimplification of reality. The execution of a complex task requires individuals to perform a number of subtasks. These subtasks can be routine, in the sense that regardless of the problem situation, the task is executed using the same methods. For example, when developing software, individuals may be using different programming languages, but all need to set up a folder structure. However, other subtasks will require individuals to adapt programming methods and procedures to the goal at hand (van Merriënboer, Clark, & de Croock, 2002), which means their execution cannot be automated. Certain domains, such as classical music or some games, are more stable and thus consist of more routine tasks than non-routine tasks. Other domains, such as journalism or research and development, are less stable as more tasks are non-routine or contain non-routine elements. Therefore, it is more appropriate to view adaptive expertise as building on routine expertise, with adaptive expertise containing elements of routine expertise.

The ability to remain performing at an expert level even though the task is unfamiliar has been labeled by others as "flexpertise" (van der Heijden, 1998), super expertise (Raufaste, Eyrolle, & Mariné, 1998), elite expertise (Chi, 2011) or reflective expertise (Olsen & Rasmussen, 1989). The common aspect among these different terms is that once individuals achieve expert performance level, a distinction can be observed in the performance of experts on non-standard domain tasks. Even though under normal conditions an individual would execute tasks at an expert level, they find that they experience problems adapting to a new situation.

This phenomenon of divergent performance among experts has been studied under different names and in different scientific domains. Bohle Carbonell and van Merriënboer (2019) identified six different, but linked, research contexts which address the question of adaptability of expert performance: child rearing, the social aspects of child rearing, adaptive expertise, transfer, flexibility, and self-regulation. Although different methods and different words to describe the phenomena may be applied, the common thread for studies on divergent performance in experts is a desire to understand why certain individuals transfer performance from one situation to another, the cognitive processes responsible for the transfer of performance, and the environmental characteristics that enable or hinder a transfer. For example, Frie, Potting, Sjoer, van der Heijden, and Korzilius (2019) use qualitative methods to investigate the social and cognitive processes that lead known flexperts to acquire new knowledge and adapt to the environment by exploring the domain, validating ideas, and creating new knowledge and skills. Similarly, the work of Olsen and Rasmussen (1989) on reflective expertise describes how individuals use skill-based and rule-based behaviors for standardized tasks, but switch to knowledge-based behaviors if the task is novel and requires interpretation of unfamiliar aspects of a situation. A key feature of Olsen and Rasmussen's (1989) work is that they argue that professional expertise requires all three types of behaviors: skill-based, rule-based, and knowledge-based. Hence, there is no clear-cut distinction between reflective and non-reflective expertise, something which is less well elaborated on within other concepts of adaptive expert performance.

In sum, adaptive expertise is developed through variation in practice and stimulated by an environment that favors and rewards the acquisition of conceptual knowledge instead of procedural knowledge. It is the ability to deal with a novel situation while avoiding a drastic drop in high performance. Adaptive expert performance is studied in a number of areas of human life, using a number of different terms and methods. This can lead to some confusion when researching the field. However, the commonality is that adapting expert performance begins with the realization that the environment or the task is different and that high performance requires a change in how the task is executed.

Stimulating the Development of Adaptive Expertise

Adaptive expertise is the result of switching from fully or semi-automated processes to fully conscious and manual behaviors by experts with domain knowledge (Ericsson, 2006). According to Olsen and Rasmussen (1989) this domain knowledge is expressed through skill-based, rule-based, and knowledge-based behaviors. The level of automaticity distinguishes these different forms of performance. While skill-based performance is fully driven by internalized procedures, knowledge-based performance requires conscious action by the individual to decide the plan of action. Building on the work of Olsen and Rasmussen (1989), van Merriënboer, Jelsma, and Paas (1992) argue that expertise performance can be composed of performance on recurrent automated skills, recurrent skills, and non-recurrent skills. Recurrent skills can be expressed through stable procedures and represent standard domain-relevant tasks. Some of these recurrent skills can be automated, while others are only semi-automated. Non-recurrent skills do not have stable procedures that can be followed when a situation is present. These are knowledge-based processes, where the execution requires a conscious effort and is guided through knowledge of the domain and the task (Olsen & Rasmussen, 1989). This means that the exact steps that have to be executed differs for every unique situation. Based on this distinction, adaptive expertise becomes visible through performance on non-recurrent skills, as these skills cannot be automated. To acquire non-recurrent skills, individuals need to possess (automated) recurrent skills. This provides them with the necessary supporting knowledge and frees cognitive resources that are needed to engage in non-recurrent skills. By freeing cognitive resources, individuals with adaptive expertise can recognize changes in contextual factors which require them to stop fully or semi-automated processes and switch to fully conscious processes.

The execution of non-recurrent skills requires acquisition of schemas, cognitive structures that link particular problems to specific problem categories, which are associated with a plan of action (Barnett & Koslowski, 2002; Schwartz et al., 2005). Van Merriënboer, Jelsma, and Paas (1992) argue that these schemas can involve causal reasoning, decision making, or qualitative reasoning. The acquisition of these schemas is aided by inductive processing leading individuals to recombine existing knowledge, which results in more general schemas that are more widely applicable across situations.

The environmental condition individuals operate in impacts their ability to deal with unfamiliar problems and develop the schemas necessary for adaptive expertise. Hatano and Inagaki (1986) argue that individuals who achieve expert performance while working in a very regulated and structured environment, like a kitchen with cups and scales or a greenhouse with climate and light control, develop a less profound knowledge about their domain of expertise. This is because these individuals only learn to execute domain-specific skills because the environment contains a specific set of structural features. If structural aspects of the environment change, performance will change as individuals have to adapt to the changes.

Adapting to the environment requires cognitive readiness (O'Neil, Lang, Perez, Escalante, & Fox, 2014), the ability and willingness to recognize changes in the environment, and to adapt to them. In essence, individuals need to switch cognitive gears by halting the automatic execution of domain procedures and switch over to conscious decision making (Louis & Sutton, 1991; Olsen & Rasmussen, 1989; van Merriënboer et al., 1992). Not all individuals are able and willing to switch from an automatic process of task execution to a manual process. This manual process of task execution requires effort, which Ericsson and Lehmann (1996) describe as deliberate practice, which consists in identifying the aspects of performance that can be improved with reasonable time and associated training. Engaging in deliberate practice is a necessary activity to raise performance levels from novice to expert and to avoid stagnating performance (Ericsson, 2009; Ericsson & Lehmann, 1996). Ericsson (1998) argues that being able to execute tasks with minimal effort, thus making behaviors automatic, is the goal of everyday activity. Once individuals can engage in a task with minimal cognitive effort, they are said to have reached expert performance in this task. To further improve their performance, individuals need to counter this automaticity in their thinking and behavior by seeking out aspects of their performance that can be improved. This countering of automaticity is done by engaging in deliberate practice.

However, deliberate practice at work requires that the work environment be highly structured (Shanteau, 1992) as individuals rely on environmental cues to evaluate their performance and adapt. Certain work environments have a high level of regularity, implying that certain environmental cues are always followed by the same consequence (Shanteau, 1992). Environments, which are characterized by a high regularity between an environmental cue and its consequence, are described as high-validity environments (Shanteau, 1992). In the workplace, such environments consist of a high proportion of recurrent work skills. This high-validity provides individuals with ample opportunities to learn the causal relationship between environmental cues and consequences. This feedback loop of cue-consequence gives individuals the opportunity to learn and acquire domain-relevant patterns. A pattern forms schemas and structure of the domain by describing domain-specific concepts or triggers, attributes, and the relationship between the attributes (Fiske & Taylor, 1991). These schemas can be understood as scripts and decision trees detailing what actions to execute when faced with a specific environmental trigger. If the scripts become too detailed, they can limit individuals' flexibility forcing the focus to be on a sequence of actions and not on causal relationships. Overall, the high frequency of cause-and-action yields clearly visible patterns, which individuals perceive as domain-relevant patterns (Kahneman, 2011) and these become internalized.

While a lack of structure in the work environment makes it more difficult to receive the necessary feedback to evaluate performance, making changes to routines and evaluating their outcomes is still necessary. A mastery approach to performance is argued to be beneficial for the acquisition of adaptive expertise (Hatano & Inagaki, 1986). Individuals who adopt a mastery approach to tasks seek as their goal not merely to achieve performance standards according to task requirements, but aim for understanding the task and improving their knowledge and skills (Elliot & McGregor, 2001). Changes in performance according to a mastery approach is thus compared to one's previous performance and knowledge, and not compared to performance standards set by others.

In addition to a certain environment, Bohle Carbonell, Könings, Segers, and van Merriënboer (2016) posit that adaptive expertise requires: the belief that domain knowledge can change (perception on domain skills) and the ability to innovate and change one's knowledge structure and skills (innovative skills). Although task variety and work experience are related to individuals' perception of domain knowledge stability, only task variety is related to the innovative skills within adaptive expertise. This means that, through work experience and variability of practice, individuals learn that domain knowledge is not stable and needs to be continuously updated to continue to perform at a high level. In other words, task variety or variety in some other form is central to the development of adaptive expertise. To develop the necessary, innovative skills to deal with unfamiliar problems, individuals need to be exposed to task variety. It is the innovative skills that differentiate individuals who are with and without adaptive expertise. The variety of tasks provides individuals with greater opportunities to observe and test relationships between environmental cues and implemented solutions. This variety of experiences leads to a mental representation of knowledge which is de-contextualized. This weakens the link between a specific situation and the solution, and thus enabling easier adaptation to changing circumstances (Bohle Carbonell et al., 2014).

For example, a gardener who is responsible for a wide variety of plants growing on different soils, and who is also in charge of landscaping will develop an abstract and decontextualized knowledge representation of plants. This person will develop knowledge about how to grow plants, which plants impact the growth of other plants, and how to use landscaping features such as ponds, walls, or hills to help plants grow and produce fruit. The result is a knowledge representation of plants with many associations between elements of plants (soil type, nutrition needs, sun needs, and so on).

Within an organizational context this means that having task variety and working in an exploratory environment leads to individuals developing a conceptual understanding of procedures and thus knowing why they should be using a specific procedure in a specific situation (Schwartz, Brophy, Lin, & Bransford, 1999). Allowing individuals to explore different solution paths can lead to the development of adaptive expertise (Bohle Carbonell et al., 2014). As noted earlier in this chapter, the repeated reuse of specific procedures leads to expert efficiency, but reduces adaptability, problem-solving, and the creativity of experts (Dane, 2010). Barnett and Koslowski (2002) report that consultants provide higher quality solutions to business problems of restaurants (even when compared to restaurant owners) due to the consultants' diversity of experiences. This variability of practice has led consultants to develop greater abstraction of problems allowing them to create a deeper understanding of their domain. This means that individuals need dynamic environments and to work on tasks outside of their area of expertise so as to facilitate the recombining of an individual's domain knowledge and to experience the limits of their schemas.

One way that variety in practice as an individual works on different problems or in different domains (Barnett & Koslowski, 2002; Dane, 2010) is addressed in stimulating adaptive expertise is through analogical reasoning. Analogic reasoning is the skill that helps individuals transfer solutions from one domain to another domain by identifying similarities between a familiar source and an unfamiliar target in order to generate inferences about the target (Holyoak, 2012). It requires individuals to develop a mental library of cases of prior situations they have encountered and dealt with. These cases provide stories, narrative description, and logical explanation summarizing past experiences. This library serves as a way to know how an individual approached situations in the past, and how successful they were (Jonassen & Hernandez-Serrano, 2002). Barnett and Ceci (2002) propose that transfer of problem-solving skills from the source to the target situation occurred if individuals understood why a certain problem-solving strategy was successful. Thus, the mental library of cases needs to include information about why a specific work approach was successful in the given situation. In uncertain environments, these cases can provide a more useful tool than abstract reasoning when having to make decisions (Jonassen & Hernandez-Serrano, 2002; Klein & Calderwood, 1988).

Of course it goes without saying that adaptive expertise, with its reliance on this mental library, cannot be developed as a novice since there is no prior knowledge of the domain (Schwartz et al., 2005) or cases to draw on. Schwartz et al. (2005) talk about an optimal adaptability corridor, where the path from novice to adaptive expertise alternates between acquiring domain-level knowledge and introducing changes to stimulate innovative skills. The optimal adaptability corridor will be shaped by task characteristics, such as regularity of feedback from the environment. Individuals need to have acquired a minimum amount of domain expertise before beginning to learn how to deal with unfamiliar problems. Only once an individual is no longer a novice, is it possible to introduce changes in the environment or the task. If changes are introduced too early, it can lead to frustration, as individuals do not have the necessary foundation for adaptation. If changes are introduced too late, individuals will struggle to adapt as their knowledge representation is embedded too much within the homogenous situations they have experienced.

Developing Adaptive Expertise in Organizations

Organizations operate in an increasingly dynamic environment with amplified frequency of technical innovation, globalized competition, and entrepreneurial actions (Schreyögg & Sydow, 2010; Wiggins & Ruefli, 2005) that can destabilize the operating environment. Given the benefits of adaptive expertise outlined to this point in the chapter, organizations hoping to succeed in a dynamic environment need to support the development of adaptive expertise. This means organizations must put in place processes to efficiently execute day-to-day activities while also creating space for flexibility to adjust to unexpected situations. More specifically, organizations need to ensure task variety, autonomy, and supportive cultural norms in order for employees to develop valuable adaptive expertise.

Organizations seeking to develop adaptive expertise in their employees need to offer individuals the opportunity to engage in a variety of tasks in the workplace. A variety of tasks gives employees the opportunity to experience diverse organizational problems. In formal learning environments, variety of practice has been reported to have a positive impact on learning to solve novel problems (Paas & van Merriënboer, 1994) and consume and use a large amount of information efficiently (Martin & Schwartz, 2009). Organizations can make use of various work functions and locations to create a variety of practice. Take, for example, expatriate assignments. While on the surface the job role may be similar, differences in sociocultural factors lead to significantly different job duties (Mendenhall & Oddou, 1985). Similarly, variety in the environment can also be created by transferring individuals to other functions. Individuals from different job functions approach problems from different perspectives (Cronin & Weingart, 2007). These differences are visible in discussions and in how tasks are executed. Thus, a move to a different department within an organization creates variance and pushes individuals to engage in analogical thinking without the more drastic life-changing events of relocating them to a different country.

Variety can also be applied to activities outside of an individual's job role. For instance, Google's 20 percent rule permits employees to spend

20 percent of their work hours on projects outside of their job role (Schrage, 2013). Other organizations could allow employees to engage in volunteer activities, to provide opportunities to work in other domains (Dane, 2010). Variety of practice, and thus exploration, through volunteering programs allows for individuals to not be evaluated on their performance, while doing work, which provides the freedom to explore new ways to execute tasks. In these ways, organizations encourage individuals to explore challenges that are not directly related to their job, but because of the lower risk it may still help develop adaptive expertise.

Second, organizations should also offer employees the autonomy to try out new methods to reach a specific organizational objective (Ellström, 2001). Autonomy at work has been reported to positively influence adaptive performance (Schraub, Stegmaier, & Sonntag, 2011) because it gives employees the opportunity to create their own variety of practice by developing new ways to complete a task. Through this autonomy, individuals further develop their knowledge structures, hence developing abstract cognitive schemas. The common idea behind variety of practice and autonomy is to let employees develop better cognitive schemas by identifying gaps in current thinking (Ward, Gore, Hutton, Conway, & Hoffman, 2018). Individuals can then use these knowledge-based rules when confronted with unfamiliar situations where automatic procedures fail (Olsen & Rasmussen, 1989). However, environments that carry high risk for individuals who deviate from the official procedures, are not beneficial for the development of adaptive expertise (Hatano & Inagaki, 1986). It is difficult for specific organizations and industries, such as healthcare, emergency care help, or the airline industry to give individuals the freedom to try out new procedures if it constitutes a high risk for patients and clients. In these environments, simulations can be used to offer employees the opportunity to deviate from practice (Joung et al., 2003; Joung, Hesketh, & Neal, 2006) and to develop adaptive expertise.

Finally, organizational cultural norms about performance are influential to employees' ability to develop adaptive expertise. Organizational norms that favor achieving high levels of performance as quickly as possible are counter to the development of adaptive expertise. In such environments, procedural knowledge is regarded as more important than conceptual knowledge. This is visible through onboarding and training processes, which do not give employees sufficient time to understand the why behind the procedures. Similarly, performance management systems that do not include sufficient emphasis on learning and what knowledge employees have gained over the year reduces the employees' willingness to deviate from practice as it can harm their performance and thus how they are evaluated by their manager.

In sum, adaptive expertise is important to successfully operating in increasingly dynamic environments. With employees exposed to novel situations more frequently, organizations that provide employees with opportunities to develop deep conceptual understanding of their domain through variety, autonomy, and supportive cultural norms are better able to navigate these dynamic environments.

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4

Identifying and Measuring Expertise in Organizations

Robin S. Grenier

Superior performance is the core criterion for defining expertise, with the top 10% of practitioners within a domain being experts (Ericsson and Lehmann, 1996). Oftentimes, these individuals have years of experience in a particular domain, exhibit task performance that is both consistent and successful, and are able to undertake complex problem solving in faster, easier, and more accurate ways than others. Such experts are, according to Swanson (1994), the performance fuel of the workplace. Thus, organizations revere experts, seeking them out because of their high-performance and decision-making skills. Yet, despite the idea that, "pushing for expertise in organizations is what leads to strategic competitive advantage" (Chermack, 2003, p. 370), exploration of expertise in Human Resource Development (HRD) and organizational development remains scarce but for a few exceptions (see Germain & Ruiz, 2009; McQuade, Sjoer, Fabian, Nascimento, & Schroeder, 2007; Swanson, 2003; Valkevaara, 2002). For the most part, existing HRD literature

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mentions expertise as an organizational goal (e.g., Beausaert, Segers, & Gijselaers, 2011; Johnson & Leach, 2001), utilizes it as a way to understand organizational or employee characteristics (Swanson, 2007), or applies it as a benchmark for establishing competence (Camuffo & Comacchio, 2005).

Competence is defined by Gilbert (1996) as an "efficient behavior" that is often categorized as a subset of expertise (Herling, 2000), while more recently, Schneider (2019) described competency as combining "the equivalent of a normally successful performance of a type of state changes (ability), on the one side, and the changes of state (demands) set from outside to be brought about, on the other" (pp. 1954–1955). Within the HRD literature Herling and Provo (2000) describe competence as the ability to act in a wide range of situations and is typified by a clustering of related factual knowledge, skills, experiences, attitudes, and value judgments directly related to one's work. This then means that experts have competencies that are highly developed within a specific domain (Sternberg, 2005). The terms competence and proficiency are often used interchangeably with expertise, but it is important to mention that an individual can be competent or proficient without being an expert. This differentiation is apparent when looking at Dreyfus and Dreyfus's (1986) stage model. Based on studies of fighter pilots and chess players they describe five stages: novice, advanced beginner, competent, proficient, and expert. Each is achieved by passing through stages of qualitatively different perceptions of a task or problem. Adding to this work is Daley (1999), who analyzed the different learning processes of novices and experts. She found that experts learn through a constructivist process of integrating concepts and self-initiated strategies. Furthermore, she discovered that experts were unique from their novice counterparts because they were able to articulate systemic issues that disrupted their learning, while novices were only able to recognize disparate individual issues. Her work situated her as a pioneer in adult education and HRD for testing the stage models to articulate the link between learning and the development of expertise.

Much of the current HRD research on expertise builds upon Daley's research, focusing largely on understanding the expert and their characteristics or on the stage models that culminate in expertise. Thus, expertise and how it is learned or developed should be set apart from other concepts. Although HRD research exploring how individuals become experts or the differentiation of expert and novice learning has, to some extent, been addressed in training and development (e.g., Swanson & Falkman, 1997; van der Heijden & Brinkman, 2001) and public and nonprofit institutions (e.g., Evers, Kreijns, van der Heijden, & Gerrichhauzen, 2011; Grenier, 2009), there is a gap in current understanding about the learning that occurs at an expert level. Although learning and expertise remain ripe for study, there is some promise in the recent emergence of scholarship in the areas of expertise measurement, expertise redevelopment, expert-knowledge elicitation and transfer, and expertise in leading organizations.

Expertise Measurement

Managing expertise is a management objective to improve performance, but also to assess knowledge, experience, problem-solving skills, and some behavioral characteristics at a given point in time. With the management of employee expertise organizations can utilize human resources strategically and plan for long-term goals and needs (van der Heijden & Brinkman, 2001). Scholars have used a number of methods to assess expertise including extensive case studies of single subjects, that collect data from experts on a large number of different tasks, as well as the use of comparisons of think-aloud verbalizations of experts and novices (Kuchinke, 1997). However, as Kuchinke (1997) notes, these methods have shortcomings and have resulted in different theories of expertise.

Scales that measure expertise across a variety of fields can help improve organizational understanding of the behavioral and attitudinal correlates of verifiable, objective, and subjective expertise, and the management of employees' expertise. No standard tool for measuring expertise across domains exists (Chalykoff & Kochan, 1989; Kidwell & Bennett, 1994; Kuchinke, 1997) due in part to issues with psychometrics (Germain, 2006; Germain & Tejeda, 2012) such as the accuracy of measurement of the constructs under examination (Barrett, 1972).

The struggle to find ways to measure expertise is summarized by Martini (2019) this way: "Expertise is a social concept, and measuring expertise is more like measuring a country's wealth, or an individual's happiness: a measuring process that must be constantly updated and corrected" (p. 119). Even with such daunting challenges to overcome, scholars have pressed forward with scale development, typically through the use of quantitative methods (e.g., Chalykoff & Kochan, 1989; Kidwell & Bennett, 1994; Kuchinke, 1997). What follows is a discussion of approaches that may serve organizations as they seek to measure and ultimately manage employee expertise across fields.

Johanna and van der Heijden (2000) note that professional expertise requires social recognition as well as different forms of knowledge and skills, plus the ability to be flexible, to generalize, and grow. Building on this, the researchers took the idea that there are clear characteristics of expert performance that are valid irrespective of the domain of expertise found in a certain professional, and constructed the *Professional Expertise Scale* (Johanna & van der Heijden, 2000). It is an instrument comprising five different scales each centered on one of five dimensions: knowledge, meta-cognitive knowledge, skills, social recognition, and growth and flexibility. These dimensions are not completely mutually exclusive, still, they signify correlated features of professional expertise. This scale comprehensively addresses characteristics of experts' performance in modern workplaces (e.g., growth and flexibility) and is constructed based on the presumption that some of the characteristics of expert performance are valid irrespective of professional domain. Given the limited body of relevant workplace expertise literature available when the scale was devised the authors acknowledge that items were chosen for the most part because of content validity. Thus, largely explorative.

With an approach to assessing expertise purely from data and based on the notion that expert judgment requires discrimination—seeing fine gradations among the stimuli and consistency evaluating similar stimuli, a second measure the *Cochran-Weiss-Shanteau Index of Performance (CWS)* comes from Weiss and Shanteau (2003) who developed it based on two key components of expertise: discrimination and consistency. The focus on discrimination is important because according to Weiss and Shanteau (2003) expertise requires an ability to discriminate between similar, yet not identical, stimuli, or situations. Discrimination is computed as the variance among responses to different stimuli while inconsistency is the variance among responses to the same stimuli. As such, the CWS is calculated so that the higher the ratio, the more consistent, discriminating, and therefore, expert the judge. The CWS can be used for teams (all team members would generate one score) or for individuals (single-subject design) and has been used in a variety of work domains to discriminate between among others, expert and novice doctors (Thomas & Pounds, 2002), and air traffic controllers (Thomas & Pounds, 2002; Thomas, Willem, Shanteau, Raacke, & Friel, 2001, 2002).

It is important to note that despite its usefulness, the CWS index has limitations, such as the claim that expert judgment may yield high CWS, yet high CWS does not guarantee expertise. Furthermore, consideration must be given to its focus on comparison that is used to determine which of two candidate experts is performing better. Distribution of expertise within a population will likely vary across domains. As such, if true expertise is rare for the requested judgments, then no expert may be included in a study. Therefore, identified "experts" may not really be all that "expert" (Weiss & Shanteau, 2001).

A third instrument, the *Expertise Measurement* (Mieg, 2009), is based on Mieg's research using self-assessment questionnaires from a sample of Swiss environmental professionals. The outcome of the measure focuses on two factors essential for experts in practical work settings. The first is professionalism which he found to be negatively associated with age or years of practice, but positively correlated with professional commitment and deliberate practice. The second, excellence in performance is highly correlated with age and years of practice and is most likely attributed to males. Mieg's measure has similarities to the Professional Expertise Scale (Johanna & van der Heijden, 2000), but instead of five dimensions Meig suggests only achievement and social recognition. Moreover, although founded on Ericsson's (1996) traditional theory of expertise development the items in the Expertise Measurement do not reflect the dynamic nature of expertise development in the workplace (e.g., growth beyond one's own field of expertise).

Yet another measure, The *Generalized Expertise Measure (GEM)* was developed by Germain (2006) to measure expertise based on employee expertise as perceived and reported by another person. Originally composed of 16 items (5 Objective and 11 Subjective items), the GEM used the term generalized to indicate a measure that can be used across various occupations. This was based on both procedures used to develop the scale and the sample used in the preliminary validation of the GEM that included workers from a wide range of occupations and fields. In 2012, Germain and Tejeda further enhanced the GEM by conducting additional analyses and now the measure includes 18 items (6 Objective and 12 Subjective items). Objective items are: having specific knowledge in a field of work and about that field, having the needed and required qualifications, being trained and conducting research. The subjective items in the GEM are: being ambitious, having drive, and being capable of improving oneself as well as being charismatic, being able to deduce things, being intuitive, being able to judge what is important, being self-assured, being self-confident, being able to assess when a situation is important, being outgoing, and being able to talk one's way through various situations.

A fifth quantitative instrument developed in 2015 by Kim assesses the general components of employee expertise development in the context of work. The *Employee Expertise Development Scale (EEDS)* was developed using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and reliability analysis to validate the conceptual structure of the instrument. EFA extracted four dimensions: Engagement in Deliberate Practice (EDP), Strategic Networking (SN), Frequent and Focused Interactions (FFI), and Developmental Work Experience (DWE). CFA confirmed the four structure of the EEDS with adequate level of fit and reliability analysis showed an adequate level of internal consistency for the four dimensions. Although the instrument lacks instances of use in organizational settings, there is potential use of the scale to advance current theories of employee expertise development. This is because it establishes the constructs of the developmental process while providing an empirically validated measurement instrument for focusing on the development of expertise in employees.

Finally, the *Adaptive Expertise Inventory* developed by Bohle Carbonell, Könings, Segers and van Merriënboer (2016) is an instrument for measuring adaptive expertise. Adaptive expertise is used to describe individuals who have the skills to deal with novel problems. The Adaptive Expertise Inventory consists of two dimensions, domain-specific and innovative skills and each of those has five items. The instrument allows for a way to determine the degree of adaptation that individuals can master. Additionally, it provides a means for measuring levels of adaptive expertise along with the knowledge that task variety influences it, thus HRD professionals can evaluate professional development initiatives that are designed to encourage the development of employees' adaptive expertise. Despite the potential applications of the instrument it should be noted that there are questions about the ability of the Adaptive Expertise Inventory to distinguish between medium and high levels of adaptive expertise. This is coupled with concerns about how the instrument distinguishes between the level of adaptive expertise in individuals working in low-, medium-, and high-validity environments.

Considerations for Organizations

According to a 2013 Skills and Employment Trends Survey from Accenture, among 400 executives from various US industries (e.g., services, construction, retail, finance, insurance, and real estate), nearly half of executives (46%) reported that organizations lack the right skills to effectively implement new strategies in the coming years (Smith, LaVelle, Marshall, & Cantrell, 2015). Furthermore, organizational structures are becoming flatter for better adaptability where individuals have more opportunities to move horizontally (i.e., sideways) than vertically (i.e., hierarchical) across various boundaries (Guile, 2012), and employees are less dependent on a single organization for job security in pursuing their careers (e.g., boundaryless career) (Defillippi & Arthur, 1994). As such, the identification or development of expertise in the workplace becomes not merely a matter of pointing out what someone is particularly good at or employees simply acquiring skills in specific areas, but instead it calls for organizations to be thoughtful and strategic in continually developing expertise in individuals to meet changing workplace demands.

The application of the expertise measures in this chapter can help professionals in a range of organizational settings in developing expert-like skills, managing performance, and selecting and placing employees or volunteers. Take for instance, knowing which subjective expertise characteristics an employee possesses can help foster a stronger job fit (Rynes, Giluk, & Brown, 2007). Traits such as sociability, initiative, and openness can influence group performance by affecting how the individual interacts with other group members (Robbins, 2003). Employee expertise may also help foretell job performance (Hurtz & Donovan, 2000; Kaiser & Kaplan, 2006; Mount, Barrick, & Strauss, 1994; Rynes et al., 2007) and potential career success (Gupta, 2005). Another example is a measure like the EEDS (Kim, 2015) that could be used to quantify relative strength and weakness in the employee expertise developmental process used by an organization as it compares an individual's scores with the means and standard deviations from Kim's study. Practitioners can then use that information to design training programs for employee expertise development. These scales provide a starting point for determining training interventions and employee development needs to accelerate the acquisition of specific knowledge and skills through practice and training. Yet, organizations should stay cognizant of the limitations including the fact that some measures only assess expertise as perceived by someone else and do not guarantee success in determining with whom to consult.

Over the last 40 years, the concept of human expertise has grown with globalization and the increased importance of organizational performance to give the construct of employee expertise a prolific future. It is now gaining recognition as a topic of research in the field of human resource development. If having a competent workforce allows organizations to maintain a competitive advantage in the marketplace (Herling & Provo, 2000), then the same might be said about an expert workforce. Organizations must move past a focus on competence and instead the development of expertise as a desired outcome in the process of improving performance (Herling, 2000) must take center stage.

For an organization to grow, it must have highly knowledgeable, skilled employees capable of solving complex problems—in other words, organizations must have employees who are experts. Researchers and practitioners are beginning to demonstrate that expertise can be measured (Germain, 2006; Germain & Tejeda, 2012), elicited, transferred, and redeveloped (Grenier & Kehrhahn, 2008), but a strong, data-driven understanding of expertise remains under developed. Previous studies of expertise, although useful in characterizing expert processes in specific contexts, offer little in exploring the complex nature of expertise and broadening our understanding of expertise in organizational contexts. Organizations need to utilize the small, but promising scholarship in the areas of expertise measurement given that it is derived from various business contexts, workplace leaders, impression management techniques, and acknowledgment of challenges to existing social power. Organizations and HRD professionals must also call on scholars to continue to expand and challenge existing assumptions of expertise practice, including employees' critical thinking and problem-solving skills. Doing so would shine a light on the need for the clear delineation between the study of competence, proficiency, and expertise and move beyond examining experts primarily in relation to novices to expand on what it means to measure expertise.

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Part II

Expertise in Organizational Settings

5

Veteran Experts: Transitioning Military Expertise into Civilian Work

Sarah E. Minnis and Michael Kirchner

For generations, military veterans have comprised a critical demographic of the United States—in both proportion and contribution to society. World War II saw the largest number of US veterans in history, with 16 million having served during the war (Millet & Maslowski, 1994). In 1968, during a time when the United States still had a draft, roughly 3.5 million were serving on active duty (Bialik, 2017). That number has decreased to present levels of approximately 1.3 million (Department of Defense, 2020). Each of these generations have gone on to make an impact on the national and global economy. After World War II, roughly half of all veterans went on to own and operate their own business (Weisul, 2016). In fact, the last 75 years have seen at least two and a half

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million companies started by veterans, including Walmart, FedEx, and RE/MAX (Akhdar, 2019). Whereas 40% of Korean War veterans went on to start their own business, a shockingly low 4.5% of Post 9/11 veterans have become entrepreneurs (Weisul, 2016). This decline may be a signal that instead of starting their own business, more veterans are applying their military expertise in an existing non-military workplace. Although the percentage of citizens with military experience has ranged over time, today's 19 million veterans (7.6% of the population) and more than two million veteran-founded companies demonstrate the rate and reach of the US military's influence on training and expertise development (Department of Veterans Affairs, n.d.; Schultz, 2017).

The US military heavily invests in the development of its members, yet few civilians know about the processes used to develop service members' work expertise (Kirchner & Akdere, 2019). Beginning in basic training, service members are continuously engaged in new training, as part of the military's on-going and intentional development of its human resources. Each training contributes toward developing the technical skills needed to perform military operations, as well as acquiring soft skills that can be applied across disciplines (Kirchner & O'Connor, 2018).

Expertise in the Military

Becoming an expert in any field requires extensive education and training, which leads to in-depth learning and application from participants. Learning is a process of gaining knowledge and expertise in an area (Knowles, Holton, & Swanson, 2014). The US military is reflective of a learning organization. In fact, the US armed forces comprise one of the largest training organizations in the world, with extensive time devoted toward the development of its members (Kirchner & Akdere, 2014, 2019). As opposed to a traditional workplace, consisting of goals related to profitability and market share, the military devotes much of its attention to the training and mission-readiness of its members. The result is a highly-trained and disciplined workforce who have committed thousands of hours toward becoming experts in their professions. The training is highly structured through a combination of classroom instruction and practical application.

Professional military education maintains a balance of education and training to enhance service members' learning. Beyond a method to break people down, basic training is the first extensive exposure new service members have toward military education. Upon completion of basic training, service members receive further instruction regarding their military job. Regardless, expertise is generally developed through a two-step process, with education being offered in a traditional classroom-type format. After classroom education is provided, it is through hands-on training that service members develop and refine their skills to reach mastery of individual tasks or competencies (Pierson, 2017). For the Army, education is about the why, whereas training emphasizes the process (Pierson, 2017). These two aspects are complementary to one another, ensuring members understand their jobs and are able to successfully perform when called upon.

Whether in a classroom or on the job, the learner needs to receive and process the information they are provided. Thus, learning is primarily internal to the learner, whereas education is mainly external, and considers strategies for presenting information or concepts to the learner (Pierson, 2017). A college classroom, training room, or exercise in the field all represent environments where education is provided unto learners, as part of their expertise development. Education offers a foundation for understanding content and developing new knowledge, which in turn can be applied into training (Pierson, 2017). The knowledge and skills developed are unique to the learner, as a result of their education, training environment, and related work experiences.

Similar to other industries, the military contributes a specific service to society that society cannot provide on its own (Department of the Army, 2015). To fulfill its mission, the armed forces maintain countless job fields for service members. The US Army alone has roughly 190 different job types available, ranging far beyond the stereotypical infantry, field artillery, and other combat-related positions (Powers, 2019a). Though not an exhaustive list, these jobs range from office/administrative work to maintenance- and healthcare-related positions—each of which may readily be translated into jobs outside of the military. The intensive, on-going investment in training allows each branch to develop its members' expertise within their chosen or assigned job.

Both the soft and technical skills service members learn, through a range of education, training, and experiential learning opportunities, enables the military to execute its primary function—to protect and serve the nation (Kirchner and O'Connor, 2018). Upon completion of service, military veterans are considered experts in their profession and are frequently credited with possessing desirable industry-recognized technical and soft skills (Harrell & Berglass, 2012).

Soft Skills Expertise

Though each branch maintains their own set of core values and every job requires a unique skill set, a number of soft skills are frequently attributed toward being developed during a veteran's time in service. *Soft skills* can be defined as skills that enable someone to work well with other people, for example being able to communicate effectively, or to work in or lead a team (MacMillan Dictionary, n.d.). More simply, soft skills often relate to who someone is, as opposed to what someone knows how to do. Soft skills require extended practice and exposure, and may require a longer development period prior to achieving expertise. In many cases, soft skills relate closely to one's leadership qualities and contribute toward a leader's effectiveness (Department of the Army, 2019).

Harrell and Berglass (2012) found employers seek to hire veterans based on their leadership, teamwork, and discipline. Interestingly, veterans are frequently cited as being leaders, despite little investigation regarding how the military develops leadership competencies of its members (Kirchner, 2018). In fact, 68 of 69 participating organizations suggested veterans' leadership skills are a direct influence on their hiring decisions (Harrell & Berglass, 2012). Other studies have identified decision-making, dependability, and critical thinking skills as being particularly valuable with veteran employees (Hardison et al., 2017). The soft skills being developed complement the technical aspects required of the service member within their branch of service and job.

Technical Skills Expertise

Although military veterans are often credited as having desirable soft skills, the technical skills developed while serving may be more important in the former service members' acquisition of expertise. Even military jobs generally considered outside the scope of non-military alternatives may still develop service members' technical skills expertise in ways that could be beneficial for non-military organizations. As noted earlier, the armed forces maintain hundreds of distinct job specialties for current and future service members, each of which has its own unique set of technical skills being developed. Although the technical skills are often position-specific, many could be translatable to a non-military career. More challenging, however, may be aligning technical skills acquired through service with career options in the civilian sector.

Technical skills relate to the skills and competence needed to be able to physically perform a job. They are less difficult to identify than job requirements and are easier to evaluate. These skill sets generally correspond with a particular job and are often assessed during performance evaluations. Examples of technical skills for an administrative assistant might include being able to create a spreadsheet in Microsoft Excel, being able to process payroll, and being able to scan a document. Technical skills are easier to demonstrate than soft skills, and thus are easier to evaluate. The necessity of technical skills varies greatly between positions, as there are only a small number of jobs requiring one or more of the described examples.

Unlike soft skills, technical skills are developed early during a service member's enlistment. Class or training time is devoted and structured to teach and evaluate a service members' learning and competence. Beyond basic training or boot camp, service members attend a specialization school to learn the technical skills required of their job. Depending on the job, specialization schools can range from a few weeks to several months. The schools are highly structured with training developed to address each of the job requirement's required technical skills. Once the specialty school is complete, service members are expected to reach proficiency within their job and continue developing expertise through the remainder of their service.

Veterans' Expertise Redevelopment

Authors have variably defined *expertise* over time as they sought to understand the way in which human skill is achieved. Within the field of human resource development (HRD)**,** more refined definitions have emerged as expertise has become better understood through research and practice. For the purposes of this chapter, we will be using Grenier and Kehrhahn's (2008) definition stating that, "Experts, in the process of engaging in their craft, combine the objective characteristics of knowledge, experience, and problem-solving with subjective characteristics that are perceived by someone else as an indication of their knowledge, abilities, or skills" (p. 184).

Considering this definition of expertise, we see a significant challenge to veterans in how to demonstrate and apply their skills expertise in new civilian work situations. Expertise is a development process experienced by an individual over a period of time through engagement in various positions and kinds of work. Like expertise models that utilize a linear process to describe the ascent to expertise status, the military's process for developing expertise may similarly be a linear process during a service members' time. As referenced by Kem, LeBoeuf, and Martin (2016), the early stages of a soldier's career tends to focus on development of the technical aspects of their job. Upon becoming experts in how to perform their job, a shift transpires where soldiers seek to increase their intellectuality and become more adaptive and innovative (Kem et al., 2016). This structured process ensures that service members have the minimum technical skills necessary to perform their primary job responsibilities, before shifting focus into attributes that can be more-broadly applied across disciplines.

The models suggesting a starting point upon which the employee proceeds forward in developing their knowledge and skills within defined areas of expertise offer a clear distinction regarding the end result of expertise. These models suggest that once expertise is achieved, it cannot be rescinded, whereas other models consider the need to maintain practice at one's craft if expertise is going to be retained (Glasser & Chi, 1988; Herling, 2000; Shanteau, 1992). This second group of models is supported by Herling (2000) who notes expertise is not a fixed state to be attained, meaning that an expert must be dedicated to keeping up to date with their knowledge and skill within a particular area (Glasser & Chi, 1988). Regardless of the model, expertise begins with a learning and information acquisition phase before integration into a more holistic expertise development experience. Grenier and Kehrhahn's (2008) MER with its three states of expertise redevelopment *dependence* to *independence* and ultimately *transcendence*, when applied to military veterans with recognition of the effect of a change in *environment*, *content*, or *constituency*, can offer a productive way to understand and support veterans as they transition and redevelop their expertise and prepare for non-military careers. Expertise redevelopment is a vital aspect of veteran career transitions. This is because the MER allows us to explain veterans' shifting expertise when moving from the military into civilian employment with the territory of expertise playing perhaps the most significant role in the veteran's expertise transition.

When considering the transition from military to civilian work veterans are, perhaps, best suited for understanding expertise redevelopment through the MER more so than any other employable population. As Grenier and Kehrhahn (2008) note, "the complexity of influences and the overall context of one's expertise that can challenge an individual's existing knowledge, skills, and knowing" (p. 206). Looking first to the territories of expertise, each territory offers a particular way for translating veterans' expertise while allowing for the natural overlap that occurs when their lived experiences do not sit in any one territory. Such overlap is not uncommon and can have an impact upon the capability one has in employing their expertise as they navigate anew, how to do so in a new territory.

Grenier and Kehrhahn (2008) use a non-linear model to describe expertise redevelopment. Through the model (see the previous chapter for more details on MER), three contexts comprise the territory of expertise: content, environment, and constituency. These may be independent or dependent of one another, but each can potentially influence the other.

When service members are navigating their military workplace transition to a civilian organization, the contexts identified in the MER are readily apparent. The first context, *content*, "describes the knowledge an individual has to demonstrate a skill and the specific information needed to function in a role" (Grenier & Kehrhahn, 2008, p. 209). Content represents the subject expertise one has related to a job or role, potentially including functions, procedures, and intended outcomes. For example, a mail carrier is likely required to be an expert in the following content areas: safe handling of packages, operating a mail delivery truck, and scanning packages into the system. Each skill set is appropriate for the job of a mail carrier and is essential to being able to perform their job. Though the content may lead to successful implementation of processes in one setting, that does not suggest the content can be universally applied in all environments. Adaptations or additions to the content may be required in order to successfully apply an individual's content to a different setting. For example, a soldier who served as a military police officer may receive interrogation training similar to those of civilian police officers. However, the procedures, policies, and guiding principles will likely differ at least somewhat for a state trooper. That soldier's existing content expertise would require adaptation, as well as redevelopment of new content expertise if they are to operate at an expert level as a state trooper.

The second context, *environment,* details how a change in environment can impact the need for expertise redevelopment. A transition into a new environment impacts how expertise is reapplied, as well as reveals needs for development of new expertise. Environment describes "the locale a person operates within, together with its culture, organizational structure, and geographical location or layout" (Grenier & Kehrhahn, 2008, p. 209). As such, the environment extends beyond simply starting a similar job at a different company. In fact, a move into a different environment can be completed in many ways including: being transferred to a different city or region, a move into an alternative part of an organization, or shifting work away from a physical to virtual location. This is an experience many service members are familiar with as they are transferred to a new post or begin a new duty. As such, service members may be adept at even small changes in the environment that require them to redevelop expertise.

The last context, *constituents,* addresses how expertise can be impacted by stakeholders who may influence or be influenced by the expert (Grenier & Kehrhahn, 2008). Even when an individual transitions into a similar work role and industry, those around the individual play a role in shaping the necessary expertise. Examples of these individuals include supervisors, direct reports, peers, clients or customers, and collaborating partners. For example, a commanding officer with extensive experience managing a unit will need time to redevelop that same expertise with a different unit.

While a veteran's expertise in a particular skill may sit at a high level when engaged in the familiar military environment, taking that same skill into a new environment, applying it to new content, and implementing it with a new constituency can have the effect of the veteran appearing to be a novice.

Environment

Even though the new job may be similar, veterans hired into a non-military workplace will likely encounter a distinguishable work environment from the one they were familiar with while serving. The military's structured and disciplined work environment, as well as overall function, is generally a common denominator across service branches and job types. Upon transitioning into a new civilian work environment, veterans may encounter novel environments that will require a redevelopment of expertise. The reason an organization exists can be a key influencer in shaping any work environment. For-profit companies or corporations primarily exist to provide a service or product to society. To survive, these organizations need to eventually make money. Non-profit organizations exist to also provide or produce goods or services, but do not have a profit-building orientation. In that way, the military and non-profit organizations are similar, though the military differs in that its primary purpose is to protect the nation and its allies. The distinct purpose of the military reduces focus on profitability or sustainability and highlights the essential needs to ensure safety and security. Service members transitioning into another work environment may perceive a lack of purpose or meaning in their work, due to the distinguishable function of a for-profit organization.

The military's structured environment is widely-visible when considering chain of command. In basic training and boot camp, service members are required to learn the rank structure and reporting lines. A superior is identified for the service member, who also provides direction for other points of contact. Essentially, a clear point of contact is always available and service members are very clear about who they report to. A new environment outside of the military might have numerous points of contact, and experience infrequent contact with their superiors. Similarly, the levels of autonomy, amounts of decision making, and required teamwork, among other military attributes, may significantly shift, and make for a more-difficult transition or ability to demonstrate prior expertise.

Constituents

The overarching purpose of the military is to protect the nation's residents. This function is understood across the service branches and remains at the forefront of all operations for service members. Few non-military organizations operate with the same functional purpose. Thus, veterans may not be able to apply existing expertise to this new constituency because of a struggle to reintegrate with a new population who may be motivated by an alternative set of guiding principles, such as status, money, or recognition. When meeting non-military affiliated employees, veterans may find understanding existing workplace stressors that appear insignificant challenging. For example, a veteran with multiple deployments and several combat engagements may struggle to communicate and understand why their counterparts who have not served are highly-stressed because of an approaching deadline. In this and other similar examples, the veterans' expertise may be underutilized because their motivation is lower and impacts their overall performance.

Similar to organizational norms, the new workforce may be less structured, top-heavy, or disciplined. Some of the more common characteristics of the armed forces is the discipline and engrained structure that allows communication to cleanly flow across the organization. Less structured organizations may leverage word of mouth communication strategies or empower employees to make decisions based on available information. The challenge for veterans becomes redeveloping expertise in order to distinguish appropriate times to expect flexibility and autonomy in decision making and day-to-day operations.

Content

Since expertise in one specialty does not necessarily translate into all contexts, veterans and non-military employers need to consider how content expertise can be adapted to fit the new work environment. This means understanding what content is and is not transferable because whether soft or technical skills, the application of these competencies will differ depending on military and civilian jobs. As we'll see in a case study presented in the next part of this chapter, an 88 M (motor transport operator) is an expert in operating wheeled vehicles over diverse terrains and employing combat defense techniques (Powers, 2019b), but those content and skills are not simply transferred into a non-military role. This is because operating a truck on challenging terrains or using combat defense strategies is not usually necessary when operating a school bus or delivering soda.

Redevelopment of Expertise for Successful Career Transition

The Model of Expertise Redevelopment (MER; Grenier & Kehrhahn, 2008) effectively captures both the situation within which the veteran's transition takes place, as well as the impact to the veteran in the experience. For example, as represented by the MER, veterans redeveloping their soft skills expertise for the civilian workforce will need to attend to the differences in territories of expertise (Grenier & Kehrhahn, 2008). The change of environment and constituency will certainly have an impact on how veterans understand and use their soft skills because "existing knowledge and skill may be unusable after the influence of contextual forces within the territory" (Grenier & Kehrhahn, 2008, p. 207). They may also need to alter the content of their soft skills, because although much of the content will remain consistent, in non-military contexts this skill will be enacted differently in new environments with different constituents. For a period of time, these changes will most certainly move a veteran into a state of *dependence* in the MER as they adjust their expertise. Although they will, for example, maintain their expertise in leadership, changes in particular to the environment and constituency means veterans will have to relearn how to lead.

Indeed, because the military is so comprehensive in developing service members in their use of soft skills, there are some veterans who will experience challenges in unlearning and redeveloping soft skills as they adjust their expertise to the non-military environment. As civilian employers become more adept at engaging military veterans in the workplace, they will become more accustomed to providing the opportunities for veterans to practice and perfect their soft skills expertise in growing independence as they move toward full transcendence and are able to fully develop civilian leadership expertise.

The often-unexpected shift in capability with a much-used skill can be both jarring and disheartening for veterans seeking civilian employment. Explained through the MER, this experience of seemingly changed levels of skill competence can be understood "where an expert experiences dramatic shifts in territory requiring an expert to operate in a new state of dependence, moving to independence, and back to transcendence" (Grenier & Kehrhahn, 2008, p. 207). Offering a more productive way of understanding how one's expertise may change depending on the career transition preparation means that military veterans have a way of revisioning their capabilities for civilian work. Understanding the natural shift in their expertise may also alleviate much of the anxiety and confusion veterans have about the civilian career transition (Davis & Minnis, 2017; Minnis, 2020). To better understand what these changes mean for veterans' expertise we now look at a case of veteran transition to civilian work.

A Case Study of Service Member Expertise Redevelopment

Service members become experts at their jobs, called military occupation specialty (MOS), while serving; however, upon transitioning into a new career, that expertise may regress, depending on changes to content, environment, and constituency. Using a scenario of a motor transport operator in the military (known as 88 M MOS), we consider how these three factors impact veterans' expertise post-military service.

The skills learned by motor transport operators in the military are often transferable in a non-military setting. The Army outlines several civilian jobs that can leverage an 88 M's (motor transport operator) skill sets, including working for moving companies, bus companies, and working as tank truck operators. This is because skills such as safely transporting personnel and overseeing proper loading and unloading of materials can be clearly articulated on a resume. Still, one cannot assume that an 88 M is an expert school bus driver since there is new content to learn. During the expertise redevelopment process the 88 M veteran would need to know the proper procedures for transporting children, what to do in the case of an accident, and how to perform maintenance on a school bus. These skills and knowledge extend beyond what was learned and used in the military, but are essential in ensuring a veteran with an 88 M MOS can successfully become a bus driver and once again operate on an expert level.

The military environment is unique from other organizations and thus plays a significant role in how one can translate expertise to non-military workplaces. After serving for years and potentially completing multiple deployments, military culture can become ingrained in how a service member interacts with their environment. The social norms, culture, and physical location of a non-military workplace can lead to a regression of sorts as the former service member acclimates to a new work environment. For instance, because work–life boundaries are largely non-existent in the military, veterans must learn how to navigate the lines between application of their skills in work separately from other areas of their lives. Building on Goffman's (1961) work identifying the military as one of a number of total institutions, Zurcher (1965) looked at how the military works to indoctrinate members early on into the military's culture in a manner that cannot easily be mirrored in another setting. As such, the most significant challenge for military service members seeking to transition their skills outside the military may be adapting to a new work culture.

Regardless of their previous military jobs, veterans moving into non-military employment settings will find themselves in unfamiliar environments. These new non-military work settings influence the ability of veterans to demonstrate the expertise shown while in the service. As Grenier and Kehrhahn (2008) outlined, environment includes the physical location, organization structure, culture, and layout of an organization. For example, veterans are sometimes perceived as being too rigid or formal (Nagomi & Pick, 2012), at least in part due to their military service experience, so a less regulated or organized work environment encountered in civilian organizations may impact a veteran's ability to demonstrate their expertise. Take a former service member who was an expert Humvee driver in Iraq. It might be assumed they would maintain that level of expertise as a driver for Coca-Cola in the United States; however, roads, safety hazards and risks, and domestic delivery vehicles are all distinct from the experience of driving Humvees in Iraq in a hostile and dangerous environment. The new environment experienced as a delivery driver may call for expertise redevelopment, since things like vehicle safety and operation, the routes and road conditions and the addition of tolls and traffic signals will distinguish an expert truck driver transporting beverages with an expert who is transporting cargo under warlike conditions.

Finally, expertise redevelopment may require adapting to changes in stakeholders. While serving in the military, service members of a particular MOS are perceived as, at a minimum, competent after completing training for their job specialization. Young adults, ranging from 18 to 24 years old, may find themselves responsible for millions of dollars' worth of equipment or a handful of direct reports. By age 30, it is not unrealistic for a Soldier, Marine, Sailor, or Airman to be responsible for 10, 20, or more personnel, all of which is part of the military's continuous investments in the development of its members. The direct reports are likely to also be young adults—slightly younger than the leader, with slightly less work experience, but near identical training. And in the case of an 88 M, their direct reports likely have similar education backgrounds and frequently associate with other service members. All these characteristics are shared amongst service members due to similar completion of schooling, promotion structure, and the corresponding MOS knowledge, skills, and attitudes. This means the constituency needed for maintaining expertise is consistent, but upon transitioning out of the military, the work community of a motor truck operator shifts significantly.

Bus operators who previously were 88Ms face a significantly distinct constituency from the military. In a new role, such as a school bus driver or shuttle drive for senior citizens the primary constituency becomes children or the elderly. Thus, expert communication strategies used in the military must be altered for a new population. Colorful language considered acceptable in the military or jargon is no longer appropriate. At the same time, the passengers may be less aware of their surroundings or the general safety requirements when riding in a vehicle. That means veterans who transition into a bus operator role will need to re-learn how to effectively communicate with passengers. To do so, they may need to learn the local phrases or names of neighborhoods passengers are familiar with, develop new generation-specific knowledge, or find ways to present expectations for riding the bus that are age appropriate. For example, disciplining a direct report in the military may include assigning extra duty, a write up, or demotion, but that will not work with civilians. The expert driver will know that a child may simply need to be scolded, moved to a new location on the bus, or told to sit silently in order to address the issue.

Valuing Military Veterans' Expertise for Civilian Employment

Veterans are often credited by non-military employers as having desirable skills that can be leveraged in the traditional workplace (Kirchner & Akdere, 2019). The training received extends beyond what service members' similarly-aged civilian counterparts generally receive (McCausland et al., 2017). During basic training and job specialty schooling and through years of direct experience, the knowledge and skills developed are continuously refined. As a result, service members preparing to transition have a distinct advantage when applying for civilian employment (McCausland et al., 2017). So while expertise developed in the military is widely regarded as transferable in the non-military workplace (Kirchner & Akdere, 2019; McCausland et al., 2017), translating and transferring knowledge and skills developed while serving is a challenge for veterans (Kirchner & O'Connor, 2018).

Recent years have seen significant improvements on the military side of the transition with programs and services established to help service members acclimate to the civilian side. Whereas previous generations received little if any support, today's service members often begin their transition process no later than 90 days prior to their exit date (Kamarck, 2018). During the transition, service members are informed about their education options and benefits, their career options, short-term training programs available, all while being taught how to successfully transition out of the military (Kamarck, 2018). Though the impact of investing in transition programs has been mostly overlooked, it remains important to consider each of the options available.

In 2011, the US Department of Defense developed a new transition assistance program (TAP) intended to support exiting veterans by helping them prepare for post-military life (Kamarck, 2018). Service members receive training around core topics, such as finances, family adjustments, and mentorship; career-related workshops, including job searching and resume building; and an elective component emphasizing in higher education, work, or as an entrepreneur (Stull, Herd, & Kirchner, 2020). During TAP, service members are exposed to new job fields and may even have the opportunity to participate in an employer-sponsored career skills program, which provides extended training for those who have a clear idea of their next career path. This cumulative approach has assuaged many of the transition issues service members face; however, time and resource constraints, combined with a plausible lack of direction on the transitioning service member, can still lead to many struggling to successfully transition.

Veterans who do not communicate their expertise to potential employers risk being screened out of career transition opportunities for which they could compete. Likewise, managers who do not understand how expertise can be redeveloped may miss candidates who could fulfill organizational needs and set a deep bench of talent. While we advocate for veterans to have a clearer understanding of how they can apply the concept of expertise redevelopment in changing careers, we also believe that non-military employers must understand how to conceptualize work from a skills-based perspective and recognize the value of skills expertise gained through different kinds of functional tasks. As such, we now consider the role of the veteran and the organization in supporting veterans' expertise redevelopment for civilian employment.

The Veteran's Role

Veterans often lack the knowledge about how to construct a skills-based resume to highlight their expertise garnered through military experience. Instead, veterans' resumes tend to focus on the functional tasks completed in addition to the awards received, which does little to identify for potential employers their potential capability to use their expertise in civilian employment. Veterans often do not conceptualize their military work in terms of skills or skills-based expertise which adds to the difficulty that employers have in understanding veterans' resumes in hiring processes.

In order to most effectively present themselves as exceptional candidates for civilian work, veterans need to understand how to separate the skills expertise from the functional tasks. Though still a pressing need, training or education about how to construct an expertise-focused resume is provided in TAP as service members prepare to exit the military. Additionally, in response to the challenges expressed by veterans in not being able to find adequate civilian employment, along with civilian employers' difficulty in making sense of veterans' experience in military work, the Department of Labor and a number of non-profit organizations began developing services aimed at filling the experience translation gap. Veterans can find effective information for understanding the skills expertise used in their military service through sources like O*Net and CareerOneStop, which provide military work translators that separate skills and knowledge gained through military work from the functional tasks completed in the job (Davis & Minnis, 2017). By giving veterans the ability to conceptualize their military work through the lens of skills expertise, these kinds of resources provide the tools needed for veterans to reframe their resumes and better understand the value of their work as it can be applied in the civilian workforce.

Additionally, veterans need to be honest with themselves and the organizations they apply to about their expertise. Determination of one's current level of expertise requires objectivity and established standards, which presents a unique challenge for veterans and their employers.

Regardless of the job or organization, any new employee—veteran or non-veteran—can enter the workplace with a high level of confidence in their abilities. When new employees perceive themselves as experts at a job early on, there are at least two potential consequences: (1) they may overlook the necessary training which will allow them to integrate existing skills into the organization and (2) their colleagues, supervisors, and direct reports may perceive them as closed-minded or arrogant about their level of expertise, potentially causing conflict among the groups.

The Organization's Role

Interest in hiring military veterans has grown and changed over time with the amount of ongoing training and education conducted by the military supporting service members' knowledge and skills has made their expertise highly sought-after. Veterans have been identified as effective candidates for non-military employment due to their positive interpersonal attributes as well as their ability to raise the level of professionalism of those around them by engaging the skills expertise acquired through their military work. Indeed, it is this expertise they will be reliant upon to engage future employment.

Recently, employers have focused on establishing military veteran hiring initiatives because of the value veterans bring to the workplace (Kirchner & Minnis, 2018; Pollak, Arshanapalli, Hobson, 2019).

Perspectives on hiring veterans in the civilian employment community have changed in the intervening years as employer understanding about the value of veterans' transferrable skills and capabilities has evolved. Early focus of veteran hiring as troops began exiting the Post 9/11 wars was in the area of law enforcement as the understanding of veterans' transferable skills had not yet taken hold. One of the first research articles addressing veterans' post-military employment needs in the career-oriented literature looked at veterans transitioning into federal jobs, which at the time were seen as a fit for their overall expertise and knowledge (Orlando, 2007). Additionally, attention to the needs of veterans with disabilities increased**,** with a focus on returning injured veterans to work while making use of their skills and abilities gained through military service (Rogan, Banks, & Herbein, 2003).

Civilian employers can take a number of steps to better identify and support military veterans' expertise redevelopment. From the initial job announcement to onboarding, hiring practices that recognize veterans' expertise can be adapted to provide opportunities for them to be more effectively engaged in the selection and hiring process. More clearly understanding the expertise veterans bring to civilian employment and the diverse ways in which their expertise can be redeveloped will enable civilian recruiters and human resources practitioners to make better selection and hiring decisions.

First, veterans need to be received as experts within their fields. A substantial transition issue relates to veterans being offered employment that does not utilize their expertise (Prudential, 2012). Consider, for example, a 28-year-old Army veteran, who served three tours in Iraq, was responsible for the safety of ten soldiers and successfully executed 30 combat missions. While this level of responsibility and accomplishment is tremendous for someone under 30 years of age, a civilian job rarely requires similar levels of responsibility, potentially impacting the perceived qualifications of the veteran applicant. For a constituent who only sees limited professional work experience, the described soldier might be viewed as a qualified candidate for an internship. This challenge is frequently encountered by those leaving the military.

Expert performance is more difficult to evaluate when the work is centered on people as opposed to specific objects or events (Grenier &

Kehrhahn, 2008). Although veterans are frequently credited with soft skills, articulating and clearly defending them on a resume or during an interview is more difficult. As Kirchner and Akdere (2019) found, veterans may struggle to distinguish the knowledge, skills, and abilities acquired during military service. Further contributing toward potential transition challenges, veterans may be hard-pressed to defend the soft skills they report having on their resume, which no doubt influences their likely job prospects with non-military employers. Skills translators, among other resources, are continually being developed and refined to help reduce the likelihood of a similar encounter with future job applicants who are military veterans with limited non-military professional work experience.

Alternately, job descriptions may be written to reflect the functional tasks of positions with less attention paid to the depth and breadth of skills required to effectively do the work of the position (Rios, Ling, Pugh, Becker, & Bacall, 2020). While noting perfunctory skills such as timeliness, effective communication, and use of general computer programs many job descriptions may not elucidate the necessary finer skills and expertise. Broadly constructed position descriptions lack clarity about the level and type of expertise needed which means there may be no effective basis for veterans to consider how their expertise might apply to the intended work. The lack of articulation of desired skills expertise results in civilian employers' inability to access effective candidates with sought after, highly developed soft and technical skills (Davis & Minnis, 2017).

Employers can also do more to develop a better understanding of the ways in which the expertise gained through military work can be viewed in their organizations. While they should not need to comprehensively know each aspect of military jobs, it would be beneficial for those responsible for reviewing and evaluating candidate expertise to understand how to effectively interrogate veterans' resumes for skills expertise rather than a cursory review of functional tasks. When the candidate is a veteran, the resume may appear to be a list of entirely unrelated tasks, awards, and abbreviations, but there is valuable expertise to be uncovered. As Davis and Minnis (2017) note, it is veterans' soft skills, which are easier to recognize and evaluate from the employers' perspectives, but it is the full value of veterans' expertise, which they bring to bear as they move forward in their career transition.

Soft Skills Expertise

Some of the expertise most highly-sought by those interested in hiring military veterans are the soft skills gained through work in the military (Davis & Minnis, 2017). Current research (Hardison et al., 2017; Kirchner & O'Connor, 2018) and practitioner-oriented guidance focuses on veterans re-engaging in the workforce through application of their soft skills such as leadership, teamwork, communication, and decision making as these represent some of the most needed and highly desired qualities of today's employees. With the potential to be high contributors in organizations, employers need to be attentive to the ways in which a veteran's soft skills expertise might relate in the non-military environment. For instance, soft skills such as leadership and teamwork may look very different in practice outside of the military. In the military, leadership means being fully responsible for the lives and equipment of all those under one's command. In many cases, even lower ranking service members leading others have responsibility for multiple lives and tens of thousands of dollars' worth of equipment at all times. Thus, decisions made by service members often have significant implications for the life and safety of themselves and those they are leading. This is a decidedly different aspect of leadership than most employers expect from job seekers, yet with the redevelopment of that expertise, the veteran is likely to be a strong leader and manager in the company.

As noted previously, service members undergo significant training and ongoing education in their technical fields. Expertise is the standard they must meet in order for the military to determine they are capable in their jobs. Indeed, expertise in one's job can often have life-and-death implications on the battlefield, on the deck of an aircraft carrier, or in a medical unit. Training is done until the service member no longer needs to think about the technical task itself and can attend to the tertiary soft skills of decision making, leadership, or communication. And much like the technical aspects of riding a bicycle, service members are able to accurately describe, or do, the task for which they were trained long after they have left the military. Unlike soft skills, however, most service members will not continue to engage their specific military job expertise once they leave military service. For example, a retired fighter pilot can't get the same job once they retire from the Air Force, but that doesn't mean that the technical skills of piloting an aircraft and maintaining flight safety can't be identified by an employer in Kansas looking for a crop dusting pilot.

We believe that for veterans to effectively engage in career transition from military to civilian work, employers must be able to understand the expertise redevelopment process. In doing so, non-military employers can mediate the impact of the transition and support the redevelopment of veterans' soft and technical skills expertise for the benefit of the organization.

Conclusion

Applications of military expertise in the non-military workplace have been mostly overlooked by scholars, which limits our knowledge of how veterans leverage their service experience after leaving the military. Whereas constituents, environment, and content each factor into the transfer expertise, their influence may not be unilaterally felt by veterans. Scholars and practitioners would benefit from exploring the comparative effects of the three areas of expertise on veteran career transitions, as findings could influence the development of future onboarding programs for military veterans. There may also be additional challenges not yet identified for military veterans regarding how they leverage their expertise in the non-military workplace. Study results could further shape our understanding of the barriers to successful career transitions and inform new workplace integration strategies. Finally, research examining strategies used by veterans to redevelop and leverage expertise in the non-military workplace may influence how non-military organizations utilize the skill sets of their veteran employee population.

As discussed in this chapter, there are challenges to the way in which military veterans' expertise is conceptualized by the veterans themselves, as well as by the non-military employers hiring for the job-openings veterans are seeking following military service. Being able to effectively articulate and engage their previous expertise in soft and technical skills is vital for veterans to make a successful transition to civilian employment. Doing so is also an important part of veterans' overall understanding of the value they bring and shift in confidence they may experience as they find new ways to use their skills. Given the importance of this transition, we believe the MER is a useful way for military veterans' skill transition to be represented. As further research into the military veteran to civilian transition is explored, the MER can provide a useful perspective to explore expertise utilization, development, and redevelopment involving former service members which includes challenges that need to be considered. Although scholars recognize the need to cultivate expertise in individuals, understanding *how* to retain and redevelop expertise—especially with military veterans—requires further discussion (Grenier and Kehrhahn, 2008).

A better understanding of the influence of a veteran's new environment, new constituents, and new content acquired may be useful in engaging military expertise but remains a challenge for all involved stakeholder groups. The translation of military expertise in non-military organizations requires further scrutiny from the military, veterans, non-military employers, and society at large. Unrealistic expectations or assumptions about retained expertise may impair the likelihood that veterans will be able to transition and redevelop their expertise and that non-military employers will be able to effectively recognize and make use of veterans' expertise. Given the importance of veterans effectively transitioning into civilian employment and making use of their skills gained through military experience, it will be important for research to continue exploring how the MER can be applied to understanding veterans' transition from military to civilian work.

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6

Expertise in Sports: What Is the Secret Behind World-Class Athletic Success?

Gabija Liutkutė, Florentina J. Hettinga, and Marije Elferink-Gemser

Sport is a universal phenomenon, which, in various formats, has been practiced since the dawn of our civilization. Today, sport remains an integral part of every modern society, extending its influence over cultural, social, political, and economic factors. For instance, the recognition by the International Olympic Committee is even seen as a precondition for a country's acknowledgment as a nation, thus equating in significance to the recognition by the United Nations (Craig, 2016). Additionally, constituting one of the largest global industries, the sports market is predicted to reach an estimated value of $614.1 billion by the year 2022 (The Business Research Company, May 2019).

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Millions of people worldwide share their love for sport, whether they engage in it as participants, spectators, or consumers. Sport offers entertainment, serves as the medium to learn and share new skills, enables the interactions with pleasant landscapes, and helps to fight the effects of our sedentary lifestyles (Giulianotti, 2005). The well-established health benefits of physical activity (World Health Organization, 1995) may be the primary reason for sports' enduring significance in our lives. Sport and physical activity are officially accepted fundamental components of healthy development in the modern world (UNICEF, 2016). Researchers identified that physical education and sports have a potential to significantly influence children's physical, lifestyle, affective, social, and cognitive development (Bailey, 2006). Not surprisingly, including physical education in every school's curriculum has become a standard practice.

So although the majority of people have been involved in sports at some point in their lives, only a small proportion of the population becomes professional athletes. As with any career path, this can be explained by a variety of personal reasons. However, the reality for those who do seek an athlete's career is that less than 1% of children involved in various sports ever reach the top (Malina, 2010). The growing interest in sports, as well as the ever-increasing level of sports performance, creates a highly competitive environment where only truly exceptional athletes performing at the highest level turn professional.

Sports associations and country governments invest a significant amount of money toward the development of their sporting talents, making the accurate selection of promising athletes of paramount importance. "All traditional athlete development pathways share a common goal to identify and develop individuals with the greatest long-term potential for success in elite competition" (Vaeyens, as cited in Jacob, Spiteri, Hart, & Anderton, 2018, p. 2). Yet, despite the multiple available assessment methods, most of the talent identification is still based on subjective judgments (Jacob et al., 2018) and therefore is fraught with failures. In essence, misunderstandings arise from the lack of consensus on what comprises expert performance in each sport.

Generally, expertise can be defined as a behavior of engaging in a craft in a way which combines person's objective characteristics of knowledge, experience, and problem solving (Herling & Provo, 2000) with subjective characteristics that are perceived by someone else as an indication of that person's knowledge, abilities, or skills (Germain, 2006; Grenier & Germain, 2014). An expert athlete is typically defined as someone who is able to consistently perform at a superior level (Starkes, 1993). The major difference between expert athletes and experts in other fields is the fact that in sports, one's physical body is used as the main 'instrument' for performance. This poses a challenge for understanding athletic success. Different from any other static instrument, many dynamic, many dynamic processes are continuously affecting the body making it harder to control for its performance-optimal condition. Thus, not only the skill and experience, but also a highly disciplined and in many ways restrictive lifestyle determines one's success. Moreover, the level of sports performance is constantly changing both due to technological advancements and the drive of humans to go beyond their limits. This constant progress results in the separation between the performances at an individual and at group levels.

For many individual sports, performance can be evaluated objectively by using time or distance as a measure. The challenge arises for other sports (such as team and jury-based) which, by nature, lack such objective criteria for measuring performance found at an individual level. In team sports for example, although individual match performance can be measured from contributions to the game (Piggott, McGuigan, & Newton, 2015), these results ultimately reflect the dynamics of the whole group. That is, interactions between the same team and the opponent team members influence and contribute to each player's behaviors and the consequent success, or a lack thereof. Every player contributes to the game in their own unique way. For this reason, the comparison between individuals becomes challenging.

The performance at an individual level refers to each athlete's personal progress, which is measured against their own personal best performance. The performance at the group level, on the other hand, refers to the collective level of performance. This means that in each event the margin for winning may differ depending on each participating athlete's preparation and is determined by the best performer in that particular competition. Thus, what may be considered a big improvement at an individual level may turn out to be completely insignificant in different competition contexts. Therefore, the status of an athlete becomes unstable as it may vary drastically from competition to competition. As a result, for an athlete to stay at an expert level an expert level of performance, they must be able to adapt to the global progress of sports and stay among the front-runners over time. This need for adaptation raises curiosity about the secrets behind the attainment of world-class success in sport. The purpose of this chapter is to respond to the following question: What is necessary in order to achieve expertise in sport? To explore this question we use the sport of cycling as an example while reviewing the current scientific knowledge in elite athletic success and expertise.

The Case for Developing a Cycling Prodigy

We chose to focus on road cycling exclusively while we move through the journey of expertise development in sport. Not only is road cycling one of the most popular sports worldwide, but it is also considered to be one of the most grueling sports on the planet with elite-level cyclists reporting exertion pain as the greatest psychological demand of the sport (Kress & Statler, 2007). Professional cyclists cover distances ranging from 30,000 to 35,000 kilometers every year during training and competition (Lucía, Hoyos, & Chicharro, 2001). Only a small number of athletes are able to withstand the tremendous physical and mental demands of the sport. Consequently, becoming a world-class cyclist requires one to be a truly exceptional athlete. Many would refer to such athletes in their younger age as talents. The notion of talent permeates the world of sports and provides the base for many important decisions; however, the current understanding of what talent really is and how to identify it is still limited.

Athletic Talent

The debate of whether talent is a result of nature (innate) or nurture (acquired) has been around for decades and has implications for athletic expertise. 'Nature' proponents would suggest that talent is a naturally inherited entity, which enables one to excel in a particular task. In their original work, Howe, Davidson, and Sloboda (1998) provided five criteria to define innate talent: (1) innate talent is, at least partially, genetically transmitted; (2) talent will have some advanced indications; (3) those with training can predict those with greater likelihood of success; (4) only a minority is talented; and (5) talent is relatively domain specific. Ericsson, Krampe, and Tesch-Romer (1993), on the other hand, argued against the existence of 'innate talent' and explained "that the differences between expert performers and normal adults reflect a life-long period of deliberate effort to improve performance in a specific domain" (p. 400). Deliberate effort, according to his definition, is an "extensive engagement in relevant practice activities supervised by teachers and coaches" (p. 392). This reductionist approach to talent has been gradually replaced with an understanding of the phenomenon as a complex and dynamic process. Baker and Wattie (2018) concluded that "talent should be conceptualized as a multidimensional construct that cannot be aggregated to a single score and is comprised from different combinations of different abilities" (Baker, Schorer, & Wattie, as cited in Baker & Wattie, 2018, p. 4).

Based on this current perspective, talent can be best described as the 'nature via nurture', meaning that a person can possess innate characteristics that may be favorable for certain sports (i.e. being tall in basketball or rowing), but those characteristics alone are not sufficient to make somebody exceptional at a particular sport. Only through active, sports-specific practice and developments of those traits can one's true potential be manifested. Newell (1986) proposed the Theory of Constraints, a theoretical model explaining the motor development as a dynamical process. "Newell's model guides us in identifying the developmental factors affecting movements, helps us create developmentally appropriate tasks and environments, and helps us understand individual movers as different from group norms or averages" (Haywood & Getchell, 2014, p. 9). In this model, constraints represent the factors that shape, limit, or contain the movement. According to Newell, there are three types of factors: the characteristics of an individual (related to their body's structure and behavioral function), the task, and the environment. The consequent interactions between those characteristics result in the emergence of specific movements (or changes).

Elferink-Gemser and Visscher (2012) adapted Newell's ideas into The Groningen Sport Talent Model (GSTM), designed exclusively to explain talent development in sports. This model proposes that athletic success is determined by interactions between different components. These components are the task characteristics, the multidimensional performance characteristics of an athlete, and the environment. In short, the task requirements describe the demands imposed by a particular sport. The multidimensional performance characteristics are the elements that underlie one's performance and they take into account both natural and trainable aspects of an athlete: anthropometric, physiological, psychological qualities, as well as technical and tactical capabilities. Finally, the environment encompasses elements such as an early exposure to sports, the opportunities and resources available to the young athlete (including coaching, facilities), as well as social support from parents, teachers, and schools. Thus, according to this theory, quality training coupled with favorable conditions, and a person's natural physical and mental endowments, which also match the task demands of the sport, is what ultimately determines the athlete's level of success.

These theoretical models of talent development can be used to understand the secret behind world-class athletic success, such as in the case of Dutch cyclist, Mathieu van der Poel. The young cyclist is famous for being one of the very few to simultaneously hold multiple champion titles for different cycling disciplines (cyclo-cross and road cycling). The level and consistency of his performances have been phenomenal. When analyzing van der Poel's example using the GST Model (Elferink-Gemser & Visscher, 2012), what strikes our attention first, is the fact that he was born to a family of professional cyclists (his father and maternal grandfather are both accomplished Grand Tour cyclists). This leads to the assumption that van der Poel was exposed to the sport early on and had the ideal circumstances both in terms of available training and strong social support. Additionally, "genetics may play an important role in determining sporting achievement, as athleticism, like many other individual characteristics, is, at least, a partially inherited trait" (Drozdovska, as cited in Jacob et al., 2018, p. 5).

Indeed, scientists now agree that 50% of sports performance-related phenotypes are explained by genetic variation. However, to unleash all the benefits from training, a person must also possess the right genetic and epigenetic variations displaying a natural talent for the sport, as well as the genetic and epigenetic variation responsible for an athlete's responsiveness to training (Moran & Pitsiladis, 2017). Thus, according to the talent model, Mathieu van der Poel meets several criteria that are essential to reaching the world-class success in cycling. However, the genetic giftedness and all the available resources would remain dormant if they were not actively pursued. Hence, what makes athletes successful is narrowed down to what they do to harness and nurture their potential.

Ericsson, Krampe, and Tesch-Rome (1993) generalized that 10,000 hours of deliberate practice spread over a decade are necessary to reach expertise in any field. With regards to sports, however, the duration of deliberate practice needed to reach expertise varies and is dependent upon the age at which the peak performance for that specific sport is expected to occur. Normally, this age coincides with the transition to the senior performance level (Elferink-Gemser, te Wierike, & Visscher, 2018). With regards to cycling, there is "espoirs competition" (youth category) starting at age 19 continuing up to the senior competition at the age of 23. However, there are exceptions to this standard when young cyclists, like van der Poel exhibit performance levels which exceed those of their age category. At that point, an early entry to senior competition is granted. Scientists also emphasize that deliberate practice should be based on one's developmental rather than chronological age due to the maturation rate of physical, mental, cognitive, and emotional aspects varying among children (Canadian Cycling Association, 2008).

Even though it may seem that the longer the involvement in deliberate practice, the greater the results, scientists warn that before the onset of peak height velocity (on average at 12 for females and at 14 years for males (Balyi & Hamilton, 2004; Malina, 2010), athletes have to develop a wider range of skills and abilities through involvement in cycling-unrelated activities and sports. This period of sports diversification, which is not so much about the competition and winning, would provide the young athletes with the time to explore different sports, identify their likes and dislikes, and build their general enthusiasm toward sport. For these reasons, it is recommended that the specialization in cycling should not begin until the age of 10 to 14 (Canadian Cycling Association, 2008).

Indeed, growing evidence from a number of sports support this idea, indicating that the most successful athletes, like van der Poel, often have a history of diverse sporting experiences. They participate in different sports at the beginning of their careers and specialize in their sport of expertise later compared to less-successful athletes (Güllich, 2014, 2017; Vaeyens, Güllich, Warr, & Philippaerts, 2009). This early sports diversification is thought to play a role in preserving risk-buffering, as well as a new resources-generating role, which can assist in long-term performance development (Güllich, 2014, 2017). Most importantly, the critical periods of trainability for skill, suppleness, stamina, strength, and speed appear during different stages of growth and maturation. During these windows of opportunity, the accelerated adaptations to each corresponding component take place, and if missed, they can inhibit an athlete's ability to optimally develop to their fullest potential (Balyi & Hamilton, 2004; Canadian Cycling Association, 2008). This highlights that, in sports, deliberate practice cannot be simplified to a 10,000-hour rule (Ericsson et al., 1993). The time necessary for practice is heavily dictated by the development and characteristics of an individual, as well as the specifics of their sport. Consequently, a more complex, intelligent approach is required; one which is tailored for each developmental stage of an athlete, and one that includes a number of relevant organized learning activities that take into account the needs of the individual.

We should, however, highlight that, by nature such deliberate training is not an inherently enjoyable or motivating activity. It incorporates high volumes of structured, effortful tasks aimed exclusively at improving one's performance. It is evident, when looking at our society, that a great number of people are not eager or potentially capable of enduring highly demanding involvement in any particular activity. It requires a true passion (Vallerand, 2012) for an individual to sacrifice many instantly gratifying experiences in hopes of attaining a single goal of long-term value. Therefore, a key indicator of a prospective talent and expertise development might be a person's willingness to meaningfully engage in an intensive, deliberate training for an extended period of time (Baker & Wattie, 2018).

Ericsson et al. (1993) talked about the existence of potential differentiating 'personality factors', which predispose individuals to engage in and sustain high levels of deliberate practice over time. Researchers suggest that both the acquisition of expertise and the ability to demonstrate it (as in performing under stress in competition) necessitate the existence of differing psychological characteristics (Baker & Horton, 2004). On the whole, Olympic athletes stand out from the less successful athletes for, among other reasons, their superior self-motivation, mental concentration, self-confidence, ability to cope with pressure, emotional stability, and their love for sports. Athletes like van der Poel engage in psychological skills such as imagery, self-talk, anxiety-management and highlight the importance of social/family support and good coaching for self-regulation (Durand-Bush & Salmela, 2002; Fletcher & Sarkar, 2012; Gibbons, Hill, McConnell, Forster, et al., 2002; Gould, Dieffenbach, & Moffett, 2001; Gulbin, Oldenziel, & Weissensteiner, 2010; Issurin, 2017; Mahoney, Gabriel, & Perkins, 1987; Orlick & Partington, 1988). Moreover, world-class athletes demonstrate a superior immunity to mental fatigue and display an overall mature psychological development which is reflective of a more complete mind-brain development (Boes, Harung, Travis, & Pensgaard, 2014; Harung et al., 2011). When compared to average athletes, world-class athletes demonstrate higher levels of brain integration and faster habituation to loud sounds, which have been associated with greater emotional stability, higher moral reasoning, and greater openness to experience (Harung et al., 2011). For that, world-class athletes must have a superior mental framework to process experiences and have exceptional self-regulation.

Self-Regulation

One's ability to acquire expertise is tightly linked to one's self-regulatory skills (Jonker, Elferink-Gemser, de Roos, & Visscher, 2012; Toering et al., 2009). Self-regulation encompasses the psychological processes by which individuals control their own behaviors by way of overriding impulses, habitual responses, controlling thoughts, emotions, and desires, all in the best interest of their long-term goals (Gailliot & Baumeister, 2007). Although self-regulatory skills can be developed, they do not accrue naturally and are best developed in a powerful, inspiring, and goal-oriented environment (Boekaerts, 1997), such as the one Mathieu van der Poel was raised in. Zimmerman (1986) defines self-regulation of learning as "the degree to which learners are meta-cognitively, motivationally and behaviorally proactive participants in their own learning process" (p. 308).

For an athlete, self-regulation of learning begins with an act of self-reflection, during which they reflect on past experiences, identify a goal for performance improvement, and evaluate their strengths and weaknesses in relation to that goal (Jonker, Elferink-Gemser, Tromp, Baker, & Visscher, 2015). Next, the athlete examines the requirements of the task and sets a concrete action plan of how they are going to meet those requirements in order to accomplish their goal. The athlete then monitors their performance and measures it against their previously selected strategy/plan. To perform optimally, various cognitive strategies which help athletes to cope with situational demands (such as stress, pain and discomfort, attention and motivation management) are employed (McCormick, Meijen, Anstiss, & Jones, 2019). After the task execution, the athlete evaluates their performance and their chosen strategies. They reflect on what went right and wrong and make necessary adjustments to their plan for the next training episode. To initiate the whole process of self-regulated learning, athletes must be motivated and, most importantly, they must believe that they are capable of achieving their goals. In sum, they must have self-efficacy beliefs, which refers to the "beliefs in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situation demands" (Wood & Bandura, 1989, p. 408) and it is responsible for the amount of effort an individual is willing to expend and their perseverance when faced with difficulties and setbacks (Bandura, 1997).

Generally, in sports, more experienced athletes are shown to engage in more self-regulated learning behaviors (Cleary & Zimmerman, 2001), which relate positively to their performance (Cleary, Zimmerman, & Keating, 2006; Kitsantas & Zimmerman, 2002). Moreover, the ability to self-regulate one's training has been identified as a characteristic feature differentiating elite athletes from the athletes at the lower performance levels (Toering et al., 2009). Overall, researchers propose that athletes who engage in self-regulation know how to optimize their learning

(Toering et al., 2009), deriving more from their practice sessions, and ultimately acquiring higher levels of sports performance. As an example, Jonker et al. (2012) demonstrated that despite having spent a similar number of hours in their training, the athletes who reached the senior international performance level used one of the self-regulation skills—self-reflection—more frequently during their junior years in comparison with their peers who moved onto a lower, national level.

With regards to cyclists, like van der Poel, self-regulation skills are highly engaged during the execution of every single bout of cycling exercise, but they are most relevant for the development of pacing skills. Cycling, by nature, represents a goal-directed behavior, which requires an athlete to make moment-to-moment decisions regarding the effort they are willing to exert, the choice of an appropriate pace, as well as to manage their feelings of pain and discomfort (Edwards & Polman, 2013; Renfree, Martin, Micklewright, & St Clair Gibson, 2014; Smits, Pepping, & Hettinga, 2014). The ability to select and maintain an appropriate pacing strategy has been shown to be fundamental for achieving success in competitive endurance activities (de Koning et al., 2011; Foster et al., 2003, 2004).

The optimal pacing strategy is the one that is selected to regulate the rate of energy expenditure in order to maximize external power output, and to prevent premature fatigue or catastrophic failure in any peripheral physiological system before the expected endpoint (Foster et al., 2003, 2004). The pacing behavior of adult athletes has been extensively researched over the last 30 years, yet little understanding exists on how pacing skills develop in junior athletes (Elferink-Gemser & Hettinga, 2017). The current knowledge indicates that pacing is a self-regulatory skill which develops throughout adolescence starting at around the age of ten and which is influenced by factors such as the physical maturation, the development of prefrontal cortical (meta-) cognitive functions, and the experience with the exercise task (Menting, Hendry, Schiphof-Godart, Elferink-Gemser, & Hettinga, 2019). Longitudinal data indicate that, for instance, in speed skating, the athletes who adopt pacing behaviors resembling those of adult elite speed skaters from an early age onward achieve elite level later in their careers, while those who do not develop their pacing optimally stayed below elite level (Wiersma, Stoter, Visscher, Hettinga, & Elferink-Gemser, 2017). Another study investigating the pacing behavior in youth athletes who were novices to a cycling time trial task, demonstrated performance improvements already after a single trial (Menting, Elferink-Gemser, Edwards, & Hettinga, 2019). Yet, their ability to anticipate the workload changed slower, varying over the total of four trials. Researchers therefore concluded that the ability to anticipate the future workload and to distribute one's energy reserves correspondingly may be one of the mechanisms that underlie the changes in pacing behavior occurring throughout adolescence. Results like these indicate how pacing behavior is relevant for talent development in cycling and other endurance sports. As a result, cycling expertise requires athletes to develop and implement optimal pacing strategies, for which the self-regulatory skills are necessary.

For example, in events such as cycling time trials (TT), where an individual competitor races alone to produce the fastest performance, the ability of experts to, over a set distance, optimize their personal pacing strategy becomes ever more important. The planning before a cycling event such as a TT may involve going through the racecourse to familiarize oneself with the technical demands. Next, a cyclist may break the racecourse into sections and determine his/her target goals (speed, cadence, power output) for each segment. Moreover, the athlete pre-plans their pre-race and in-race nutrition and hydration strategy (regarding the timing and the amount of water/fuel consumption). Using imagery, the athlete would once again run through the racecourse, visualize difficult elements (i.e. corners), see themselves adopting the appropriate technique, and riding through those challenging elements successfully. During the execution phase, the athlete would continuously monitor their performance and engage in attentional and cognitive control strategies to regulate their pace to match it with their pre-selected strategy (Brick, MacIntyre, & Campbell, 2016). After the race or training session is over, the cyclist would reflect on their performance, identifying what went well/wrong, and most importantly why. They would finally establish what needs to be improved in order to maximize their next performance and set new attainment goals (Elferink-Gemser & Hettinga, 2017).

Nevertheless, cycling is a sport where athletes more often compete against each other, rather than race alone, so it is important to note that athletes regulate their exercise intensity differently in head-to-head competition when compared to time trial exercise (Hettinga, Konings, & Pepping, 2017). This emphasizes the fact that cyclist-environment interactions in head-to-head competition are critical for understanding pacing behavior (Hettinga et al., 2017; Smits et al., 2014). Laboratory studies with adults show that the presence of an opponent is an effective method of improving the overall performance in competitive running and cycling, prompting the athletes to go faster than they would normally do (Brick et al., 2016; Hettinga et al., 2017; Konings & Hettinga, 2018a; Konings, Schoenmakers, Walker, & Hettinga, 2016; Williams et al., 2015). Yet, in real-life race situations, being influenced too much by one's competitor may also turn out to be a negative. If the adopted pace is too fast to sustain for the whole duration of the race it may lead to performance deterioration later on (Konings & Hettinga, 2018b). This demonstrates that a single skill requires a multidimensional approach for an optimum development. It is, therefore, important for an athlete such as van der Poel to be exposed to many different competitive situations where they train and compete with others in order to develop expertise. Over time, he, like other elite athletes, develop their tactical skills, learn to interpret different opponents' behaviors, and to integrate their own pacing behaviors in various competition scenarios through their deliberate practice.

Physical and Technical Demands of Cycling

The format of cycling races is often very dynamic and depends on the nature of the event. Vogt, Schumacher, Roecker, et al. (2006) and Vogt, Schumacher, Blum, et al. (2007) identified the differences in power outputs (PO) between flat and mountainous stages during the Tour de France and Giro D'Italia tour races, highlighting that flat stages are characterized by a large variability in PO, with short bursts of high power and longer periods of reduced intensity efforts; whereas mountain stages require high submaximal, constant PO over extended periods of time. The different race formats and terrains pose ever-changing energy requirements on the cyclists and call for different physical and tactical abilities to attain expertise. It is common that different riders excel in one or several terrains or race formats (e.g. climbers, punchers, time trialists, sprinters, domestiques and all-rounders), and can be considered specialists in that element. Nonetheless, during a road race, every rider has to cover all stages of the competition.

When knowing the technical task requirements, an athlete can assess their own performance and direct their training accordingly. However, it is not enough to only target global fitness requirements. Expert athletes understand that training has to be highly individualized and relevant to the athletes' specific performance goals. One needs to address the specifics related to the events they are participating in, their role in the team (if racing with the team), and their own strengths and weaknesses. They must also work on improving those aspects that directly translate into better performance in these circumstances. te Wiereke, Huijgen, Jonker, Elferink-Gemser, and Visscher (2017) demonstrated that despite elite-level basketball players being self-regulated learners, their ball-handling skill differed based on their position in the team. This meant that skills other than ball handling are more important for certain players. The same concept applies in cycling. Thus, to become an expert cyclist, like van der Poel, one has to dedicate their quality training towards skills that are the most meaningful for their personal performance.

The Psychological Demands of Cycling

There are major psychological demands encountered in all endurance sports. Tuffey (2000) summarizes those as: (1) long, repetitive training sessions, which can undermine motivation; (2) pain, discomfort, and fatigue experienced in training and competition; and (3) preparation for competition, including planning for pain and discomfort and developing and committing to a race plan. To ultimately succeed in cycling, certain mental attributes must be present that motivate and enable an athlete to not only handle, but also to thrive under extreme physical demands and psychological pressures (Schiphof-Godart & Hettinga, 2017). One study indicated that deliberate practice in cycling was focused mainly on physiological preparation with psychological training believed to accrue naturally as its by-product (Baghurst, 2012), those of affect, anxiety, mood, and pain and fatigue.

Affect

Emotions have been identified as being the core of our being and actions (Young, 1975). Therefore, it is reasonable to assert that they are involved in the regulation of our behavior and consequently exercise. Existing data propose that a range of emotions might influence athletes' performance through changes in cognitive functioning (attention, decision making), motivation, and physiological processes (Uphill & Jones, 2012). Affect is a psycho-physiological construct representing the feeling state experienced by an individual in a particular situation and is dependent upon the individual's interpretations of that situation (Renfree et al., 2014). Damasio (1994) explained how affect is involved in the decision-making processes. He proposed that emotions arise after the physiological changes are passed on and transformed in the brain. Over time, specific physiological changes and their corresponding emotions become associated with certain situations and their outcomes. These physiological markers and their evoked emotions consciously or unconsciously influence decision making, favoring certain behaviors, while, at the same time, avoiding others based on previous experiences. When a somatic marker is associated with a positive outcome, a person may feel happy, and consequently, becomes motivated to engage in a certain behavior. On the other hand, when a marker is matched with a negative past outcome, it may sound the alarm, warning the individual to refrain from the course of action. As a result, these affective states guide our behavior in favor of more advantageous choices.

Because affect serves as a readily available impression, it may facilitate some judgments when the situation is complex and all pros and cons cannot be weighed promptly (Slovic, Finucane, Peters, & MacGregor, 2004)—making it an important element in understanding expertise in sport. It has been suggested that risks are assessed through rational and experiential processing systems. Rational processing is understood as a logical evaluation of available information. Affect contributes to risk assessment through experiential system, which creates our reality through images and metaphors (Renfree et al., 2014). Hardy and Rejeski (1989) created the 'Feeling Scale' to evaluate affective states based on the core emotions: pleasure and displeasure. In their experiments, they found a tendency for affect to decrease while the perceptions of effort increased, suggesting that more demanding exercise was associated with more negative experiences. Another study (Renfree, West, Corbett, Rhoden, & St Clair Gibson, 2012) demonstrated that faster cycling TT results were achieved when athletes expressed more positive affect, whereas slower TT were observed among athletes with more negative affective scores despite no difference in ratings of perceived exertion (RPE) between the groups. Importantly, these affective states were present from the beginning of the TT and did not develop as the exercise progressed, implying that affect influenced the pace-related judgements directly, and were not produced as a result of the current performance. More aggressive pacing strategy amongst athletes demonstrating more positivity was also observed. This finding supports the idea that if an athlete experiences pleasant feelings during the activity, they tend to judge risks lower and the benefits higher. In contrast, if their affective states are more negative, the risks are perceived to outweigh the benefits, resulting in likely reductions in effort and performance (Renfree et al., 2014).

Anxiety

Another psychological demand important to consider in athlete expertise is anxiety. Dunn and Dishman (2005) explored the relationship between anxiety and performance in successful elite cyclists competing in Tour de France and Tour de France Féminin. First, they observed that cyclists experience both pre- and during-race anxiety, which increases with the duration of a competitive race. Most notably, pre-race state anxiety negatively impacted performance in male cyclists. For females, however, anxiety scores were not predictive of performance; instead high-confidence levels correlated with worse results—a finding which still requires further explanation. McCann, Murphy, and Raedeke (1992) in an earlier study also demonstrated a relationship between state anxiety and cycling TT performance among senior elite cyclists. High cognitive and somatic anxiety was correlated with weaker performance, whereas high self-confidence was linked to better performance.

In addition, scientists identified that the trait anxiety of a subject mediated the effects of state anxiety on expert performance. According to Gidron (2013), "trait anxiety refers to the stable tendency to attend to, experience, and report negative emotions such as fears, worries, and anxiety across many situations" (p. 1989). Thus, for athletes in McCann et al.' (1992) study who already exhibited more anxious dispositions, additional increases in anxiety levels negatively affected their performance. Conversely, those who were naturally less anxious benefited from increased anxiety. Dunn and Dishman (2005), on the other hand, did not find any relationship between trait anxiety and performance. Given the inevitability of anxiety in high-performance sports, it is essential that athletes are capable or learn to cope with their feelings of anxiety as it can drastically hinder their ability to demonstrate their true expertise while performing.

Mood

In sports, mood can influence decision making under pressure (Cooke, Kavussanu, McIntyre, Boardley, & Ring, 2011 and Laborde and Raab (2013) posit that mood might be one way to connect prior experience and knowledge—a process central to expertise. Differently from emotions, which can last for as little as a few minutes and fluctuate markedly in their intensity, moods are more stable states that last from hours to days. To make matters more complex, the source of moods is mostly difficult to discern (Thagard, 2018). Despite this, on the whole, top athletes, such as Olympic champions, are identified as having more positive psychological characteristics (Fletcher & Sarkar, 2012) and demonstrating distinctive positive mood profiles (Hagberg, Mullin, Bahrke, & Limburg, 1979). Hagberg et al. (1979) found that elite cyclists score below the mean on confusion, tension, depression, and anger, and above the mean on vigor when measured with the Profile of Mood States (POMS) questionnaire. Some researchers indicated that positive mental health can be associated with high-performance levels, while mood disturbances are predictive of performance decrements (Morgan, Brown, Raglin, O'Connor, & Ellickson, 1987).

Although mood changes can serve as an indicator of physiological distress, they do not seem to have any considerable effects on cycling performance (De Cuyper, Boen, Van Beirendonck, Vanbeselaere, & Fransen, 2016; Dunn & Dishman, 2005). This could be due to the fact that professional athletes assign a very high value to their sport and mood swings are not influential enough to alter this perception, which would lead athletes into sacrificing their performance. Additionally, vigorous physical activity is also known to stimulate the release of endorphins, dopamine, and endocannabinoids which act on the brain's reward pathway (Lembke & Raheemullah, 2019). Thus, in most cases, the psychological and physiological rewards of the activity are likely to outweigh any negative effects of mood states.

Pain and Fatigue

When dealing with pain, cyclists engage in associative and dissociative attention-based strategies, which help them to modify their perceptions of effort and, consequently, improve their performance. Cyclists reveal the tendency to classify pain as either 'good' or 'bad' depending on the success of the situation (Baghurst, 2012; Kress & Statler, 2007). 'Bad' pain has been associated with feelings of fatigue and it occurred during unsuccessful training or competition. In those cases, cyclists turned to dissociative strategies to 'block the pain'. Conversely, when the situation was in their favor, athletes used associative strategies, paying attention to their sensations, and viewing the pain as facilitative to their performance, thus 'good' (Baghurst, 2012).

When comparing the middle and back of the pack ultra-endurance triathletes, experts were shown to engage in thoughts that were related to their performance (association), whereas non-experts tended to be more distracted by performance-unrelated, passive thoughts and irrelevant active thoughts (dissociation). In addition, experts demonstrated greater pro-activity (defined as the ability to identify opportunities and act on them; Baker, Côté, & Deakin, 2005). On the other hand, Comani, Di Fronso, Filho, et al. (2014) suggest that dissociative strategies are preferable based on the argument that they promote optimal 'flow' performance states and specific electrophysiological patterns associated with better performance. They found that associative strategies were of no benefit to the performance. Nonetheless, by focusing on the core components of activity (associating) the awareness of afferent feedback diminishes in athletes. The result is a possible delay in the increase in perceptions of effort, thus indirectly aiding performance. Whether cyclists in Baghurst's (2012) study were focused solely on afferent feedback (pain) or together with the core components (i.e. cadence) is not clear, yet it seems that different strategies are effective in different situations. Dissociative techniques can aid athletes during difficult times by enabling them to continue with the task. Delaying the feelings of pain and fatigue associated with the task seems to be more beneficial under optimal circumstances and is a strategy commonly employed by expert athletes.

Perception of effort is not a sole product of physical sensations. It is highly influenced by mental factors such as mental fatigue. Viana, Pires, Inoue, Micklewright, and Santos (2016) observed that when tested on a mentally demanding Stroop task (a psychological experiment assessing the delay in reaction time between congruent and incongruent stimuli) professional road cyclists were shown to exhibit a much greater inhibitory control compared to recreational cyclists. Moreover, Martin, Staiano, Menaspa, Hennessey, et al. (2016) found that professional cyclists displayed a greater resistance to mental fatigue by maintaining the level of their TT performance and demonstrating no changes in their perceptions of effort after mental exertion. The ability to resist the negative influences of mental fatigue seems, therefore, to be a pertinent component of athletic expertise in endurance sports. Such evidence has led Hutchinson (2018) to predict that 'brain endurance training', aimed at improving one's ability to withstand mental fatigue, will be important to athletes in the coming years. The rationale behind such training is the evidence showing that mentally fatiguing tasks based on visual stimuli (such as Stroop) activate anterior cingulate cortex (ACC) in the brain, which is responsible for the perceptions of effort (Williamson et al., 2001). Due to the brain's plasticity, the frequent exposure to mentally fatiguing activities over time would lead to changes in the brain structure and function (Kolb, 1995), thus adapting to mental fatigue. Although top cyclists are most likely to develop superior resistance to mental fatigue through their regular physical training, the supplementary 'brain training' could offer a supplemental way to push their boundaries even further or serve as a tool for any endurance athlete lacking in this area.

Conclusion

Sport serves as an ideal platform to explore what it means to be an expert because elite athletes operate at the very top limit of human capabilities and train relentlessly in order to develop and retain expertise. No single recipe exists to ensure a person's success in sports, yet scientists are constantly advancing our understanding, providing more insight into what the best talent development approach may be. As we have seen in this chapter, expert development in athletes like elite cyclist, Mathieu van der Poel, is a complex multidimensional process. It is neither a mere consequence of some supernatural talent that a person inherently possesses, nor is it the result of an absent-minded repetition of a task. Instead, it is the product of complex, ongoing interactions between the characteristics of an individual, their environment, and the task in question. The environment both introduces and limits the number of opportunities (tasks) available to the individual. Each task dictates the requirements that individuals have to meet. Eventually, both a person's inherited characteristics and their capability to acquire the necessary new skills will determine their level of success in that particular task. Provided that the ideal circumstances are created for a person with great potential to become an athlete, we argue that the most important aspect that separates champion athletes from the average ones lies internally, in their psychological characteristics.

Central to our discussion in this chapter is the concept of self-regulation as the ultimate determinant for attainment and execution of expert performance. Self-regulation is the core component that enables successful deliberate practice. Athletes who achieve the best results are the proactive and committed learners who use reflection, goal setting, planning, monitoring, and evaluation of their performance on a regular basis. Moreover, self-regulatory mechanisms are constantly engaged during sport performance. By nature, sport presents a multitude of psychological challenges to overcome. In cycling, we saw that anxiety, affect, mood, pain and fatigue are the most common issues athletes deal with. Those who master self-regulatory skills and overcome those psychological and physical challenges faced before, during, and after their performance are likely to eventually claim their expert title.

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7

An Assemblage of Knowledge: Novices, Experts, and Expertise in Universities

Zachery Spire

From medieval universities in Italy, France, and England to contemporary universities across Australia and the United States, authors challenge us to revisit and research what being a university has meant across history. Recently, the changing funding regimes, monitoring schemes, and sharp changes in cost-sharing of university education by states and individuals have compelled many to consider a more open, emergent, and complex approach to understanding the forms, functions, stated purpose, and the role of universities in society (Bengtsen & Barnett, 2018). Universities are emergent and complex institutions, operating at the intersection of knowledge creation and reformation. These institutions of higher education are places where space is purposefully and intentionally made for novices and experts to congregate and contribute to knowledge of 'self' and 'other' within a larger social context (Barnett, 2007). A university has its roots in the assembling of a set of scholars, pursuing knowledge in a number of forms, across disciplines and fields, acting and interacting at

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institutional, local, regional, national, and international levels (Barnett & Jackson, 2019). Barnett and Jackson (2019) explore this more closely by examining the ideas of learning ecologies. They highlight how, in a liquid modernity, what counts as knowledge and truth is often reflective of a moving and often fluid conceptualization of expertise, the position of experts within a social context, and the degree to which living purposefully is considered a strength and a limit of knowledge.

Today universities face many challenges. For one, the demand for student placement over the last 20 years in the United States and United Kingdom (the two largest higher education sectors at the time of writing this chapter) has frequently outpaced the ability of place-based universities (i.e., residential universities) to accommodate the number of prospective students (Marmot & Spire, 2019). This influences a growing managerial and business approach to the organization and operations of universities that is made more complicated by the rights, responsibilities, ethics, and political interests operating across universities. The supply of post-compulsory education across the United States and the United Kingdom creates boundaries for demand and provision of place-based and virtual learning environments. Supply and demand for post-compulsory education raises a debate about post-compulsory education as a 'market' and/or a common good (Marginson, 2018), as well as the growing role of information as a consumable good (Baudrillard, 2010), but not necessarily a common good (Marginson, 2018). Moreover, universities struggle to champion active, engaged teaching, learning, and research in the face of information and performativity that ignores a knowledge framework (Barnett, 2015). What is needed are ways of addressing long-standing and short-term concerns over the formulation, function, purpose, and ownership of knowledge in universities and society more generally.

This chapter explores those concerns by taking up what expertise looks like in universities and then presents assemblage theory (Bacevic, 2018) as a way to frame expertise, experts, and novices within institutions of higher education. Assemblage theory creates space for reconsidering whether, and how, institutions remain present and utilize internal processes, practices, and expertise to continuously revisit policy, practice, and provision (Deleuze & Guattari, 1988). Programs from two universities, Stanford University's Institutional Research & Decision Making Support (Stanford IR&DS), and, the University College London (UCL) Arena Centre for Research Based Education (UCL Arena) situate a broader discussion about the potential of expertise, experts, and novices in universities.

Universities as Sites of Expertise

Educational historians like John Dewey (1923) describe education as a translational and transformational set of processes within which students are adopted and socialized in and across a set of life-stages (birth to youth and onward into adulthood). He goes on to highlight economic (e.g., manufacturing of material life, production of knowledge, or job creation) and political drivers (i.e., social class, political party) that are set against a thesis of education as social transmission. Thus, education is a mechanism to structure social relationships and human social activity. More recently Robert Brenner (2003) explores how education and universities parallel changes in social conditions brought into and about by economic competition in and between nation-states. If an employer and employee are situated in a game of fragmented global competition, education serves as a mechanism to inform and influence the forms, functions, stated purpose, and outcomes of that game for the individual and their related social spheres of learning. In this view, education is a personal interest, situated within the context of wider national interests. As such, educating an individual citizen becomes part of a national strategy for remaining competitive in an increasingly global, competitive, and precarious social environment.

These definitions of education highlight the social nature of universities. At their core are the people, places, policies, and practices that shape the university space where teaching, learning, and research are undertaken. Physical spaces often mediate the social and personal spaces by which students and staff define and develop knowledge. However, knowledge continues to be the outcome of human social activity. The activities of institutions, staff, and students are continuously influenced (and influencing) internal and external measures of teaching, learning, and research.

From time to time debate over expertise in universities resurfaces. This might be because expertise is a driver of universities as it can serve to operate and organize university activities, policies, and outcomes. In universities expertise is created and legitimized as individuals and groups advance their personal and shared knowledge. Thus, expertise acts as a driver of university activities, that is part process and part outcomes. This debate reminds us that what expertise looks like and what it means to be an expert or a novice in a university is not found in a simple answer.

Expertise in Universities

Although expertise is frequently defined across a spectrum of objective and subjective items in scales, Grenier and Germain (2014) note that definitions for expertise often give primacy to what some have called objectively measurable attributes and knowledge. In this way human expertise can be defined as "displayed behavior within a specialized domain and/or related domain in the form of consistently demonstrated actions of an individual that are both optimally efficient in their execution and effective in their results" (Herling, 2000, p. 20). For example, content-specific knowledge about specific subject matter and related procedural knowledge about processes related to a subject (Chi, Glaser, & Farr, 2014). Primacy is given to whether (or not) an individual can demonstrate knowledge related to specific content, such as measured within examinations for university courses (i.e., final exams). Expertise in universities is often defined and measured across a number of metrics and key performance indicators (KPIs) of objective measures including student-staff engagement, student satisfaction, teaching quality, and research productivity.

Measuring teaching, learning, and research outcomes through instruments like surveys is a way of organizing, evaluating, and assessing staff and students' academic and non-academic outcomes as they engage in their learning environments (Astin, 1975; Pace, 1984). In universities, subjective measures might include satisfaction with courses, availability of academic and non-academic student services, ease of obtaining counseling and guidance for a course of study. Subjective measures have defined expertise through content-specific knowledge about a certain subject matter, as well as necessary procedural knowledge related to executing appropriate responses, at appropriate times, and under appropriate conditions.

Experts and Novices in Universities

An additional consideration for understanding expertise in universities is addressing what it means to be a novice and an expert. Luntley (2009) posits that such a starting point is common in the education literature, especially professional education, where 'teacher' and 'student', are considered interchangeable with 'expert' and 'learner'. One approach for identifying novices and experts in a university is the application of the model from Dreyfus and Dreyfus (1980). The model sees novices and experts along four binary qualities, including: recollection (non-situational or situational), recognition (decomposed or holistic), decision (analytical or intuitive), and awareness (monitoring or absorbed). The model as represented in Table 7.1 includes skill level/mental function across a set of five types: novice, advanced beginner, competence, proficient, and expert (Dreyfus & Dreyfus, 1980, 2004).

While the model has been adopted widely, it has also been heavily critiqued. Gobet and Chassy (2009) argued for an alternative theory of intuition in relation to movement in and across levels and between a novice and an expert. The authors contended that there was no empirical evidence for the presence of stages in the development of expertise. Indeed, being a novice involves understanding the different levels of expertise around any topic or issue. This means that the level of domain-specific knowledge and experience is deployed and understood between experts and novices alike. While Gobet and Chassy (2009) note that experts leverage analytical thinking in what the authors have characterized as 'slow' problem solving, their taxonomy situates expertise along a continuum from novice to expert. It is also helpful when considering what it means to be an expert in a university to apply Schon's (1984) concept of 'reflection in action', which emphasizes concepts of 'knowing in action' and the role of 'know-how' in describing expert performance as

Table 7.1 Five-stage model of the mental activities involved in directed skill acquisition

Skill level/mental function	Novice	Advanced beginner	Competence	Proficient	Expert
Recollection	Non-situational	Situational	Situational	Situational	Situational
Recognition	Decomposed	Decomposed	Holistic	Holistic	Holistic
Decision	Analytical	Analytical	Analytical	Intuitive	Intuitive
Awareness	Monitoring	Monitoring	Monitoring	Monitoring	Absorbed

similarly influential (p. 357). Luntley (2009) posits that what distinguishes an expert from a novice is what is known and how what is known is applied. Categories reflect a defined and measured understanding and awareness of a domain of knowledge, and, perhaps importantly, the expert's application of knowledge and skill in the world. Although how experts are defined is key in university contexts, so is the level of expertise that can be demonstrated. From beginner to advanced, titles like professor or provost are important, but experience is crucial. For Luntley (2009), expertise is developed through practice as they engage in a process of developing existing expertise (from beginning to advanced). Because of this the tradition of university titles and categories is an insufficient signifier of an expert. Instead, what matters is demonstrating expertise and continuously working to refine their understanding, knowledge, and skills.

Universities as Assemblages of Knowledge

Although one can think of experts and novices and the expertise found in and created from universities as discrete entities, universities might be better positioned as assemblages of expertise. This is particularly useful given the current challenges faced in higher education as they struggle to transform in ways that address "the new economies, ecologies and geographies of knowledge production" (Bacevic, 2018, p. 2). Bacevic (2018) notes that the forces of capital and technology, including the rapid growth in technology-mediated teaching, learning, and research (i.e., Zoom, ICT, Virtual Learning Environments) have destabilized our orthodox and traditionalist views of universities as the center of knowledge-based societies and economies. Today, universities are shaped and reshaped to reflect fractures and fissures in the forms, functions, and stated purpose of knowledge and knowledge institutions.

Defined as complex, co-created, and co-constructed teaching, learning, and research environments, assemblages of knowledge serve to position experts and novices in a relationship.

Universities, as assemblages, exercise a degree of agency through their particular composition and characteristics (i.e., admissions, professional programs, physical environment, specialist activities, or position within the educational field), for example, the assembly of individuals and groups of individuals who are considered legitimate experts in their respective fields and disciplines. The physical and social milieu of a university is a medium upon and through which otherwise disparate experts of varying levels of experience and expertise (from novice to advanced expert) are assembled and whose activities are coordinated in relation to the physical, social, and personal spaces and places that make up what we define as a university (Barnett, 2017; Temple, 2018). From art to science and engineering to mathematics, universities (general and specialized) are formed around the expertise of their related experts (faculty, administrators, students, visiting scholars, and guests). Bacevic (2018) asserts "assemblages, in this sense, exercise agency not by the virtue of their internal composition, but because of the way in which their composition interacts with their environment" (p. 3). These assemblages become "irreducible social wholes composed of heterogeneous elements. Some of these elements are persons, but some are buildings, machines, trees, animals, etc... Rather than being a stable or bounded entity, an agent can thus be thought of as a network or 'bundle' of objects, persons, and relations, which change over time" (Bacevic, 2018, p. 11).

Because universities continuously reconfigure themselves in relation to various pressures (Bacevic, 2018) an assemblage of knowledge approach can offer a means for knowing thyself and others in order to distribute authority and deploy expertise in the institution. However, respective of the level of expertise an expert and a novice may maintain, an alternative starting point to expert-novice relations reveals a need to accept that, for both categories and parties, a liminal space is opened up when we consider how little can be known about the level of expertise of experts and novices. Such a view foregrounds the emergent and complex nature of expertise and how, especially in educational environments, the differential and often asymmetric power relations within the environment shape what is expected and allowed for by either experts or novices.

This does not mean that experts and novices are always operating within asymmetric power relations at all times. Instead the nature and habitus (Bourdieu, 1989) of the educational environment can mean that the 'capitals' (i.e., expertise, reputation, expectations) of experts and novices become interdependent. Notions of capital are situated and rest on whether and how both experts and novices operate in relation to expertise. The consequence of positioning expert and novice in relation to expertise is a result of co-constructed platforms. Being a novice, like being an expert, is co-constructed and co-created around individual and group relations to what has been defined here as expertise. Expertise infuses/imbues the expert and novice with varying levels of authority to speak on a subject. The expert is defined more by their ability to coordinate and organize the table, so to speak, at which experts and novices sit together. In some settings and contexts, experts and novices are focused on shared understanding of knowledge. It is clear that if knowledge and expertise are to win the day, it cannot be a matter of who presumes/assumes based on asymmetrical power and authority relations the individual(s) as expert(s). Rather, it is not the loudest and presumptive who wins in expertise, but at least to one degree or another, the expert is one who is capable of shaping and guiding both experts and novices through quality questions and epistemic rifts in order to arrive at a space in place where the idea(s) and expertise are co-constructed and co-created and made to be the central concern of all parties involved. Simply said, let the best ideas be the guiding aim and objective of experts and novices. Acknowledge that experts and novices rely on each other to understand the contextual, situated, and contingent nature of their expertise. And, be aware that a number of implicit and explicit power, authority, and bias operate in the work of experts and novices together and define the quality both experts and novices derive from their interactions.

An assemblage of knowledge approach can also serve to emphasize expertise in universities as socially and culturally constituted. Bacevic (2018) notes:

> …the processes by which elements become parts of emergent totalities are culturally and socially constituted, which means that they have to be understood in specific political and historical contexts. Rather than assuming a 'natural' or morally preferable fit between processes of teaching and research, this allows us to ask how is it that these activities became essential to a specific concept of what a university is, and what work does treating them as such perform. (p. 4)

Through this position, universities, experts, and expertise are emergent and culturally and historically constituted. Rather than an end result of study and practice, expertise is embedded in the pursuit of knowledge—the social processes of teaching, learning, and research. In the emergent and complex space of the university, the constant work of universities is to be comfortable with the unknown, to explore and evidence activities through assembling individuals of various types and levels of expertise to extend existing knowledge. As Bacevic (2018) posits, using assemblages of knowledge to reframe universities changes how we think about knowledge production in higher education institutions. She states, this reframing allows for "... a more variegated ecology of knowledge and expertise, in which the identity of particular agents (or actors) is not exhausted in their position with (in) or without the university, but rather performed through a process of generating, framing, and converting capitals" (Bacevic, 2018, p. 11).

Seeing universities as assemblages of knowledge is not simply an imaginary possibility. The following are two cases where the assemblage of knowledge approach has been applied in universities. Universities have come under rising pressure to demonstrate awareness and alignment between policy, practice, and provision of higher education. Coordinating institutional efforts to align policy and practice, universities, such as Stanford University and University College London have adopted internal research and decision-making support to harness expertise.

The Stanford University Institutional Research & Decision Support (Stanford IR&DS) is described as a department charged with providing integrated analysis and research needed by university decision-makers; publishing reports that provide insight into the performance of the institution; assessing and evaluating Stanford's academic and co-curricular support programs; building data collections and facilitating access to data, including providing training and tools; and disseminating and facilitating best practices in the collection, use, and interpretation of data and advocating for data quality and integrity (Stanford University, 2020). To accomplish this, Stanford IR&DS accesses, utilizes, analyzes, and reports on data from all of the major administrative systems at the university including student, faculty, course, research, and financial data (Stanford University, 2020).

The Stanford IR&DS focuses on decision-making and administrative support. In their electronic resources, the Stanford IR&DS describes the diffusion of its responsibilities and activities across a set of teams who aggregate and share knowledge across departments, faculties and the institution more generally (Stanford University, 2020) that mirror an assemblage of knowledge. These teams position their work as a provider of "timely, high-quality, accessible management information and analysis for informed decision-making" at Stanford. Stanford IR&DS performs and facilitates complex analyses for both departments and central offices, including collaborating with other universities to provide comparative data, and proactively publishing management reports. This means their work is integral and ecological, focusing on fostering an environment where cogent, contextualized, and insightful information is provided to decision-makers across the institution.

Similar to Stanford IR&DS, University College London deploys an evidence-based approach to defining and developing a research-based educational strategy. University College London founded and developed the Arena Centre for Research-Based Education as a consortium of scholars from across UCL faculties whose mission is to examine the teaching, learning, and research resources across the institution in order to inform and influence research and education integration at the university (UCL Arena, 2020). This materializes in one instance through the UCL Education Strategy 2016–2021. The strategy aims to personalize student support, put research and enquiry at the heart of learning, improve assessment and feedback, develop student engagement and leadership, revitalize postgraduate taught education, create a teaching estate to meet our needs, enrich digital learning, and prepare students for the workplace and the world (UCL Arena, 2020).

The strategy harnesses UCL expertise to create, develop, and apply a "framework for the improvement to UCL teaching and learning, putting teaching on par with research" across the institution (UCL Arena, 2020). In doing so the assemblage of knowledge draws on a holistic, cross-departmental, and institution-wide approach using interdisciplinary expertise and internal and external strategy to inform the institution's undergraduate and graduate teaching and learning, as well as research initiatives.

As Stanford and UCL note, generating feedback from institutional stakeholders on teaching, learning, and research is not a new phenomenon (Stanford, 2020; UCL Arena, 2020). However, trust in the approaches, outcomes, and recommendations of institutional assessment is enhanced when individuals see their expertise applied to institutional policy, planning, and practice. Furthermore, internal and external stakeholders benefit from work to evaluate and assess teaching, learning, and research outcomes against clear rubrics for student and institutional teaching, learning, and research outcomes. Thus, these holistic approaches that reflect the spirit of an assemblage of knowledge honor all forms of expertise and experience from multiple stakeholders to connect institutional strategy to internal and external assessment exercises and frameworks.

Shaping educational strategy, research, teaching and learning outcomes have become central to university governance. The Stanford IR&DS and the UCL Arena Centre for Research-Based Education act as sites for creating, funding, and supporting an institutional framework that shapes the teaching, learning, and research practices at their universities. But they are not the keepers or creators of the expertise needed to achieve their missions. The Stanford IR&DS and UCL Arena Centre provide a baseline for key institutional activities like teaching, learning, and research, and university departments develop and contribute research, decision-making, and strategy. These departments are part of a broader institutional ecology related to devolved and shared decision-making and responsibility for university outcomes.

Additionally, the work of the Stanford IR&DS and the UCL Arena Centre conveys a cultural value for circling back to institutional work and exploring whether and how the institutions' understanding, and intentions actually materialize in the realities of the institutions. It is key that, insofar as universities are assemblages of experts and expertise in a number of domains and fields, their activities and actions of organizational departments such as the IR&DS and the Arena Centre at UCL are not perceived as simply 'tick-box' exercises. Feedback must be intentional in its generation and implementation. Staff and students will quickly pick up on whether or not feedback that is generated in such departments is influencing the organizational structure and cascading into the daily life of staff and students. If feedback becomes an exercise for the sake of stating that an educational institution is concerned but not bothered enough to affect change based on stakeholders' feedback, this might have a damaging influence on stakeholders' trust and long-term care for the respective institution. Universities rely on the expert knowledge of their stakeholders, which makes a sense of connection and valuing the individual in any capacity and across every level key to institutional success.

Stanford IR&DS and the UCL Arena Centre highlight how even when an assemblage of knowledge is desired, the performative nature of universities often requires a mechanism to track and archive institutional decision-making, strategy, and outcomes from policies and university practices. Even still, these examples illustrate the role these centers provide in creating clear threads of study and information gathering upon which key stakeholders and critical institutional decision-makers define their work. In this way the idea and ideal that universities value expertise and are interested in and compelled to respond to stakeholder feedback on critical activities are attended to.

Conclusion

At the core of universities is their ability to generate and contribute new knowledge. This chapter explored the concept of expertise in universities, including how expertise, experts, and novices are situated within universities and how these can come together as assemblages of knowledge. Moving from framing expertise, novices, and experts to positioning universities as emergent and complex institutions with the possibility of acting as assemblages of knowledge was viewed through the organizational governance of two institutions, Stanford University and University College London. These cases illustrated how expertise was provided from the level of the individual (novice and expert), group (department), and across the institution (universities), with IR&DS and the Arena Centre for Research-Based Education acting as internal platforms to evaluate, assess, and synthesize university expertise. These examples illustrate points made in this chapter.

Addressing different approaches to defining and understanding expertise, experts, and novices are important in the university setting. What defines experts from novices goes beyond objective and subjective knowledge. Ronald Barnett (2017) proposes that expertise is a field where experts and novices are situated and positioned by time, energy and attention devoted to a subject of study. Expertise is the drive and outcome of co-created and co-constructed knowledge among novices, experts, and universities. Such a holistic and ecological approach is part of a present trend aimed at providing opportunities for participatory governance to shape the forms, functions, and stated purpose of the institution, accounting for internal and external stakeholder feedback. These approaches have been adapted by institutions and have generated varying degrees of governing success. It is crucial that participation, representation, reflection, and reflexivity are integrated into the forms, functions, and stated purpose of institutional practice.

Universities are uniquely positioned to create possibilities for experts and novices to develop individual and social knowledge. The result is the opportunity to serve the self, public, and common good. The definition of universities as territories and the influence of deterritorializing the forms, functions, and the stated purpose of universities across history (Bacevic, 2018) help to make sense of the shifting social attitudes toward higher education, as well as the forms, functions, and stated purpose of these institutions (Tight, 2011). The growing complexity of universities requires a consistent commitment by experts and novices to learn and influence the teaching, learning, and research aims and objectives of universities.

In this chapter, assemblage theory offered an opportunity to create new possibilities for understanding expertise as knowledge is created and disseminated and stakeholders are consulted. These assemblages of experts are key to addressing challenges and how universities deploy their expertise through the collaborative, co-constructed, and co-created work of novices and experts. Works by novices and experts develop new pathways of knowledge, and modes and methods of study. Such assemblages of knowledge inspired participatory governance and modeling such as those adopted by Stanford and UCL. Assemblages of knowledge attend to a need for access, participation, recruitment, and retention of expertise in universities and contribute to the local and specific nature of how expertise is applied at an organizational level. The aim of expertise in such contexts is to generate meaning and value for the institution and its stakeholders through coordination of efforts to create safe, supportive, and inclusive environments internal to and beyond the academy. In this view expertise offers the opportunity to put creativity and experimentation at the center of the work of universities. The assemblage of knowledge can liberate scholars (novices and experts alike) to pursue new knowledge pathways and generate new opportunities and to develop socially constructed insights from experts across various fields and disciplines of study.

Assemblage theory and expertise generate possibilities for scholars to be at the leading edge of creation of new technology, thought, creativity, and exploration. First, from science, technology, sociology, economics, to art history and dance, the pursuit of knowledge for its own sake and the chance to emerge from study as a reflective and self-reflexive practitioner should be central to novices and experts who are connected to the values, aims, objectives, and beliefs of their universities. Expertise forms the connective tissue between novice and expert. In adopting what you might call an *expertise as an intermediary approach*, a space opens up. In this space, what is important is not so much assumed and implicit authority and power, rather it is the assemblage of university expertise to tackle emergent and complex projects that are influenced by while also influencing both novices and experts. Taking up such an approach could cement universities as institutions whose expertise contributes to knowledge at both a personal and social level.

Concepts covered in this chapter also raise the call for longer and more elaborate study of the contemporary political economy (and ecology) of knowledge production, which would need to take into account multiple other actors and networks from the more obvious, such as Twitter, to less 'tangible' ones that these afford such as differently imagined audiences for intellectual products. Lastly, universities must not lose sight of the importance of trust: trust in people, in processes that are co-created. Expertise as discussed in this chapter needs adequate representation. Feedback is important, but a strong assemblage of knowledge aims for generating participation and representation in and across the university. Participation and representation must be an integral component of institutional decision-making and practice. This reflects an underlying belief that participation and representation generate a connection between staff, students, and administrators as connected to the institution. This is complex, but by adopting a feedback driven, participatory framework staff, students, and administrators are connected into a wider ecological approach to the institution and its organizational expertise.

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Part III

Emerging Concepts of Expertise in Organizations

8

A Brief History of the Relationship Between Expertise and Artificial Intelligence

Jan Maarten Schraagen and Jurriaan van Diggelen

This chapter explores the role artificial intelligence (AI) plays in human expertise, for instance by either enhancing, changing, or degrading it. We also address how expertise can play a role in moderating, advancing, using, collaborating with, or exploiting AI. We should make clear that we will neither set up a simple dichotomy between experts and AI, nor will we investigate claims of people being surpassed in expertise by artificial general intelligence (AGI), or people becoming unemployable due to AI developments. However, we do not deny the partial validity of some of these claims. Rather, we view experts and AI systems as 'joint cognitive systems' that form a unit (Woods & Hollnagel, 2006). There are numerous ways for humans, and experts in particular, to jointly collaborate with AI systems, and we discuss the empirical evidence for particular patterns of collaboration. Moving beyond a 'joint cognitive systems' approach, we

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also discuss more recent ways in which AI has manifested itself as a networked and distributed phenomenon and has shown itself to either enhance or degrade human expertise. To achieve this, we first present a brief history of AI and expertise studies. Next, we provide examples of empirical research on experts working together with intelligent systems and emphasize the patterns that emerge from that research to shed light on the role of AI in expertise. Subsequently, we discuss a case study in radiology that illustrates how human experts and AI approach this topic. Finally, we conclude and provide some recommendations for future research.

The concepts of expertise, intelligence, and artificial intelligence are used frequently in this chapter. The distinction between expertise and intelligence is one between domain-specific and domain-generic knowledge (Vergne, 2017). Typically, expertise is defined in terms of "reliably superior performance on representative tasks" (Ericsson, 2006, p. 13), although this definition is arguably more applicable to tasks that can be measured, standardized, or simulated easily (e.g., chess, music, typing, or playing tennis) rather than complex cognitive work where performance measurement is difficult or impossible (Ward et al., 2020). Intelligence, in contrast, may be defined as "a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience" (Gottfredson, 1997, p. 13). Evidence shows that intelligence is a reasonably good predictor of performance early in learning, but does not predict asymptotic levels of learning very well (Hunt, 2006). In a recent review, Hambrick, Burgoyne, and Oswald (2020) concluded that the evidence for the role of general cognitive ability in expertise is inconclusive and in the majority of studies the evidence was in fact absent. On the other hand, cognitive ability did play a role in job performance well beyond the initial training. The difference between expertise and job performance studies is that the former typically studies consistent mappings between stimulus and response (as in the routine execution of psychomotor responses or the recognition of typical patterns of stimuli), whereas the latter involves acquiring new knowledge and skill, dealing with varied mappings between stimulus and response or the need to develop mental models of a situation. Thus, general cognitive ability (of which intelligence is one construct) plays a role whenever the environment presents us with new or complex situations. Whenever the environment presents us with well-known, standardized situations, we draw upon domain-specific knowledge and call it 'expertise'.

The European Union High-Level Expert Group on Artificial Intelligence recently provided an updated definition of AI, which we use in this chapter:

> Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions. (European Commission, 2019, p. 6)

AI systems achieve intelligent, that is, rational behavior, by choosing the best action to take in order to achieve a certain goal. Current AI systems can be characterized as narrow AI systems which perform one or a few specific tasks and cannot deal well with any new or abnormal situation. These systems resemble our definition of expertise as "reliably superior performance on representative tasks" (which is not to say that narrow AI systems should be equated with human experts, as the latter also possess general cognitive ability that the narrow AI systems by definition do not).

Taking these definitions into account, discussing the role of AI in expertise can mean a number of things. Given that currently deployed AI systems are examples of narrow AI, the issue becomes one of how human experts, within their domain of expertise, work together with systems that can perform one or a few specific tasks within that domain of expertise. In other words, experts work with AI as symbiotic partners to exploit what each party does best (Daugherty & Wilson, 2018).

History, Current Status, and Prospects of Artificial Intelligence

The history of AI is often divided into multiple phases that characterize the field as defined by a particular research interest, or technological success. In this section, we briefly discuss these phases through the lens of understanding the role of AI in expertise. As a guideline, we follow the phases as distinguished by Nilsson (2009) and shown in Table 8.1. We finish the section with a phase describing our expectation for the future.

Early Days (1956–1974)

The field of artificial intelligence was founded during the legendary Dartmouth workshop in 1956. In the years that followed, the workshop participants (among others) developed many of the core techniques and ideas in AI that would continue to exist today. The first important idea was that knowledge could be represented symbolically (at the time referred to as a semantic network by Quillian (1963)), and logic could be used to reason over it. Another important idea was that knowledge could also be represented using a connectionist approach in an artificial neural network (at the time referred to as perceptron), being loosely inspired by the working of the human brain. The wide range of possibilities and various successful early prototypes, such as chess computers, and programs processing natural language led to high expectations of this new emerging field. Prominent researchers such as Herbert Simon and Marvin

Table 8.1 Phases of artificial intelligence (AI)

Years	Characterization of AI
1956–1974	Early days of symbolic reasoning
1974–1980	First AI winter
1980–1987	Expert systems
1987–1993	Second AI winter
1993–2011	Multi-agent systems and semantic web
2011–present	Big data and deep learning
Future paradigm of AI	Hybrid AI

Minsky predicted that AI would surpass human experts on selected tasks within a few decades.

However, progress was hampered by a number of problems. The first problem was the lack of computing power in early computers. The second problem was the burden of manual work required to engineer all the facts and rules required for intelligent reasoning. It gradually became apparent that general search strategies (so-called weak methods) were insufficient for attaining high levels of performance, and that these strategies needed to be complemented with a lot of domain knowledge. The third problem was that AI models turned out to be *brittle,* meaning that they only performed well on the limited scope they were designed for. The latter two problems were conceived as part of the research process: just as in other successful sciences like physics, basic principles should first be investigated using simplified models. Researchers focused on *micro worlds* (Minsky & Papert, 1972), which would be narrow at first, but could later be generalized to more realistic settings. This generalizability turned out to be problematic, hampering practical applications.

First AI Winter (1974–1980)

These problems, coupled with the unrealistically high expectations, led to what is generally called the first AI winter. Research funding was cut, and the general expectations of AI were dramatically lowered. Researchers came to realize that the problem of modeling intelligence in a computer was to be much harder than they initially thought.

Expert Systems (1980–1987)

Following the realization that weak methods were insufficient for realizing high levels of performance, researchers turned to ways of incorporating large amounts of domain knowledge into systems. These systems were called expert systems, as they were assumed to encapsulate the knowledge of experts in a particular domain. Expert systems were building on early insights in symbolic knowledge representation. Knowledge was represented using production rules (usually handcrafted by human experts), and a reasoning engine was applied to derive consequences given a set of facts. Popular applications were the medical domain (e.g., Mycin) and law. The goal was to "*incorporate the knowledge and expertise in computer programs, making the knowledge and expertise easily replicated, readily distributed, and essentially immortal*" (Davis, 1984, p. 18, our emphasis). Just as in the early days of AI, expectations were high (Bobrow, 1984).

Besides the progress in expert systems, significant advances were also made in the connectionist approach to AI due to the discovery of the multi-layer perceptron that solved one of the fundamental problems of the old perceptron model from the 1960s. However, these developments did not create as much enthusiasm as expert systems, and it was unclear how the two approaches could be combined. Additionally, the problems with expert systems were essentially the same as in the early days: brittleness, and burden of manual work. The main strategy to counter these threats was to limit the application to a narrowly defined topic, avoiding the need to model common-sense knowledge in the system. Another strategy was to try to enable end users to model the expert system rules. Nevertheless, expert systems did not live up to their expectations, and rarely made it out of the lab to real life usage (Leith, 2016).

Second AI Winter (1987–1993)

Similar to the first AI winter, the inability to live up to the high expectations caused a second AI winter. This led many researchers to look for a different paradigm. Some researchers argued for an entirely different approach, referring to the symbolic approach to AI as GOFAI (Good Old-Fashioned AI), which was perceived as fundamentally flawed (Brooks, 1990). Furthermore, the term expert system was replaced by *decision support system* to reflect a 'downscaled' ambition where the computer serves as a helper of a human expert instead of being an expert itself.

Multi-agent Systems and the Semantic Web (1993–2011)

Renewed hope in artificial intelligence was raised by a new technology that would fundamentally transform computer science: the internet. One development was multi-agent systems (MAS), which is a paradigm for distributed artificial intelligence. A MAS comprises multiple active AI-entities and lacks a single point of control and can therefore be considered as more robust (potentially overcoming the *brittleness* problem). Furthermore, it allows multiple developers to work on a system with little or no coordination. This was believed to be a potential solution for relieving the burden of work. Another new development was the semantic web, which was viewed as a next step in the evolution of symbolic knowledge representation. The novelty was that it was distributed. Ontologies serve as formal specifications of the conceptualizations that are shared between the knowledge sources (Gruber, 1993). Unfortunately, both MAS and the semantic web did not live up to their high expectations, and few practical applications resulted from it.

Big Data and Deep Learning (2011–Present)

The difficulties of MAS and the semantic web did not result in another AI winter. Large amounts of data (also known as 'big data') were created as a result of increased computer memory, sensor technology, and (again) the internet. Big data turned out to be a missing ingredient required to make the connectionist approach work. The large availability of data and computing power made it possible to develop deep neural networks (DNN) with up to one hundred million parameters that automatically optimize using machine learning techniques (many of which had already been discovered decades ago). Deep learning turned out to be very successful, leading to unprecedented outcomes such as superhuman performance on image classification tasks, game-playing such as the board game Go, and major breakthroughs in voice recognition and automatic language translation among many others. For the first time in history, AI became a huge commercial success, giving rise to billion-dollar industries in highly automated driving and data-analytics.

Not surprisingly, these successes revived speculations about the glorious future of AI, including the possible development of artificial general intelligence (AGI), and super intelligence (Bostrom, 2017). Many people believed that deep learning had finally solved the problem of brittleness and manual engineering, thus making all previous approaches in AI obsolete. With respect to the problems of brittleness and burden of manual work, there has certainly been progress. Advocates of end-to-end DNNs point out that feature extraction (e.g., extracting phonemes in audio) is no longer required. The raw features (e.g., the waveform itself) should be directly fed into the DNN, which should be trained to produce the output in one go. This bypasses the manual engineering of domain-specific feature extraction algorithms. Furthermore, it enhances performance, hence reducing brittleness. However, there are two main problems with this approach, which indicates a fundamental shortcoming of end-to-end deep learning.

First, deep learning requires a lot of data. For an image classifier, requiring one million training examples is common. The problem is that these images must be accompanied by a label. A label could, for example, state that a certain image qualifies as 'a cat' and another as 'a dog'. Because deep learning is a supervised learning algorithm, it requires these labels to learn. To obtain a label, a dataset usually requires humans to point out the area and indicate which type of object resides there. Whereas manually engineering a dataset for highly automated cars may be considered worth the effort, for more rare and specialized applications this burden of manual labeling work is often too large or simply not feasible.

A second problem with end-to-end DNNs is that they are no longer understandable by humans. The network cannot explain why it has reached a certain conclusion, which is problematic when humans have to judge the trustworthiness of an AI algorithm's outcome. Although much research is currently performed on explainable AI (Gunning & Aha, 2019), this research is still in its infancy and most likely requires more than a DNN to be solvable. Performing calculations with tens of millions of parameters, the functioning of a deep learning network is inherently incomprehensible to humans. This can lead to unexpected behaviors and errors. For example, researchers discovered that small perturbations in the input image (invisible to the human eye) could easily fool a neural image classifier (e.g., confusing a whale with a turtle) (Moosavi-Dezfooli, Fawzi, & Frossard, 2016). The network turned out to be brittle after all, but in a way that is totally unimaginable for humans and that could not be explained by the AI either.

Hybrid AI (The Future Paradigm of AI)

Whereas deep learning undoubtedly has proven its usefulness in pattern recognition tasks, many believe that the approach is not extendable to more complex tasks (Marcus & Davis, 2019). For example, consider an AI algorithm that could predict whether a business strategy will be successful or not. Imagine an end-to-end DNN that takes a description of a strategy and situation as input, and produces an output that labels the strategy as 'good' or 'bad'. As attractive as such a solution may seem, the data to train such a network are simply not available in the right format and quantity. Furthermore, the output will probably never be that black and white, requiring the algorithm to explain its advice, something which DNNs are inherently poor at.

While no one can predict the future, we believe that a future AI era will go beyond deep learning (Peeters et al., 2020). In fact, its contours are already beginning to take shape. In this era, AI will evolve into a hybrid of multiple connectionist AI techniques, symbolic approaches, and humans. By merging symbolic and connectionist approaches (van Harmelen & Teije, 2019), a hybrid AI system can be developed, which combines human-understandability and high-level reasoning with pattern recognition capabilities. Furthermore, humans will also become an essential part of the system fulfilling essential roles as bearers of responsibility, handling unexpected situations that the AI is incapable of deriving, and discovering causal relationships that are not discoverable by observing data alone (Pearl & Mackenzie, 2018).

History of Expertise Studies

In the 1950s and 1960s, research on expertise, particularly in the United States, was relatively scarce. Woodworth and Schlosberg's (1954) *Experimental Psychology* does not mention the topic at all. One of the few exceptions was the work on chess expertise by the Dutch psychologist Adriaan de Groot (1946, 1965). De Groot collected think-aloud protocols of chess players of varying expertise between 1938 and 1943. Although many at the time thought there would be large differences in the number of moves considered or the depth of search between grandmasters and amateurs, de Groot found no evidence for such differences. However, he did find differences in the speed with which complex board positions could be stored in memory and remembered correctly after being presented for only five seconds. Chess masters could correctly reconstruct positions of more than 20 pieces after just five seconds of study, whereas the amateurs could reconstruct only four or five pieces. Apparently, the chess masters were able to recognize meaningful patterns on the board, later called 'chunks', indicating that domain-specific chess knowledge was the determining factor in the observed difference between experts and beginners.

The work by de Groot turned out to be highly influential and foundational once it was translated into English in 1965. Around this time, research in AI reached a dead end in that it had failed to construct computer programs that could outperform humans (Feigenbaum, 1989; Glaser & Chi, 1988). The weak search methods implemented in these programs employed heuristics to prune exhaustive search trees, but to no avail. Although heuristics are knowledge, they are a form of general knowledge. Looking at this state of affairs with de Groot's findings in mind, researchers became aware of the importance of domain-specific knowledge in expertise. Chess masters don't differ from amateurs because of their efficient wielding of general search heuristics, but because of their large storage of knowledge of chess patterns and associated moves. Simon and Gilmartin (1973) estimated that masters have acquired on the order of 50,000 different chess patterns, that they can quickly recognize such patterns on a chessboard and that this ability is what underlies their superior performance in chess.

The 'classic expertise approach' (for an overview see Gobet, 2020) started with the originating work by Chase and Simon (1973) on chess at Carnegie-Mellon University in the early 1970s. This approach is characterized by detailed analyses of problem-solving processes by a relatively small number of participants, emphasis on content, and use of computer programs to express theories. Chase and Simon also introduced a variation on de Groot's memory task, basically serving as a control condition: apart from presenting actual board configurations, participants were also given random board configurations. In the latter case, no differences were observed between experts and beginners (Chase & Simon, 1973). This showed that the results obtained with actual board configurations were not due to superior visual memory for isolated pieces, but rather depended critically upon the 'meaning' of the constellations of pieces ('chunks'). This research spawned a flurry of experimental papers in the late 1970s and early 1980s that would be summarized by Anderson (1981) and Chi, Glaser, and Farr (1988). Not only was the skill effect in the memory recall task replicated in several domains, but it was also found that experts see and represent a problem in their domain at a deeper (more principled) level than novices (Chi, Feltovich, & Glaser, 1981).

In 1991, Holyoak asserted that "[t]heories of expertise have now passed through two generations" (p. 301). The first generation viewed expertise as essentially a problem-solving activity that employed general heuristic search methods (akin to the 'weak methods' discussed previously) to a broad range of domains. However, in the 1970s and early 1980s, it became clear that expertise depended crucially on extensive domain knowledge and was therefore limited in scope and did not transfer across domains (for an overview see Feltovich, Prietula, & Anders Ericsson, 2006). Interestingly, the field of AI had gone through a similar major shift in focus in the 1966–1976 period, essentially moving from a search paradigm to a knowledge-based one (Goldstein & Papert, 1977), culminating in the heyday of highly domain-specific expert systems (Feigenbaum, McCorduck, & Nii, 1988). It seemed clear from all of this research that "knowledge is power" (Feigenbaum, 1989), which captured the essence of the second generation of theories of expertise.

Yet, in 1991, Holyoak listed numerous empirical findings that were at odds with the second generation of expertise theories. He found that experts were much more flexible than previously thought and summarized his findings by stating that "[i]n general, an expert will have succeeded in adapting to the inherent constraints of the task" (Holyoak, 1991, p. 309). In other words, rather than reliably attaining specific goals within a specific domain (the second-generation definition of 'routine expertise'), expertise should be viewed as the ability to make an appropriate response to a situation that contains a degree of unpredictability. The latter definition of expertise was first advanced by Hatano and Inagaki (1986) and was called adaptive expertise. Holyoak (1991) went on to outline a connectionist view of expertise. However, he did not convincingly demonstrate that a symbolic connectionist approach could explain the empirical findings that were at odds with the second-generation theories of expertise and this approach to expertise was not taken up widely (it may have been before its time). In fact, the classic expertise approach has remained one of the dominant approaches to expertise (Gobet, 2020) and has been extended to expert decision making in real-world situations in the field of Naturalistic Decision Making (see Schraagen, 2018, for how this field relates to the theoretical foundations laid by the classic approach to expertise). In the field of Human Resource Development, the classic expertise approach, with its focus on knowledge, experience, and problem solving, has been extended with subjective characteristics that are perceived by someone else as an indication of an expert's knowledge, abilities, or skills, for instance, being motivated, self-confident, or having high interpersonal skills (Germain, 2006; Germain & Tejeda, 2012; Grenier & Germain, 2014).

Currently, there is no single overarching and commonly accepted definition of expertise. In the recent *Oxford Handbook of Expertise*, Ward et al. (2020) distinguish many communities of practice that all use the word expertise in different ways. Apart from the classic expertise approach, the Cognitive Systems Engineering community of practice offers perhaps the most distinctive alternative. It does not view expertise as an individual phenomenon or a particular stage of information processing, as the classic expertise approach, but rather as a coupling between an expert with a problem ecology through a representation. In this view, expertise is a matter of sensitivity to environmental constraints and opportunities.

The pendulum on the generality-specificity dimension has therefore swung back to some extent, and many researchers now view expertise as "skilled adaptation to complexity and novelty" (Ward, Gore, Hutton, Conway, & Hoffman, 2018), therefore stressing generality somewhat more than specificity. Research has confirmed the importance of conscious, analytical reasoning (as an instance of skilled adaptation or flexibility) in experts, but only when confronted with complex, atypical problems (Mamede et al., 2010; Moxley, Anders Ericsson, Charness, & Krampe, 2012). When having to solve simple problems, experts use a recognitional strategy, as predicted by the classic expertise approach, and the first option considered is usually the best (e.g., Johnson & Raab, 2003; Klein, Wolf, Militello, & Zsambok, 1995). The importance of a flexible and adaptive skill capacity (e.g., flexible sensemaking and flexible action execution) will only increase as the societal and human-technological challenges ahead of us proliferate.

Interestingly, whereas flexibility and adaptation are prominent concepts in current conceptualizations of expertise, current conceptualizations of AI still focus on attaining specific goals within a specific domain. Most AI systems of note have so far achieved world-class performance in specific domains such as the competitive games of chess (Campbell, Hoane Jr., & Hsu, 2002), Go (Silver et al., 2017), Jeopardy (Chen, Elenee Argentinis, & Weber, 2016; Ferrucci, 2012), and Poker (Brown & Sandholm, 2018). Nevertheless, they are still far away from what is sometimes referred to as Artificial General Intelligence (AGI), meaning that it can perform any intellectual task that a human can. Having discussed the history of both AI and expertise studies, we will now turn to studies on 'joint cognitive systems', in which experts and intelligent systems are viewed as pairs that work together to achieve particular goals.

Empirical Research on Joint Cognitive Systems

An early example of an empirical study on the coupling of human intelligence and machine power is the study by Roth, Bennett, and Woods (1987) on technicians diagnosing faults with the aid of an expert system. The expert system was developed according to what the authors refer to as a prosthesis paradigm, which may be contrasted with a cognitive instrument paradigm. In the cognitive tool as a prosthesis paradigm, "[t]he machine expert guides all problem solving activities dictating what observations and actions the user is to take to solve the problem" (Roth et al., 1987, p. 480). The expert system is considered a prosthesis in the sense that it presumably compensates for human deficiencies in generating hypotheses and the human is relegated to the role of passive data gatherer and action implementer in order to serve the machine's needs.

The study showed that those technicians who were actively involved in the troubleshooting process not only achieved faster and better solutions, but also coped better with unanticipated variability, monitored the machine's behavior, recognized unproductive paths, and redirected the machine to more productive paths. Technicians who passively followed the machine's instructions dwelled on unproductive paths and reached dead-ends more often. It turned out that one of the six problems presented to the technicians was unsolvable due to a bug in the expert system's knowledge base. Substantive interventions by the knowledge engineer were also required to point out input errors or redirect the diagnosis. Technicians varied widely in how they approached the problem and substantial deviations from the canonical path arose even when the problem was solved correctly. It turned out that technicians needed knowledge of the structure and function of the device in order to follow underspecified instructions by the expert system, to infer machine intentions, to resolve impasses, and to recover from errors that led the expert system off-track (once off-track, it could not recover by itself and needed human help to be directed back to a more productive path). In brief, the expert system was not observable, predictable, and directable by the human expert.

The machine-as-prosthesis paradigm results in typical breakdowns in performance whenever humans are assigned the passive role of following instructions. Alternatively, cognitive tools can also be viewed as instruments that support effective performance in any environment. This instrumental view of tools is very much in alignment with the view of expertise as skilled adaptation to complexity and novelty. Tools as instruments should enhance a human problem solver's adaptability to the unanticipated variability that inevitably arises in the pursuit of domain goals. The problem solver is in charge, the AI tool functions more as a staff member providing knowledge resources.

This example of a joint cognitive system focused on a single human and a single system, even though it became clear during this particular research project that the scope had to be extended to include the knowledge engineer and two observers who could help and guide the technician where necessary. Later research on joint cognitive systems extended to multiple experts cooperating with multiple intelligent systems. One typical domain would be automation in the airplane cockpit, where the cockpit crew needs to cooperate with numerous automated systems. Not all these systems qualify as artificial intelligence, as some of them hardly 'interpret information' or 'reason based on knowledge', but that is beside the point here. The point that we want to make, and that has been stated repeatedly by the field of Cognitive Systems Engineering (e.g., Woods, Dekker, Cook, Johannesen, & Sarter, 2010; Woods & Hollnagel, 2006), is that a clumsy use of technology is about miscoordination between the human and machine portion of a single ensemble (Christoffersen & Woods, 2002). Automation and people have to coordinate as a joint system, a single team (Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004). Breakdown in this team's coordination is an important path toward disaster, as can be seen vividly in the Air France Flight 447 disaster (2009) or the Lion Air (2018) and Ethiopian Air (2019) crashes involving the Boeing 737 Max MCAS system.

In essence, what happens with many (cockpit) automation projects is that systems are designed to operate in a multitude of modes, and mode changes are not always communicated clearly to operators. Mode errors occur when an operator executes an intention that is appropriate for one mode, when in fact the system is in a different mode. For instance, when a pilot enters the correct digits for a planned descent (e.g., '33', intending to mean an angle of descent of 3.3 degrees), this may be interpreted by the automation (being in a different descend mode than the pilot thinks) as a rate of descent of 3300 feet per minute. This particular mode error occurred with Air Inter Flight 148 in 1992 near Strasbourg, France, killing 87 of the 96 people on board. On a more day-to-day level, cruise control systems in cars provide opportunities for mode errors as well. For instance, one may manually override the speed set by the cruise control by pressing the gas pedal for a while, then forgetting about the cruise control being engaged, only to be reminded of it when releasing the gas pedal and letting the car gradually slow down. If one's intention was to slow down to zero mile per hour, the cruise control would suddenly kick in at the set speed, and one will experience an 'automation surprise' (Sarter & Woods, 1995), much like pilots in a cockpit. Drivers may also believe that the cruise control is engaged, when in fact it is only on. How the various modes are communicated to the driver is highly dependent on the particular cruise control interface, and different car manufacturers have different ways of resolving this issue.

Mode errors are only one example of where automation has not lived up to its promise. Other examples are clumsy automation (Wiener, 1989) where automation creates new coordination demands precisely at the very time when practitioners are most in need of true assistance, overreliance on technology (Billings, 1991) where operators rely on systems when in fact those systems cannot cope, as they are outside their competence envelope, and deskilling (Bainbridge, 1983) where operators gradually lose manual skills as they increasingly depend upon automation. Underlying these problems with automation are several misconceptions regarding the way tasks are to be distributed among people and technology (Bradshaw, Hoffman, Johnson, & Woods, 2013):

1. Compensation: machines have strong points that compensate for weak points of humans;
2. Substitution: tasks can be automated without consequences; hence human tasks can be replaced with machine tasks;
3. Automation: automation is autonomous;
4. Allocation: tasks can be neatly divided into parts and assigned to either a human or a machine (not both at the same time); and
5. Workload and productivity: more automation leads to fewer people, hence fewer errors, hence lower costs, but with higher productivity.

Many of the current discussions around AI can be framed as novel instantiations of the same discussions on automation: if one replaces 'machine' or 'automation' with 'AI' in the misconceptions above, one would find themselves in the same position as cognitive engineers in the

1980s and 1990s. Many of the lessons learned then with automation still apply in the case of AI, even though the empirical evidence is still unavailable. The following arguments may be advanced in response to some of the misconceptions:

1. Compensation: machines/AI are good at certain things and people are good at certain things, but that does not change the fundamental interdependence between the two. Team play with people and AI is critical to success. No matter how much information the AI processes, humans must trust the conclusions because they are ultimately responsible. Therefore, AI needs to explain itself.
2. Substitution: practice is transformed by automation and the roles of people change. This may not always be obvious from an outsider's perspective, due to the Law of Fluency that states that 'well'-adapted work occurs with a facility that belies the difficulty of the demands resolved and the dilemmas balanced (Woods & Hollnagel, 2006). In other words, when an outsider studies work that seems to be well-adapted, what remains hidden from view are the numerous ways in which humans have coped with complexity and the various trade-offs they had to make. As the constraints adapted to are hidden from view, the work may actually not be so 'well'-adapted. Humans will adapt to changes in the tasks as a result of automation, but that adaptation comes at a price, for instance deskilling, increased monitoring, or increased coordination. These vulnerabilities will become apparent when situational demands increase, and surprise events occur.
3. Automation: Machines are self-sufficient only up to a certain extent and only in particular circumstances. Surprise is continuous and ever-present. There is always the need to close the gap between the demonstration and the real thing (Woods, 2016). This requires new methods to assess brittleness, for instance the turnaround test—how much work does it take to get a system ready to handle the next mission/case/environment, when the next is not a simple parametric variation of the previous demonstration (Woods, 2016)? As a second rebuttal, it has recently been claimed that "no AI is an island" (Johnson & Vera, 2019). According to Johnson and Vera (2019), AI will reach its full potential only if, as part of its intelligence, it also has enough

teaming intelligence to work well with people. Although seemingly counterintuitive, the more intelligent the technological system, the greater the need for collaborative skills.

4. Allocation: reality shows that tasks are always interdependent, and humans and machines/AI always need to cooperate. When tasks are divided into parts, the interdependencies are frequently overlooked. The easiest subtask is then automated and the other subtasks are ignored. The moment the machine can no longer perform its subtask, as surprise is continuous, control is suddenly transferred to a human being who then experiences an 'automation surprise'.
5. Workload and productivity: according to the Law of Stretched Systems (Woods & Hollnagel, 2006), automation is always exploited fully, requiring people to do more, do it faster, or in more complex ways, thereby increasing rather than decreasing workload. Also, new types of cognitive work are being created, often at the wrong moments ('clumsy automation'), which leads to new types of errors.

This discussion on research on joint cognitive systems has prepared us for a discussion of how AI could enhance (or degrade) human expertise in various settings. In this next section, we illustrate the general principles we have described through a case study.

Case Study: Radiology

The modern work practice of radiology involves several healthcare professions working together as a team. A radiologist is a medical doctor who interprets medical images, communicates these findings to other physicians, and performs medical procedures using imaging. The radiographer produces medical images for the radiologist to interpret. The nurse is involved in patient care before and after imaging or procedures. It is clear that teamwork is vital, with a lot of interdependencies between various healthcare professions. Also, a variety of imaging techniques are used: radiographs (X-ray imaging), ultrasound, computed tomography, magnetic resonance imaging, and nuclear medicine. Each of these techniques requires specific expertise in terms of preconditions for use and sensitivity of data.

Radiological expertise not only involves a substantial perceptual component, but also involves the integration of several distinct bodies of knowledge with separate organizing principles, including physiology, anatomy, medical theories of disease, and the projective geometry of radiography (Lesgold et al., 1988). Lesgold and colleagues found that expert radiologists, when examining radiographs, would quickly (within two seconds) invoke a diagnosis schema that has prerequisites or tests that must be satisfied before it can control the diagnosis and viewing. The patient's anatomy is constructed as the schemata are applied. The expert works efficiently to reach the stage where an appropriate general schema is in control. When a schema does not fit the data, it is discarded quickly. On the other hand, schemata also drive perception by setting hypotheses on what to expect in an image. Each schema contains a set of processes that allows the viewer to reach a diagnosis and confirm it. The expert works both bottom-up, data-driven, as well as top-down, schema-driven, in a continuous cycle. This confirms the general picture of expertise we outlined, as it includes both recognitional decision making, based on a large and diverse memory for exemplars (Norman, Coblentz, Brooks, & Babcook, 1992), and being flexible and adaptive, but with more resource-intensive reasoning components, with the latter being employed in more difficult cases (Patel, Kaufman, & Kannampallil, 2020).

Over the last decade, modern AI technologies (particularly deep learning) have caused breakthrough successes in almost all areas of AI-assisted radiology. Examples include detecting and segmenting lung cancer tumors in radiographs, interpretation of MRI scans, and monitoring disease progress. For some of these tasks, AI achieved human level performance or better (Hosny, Parmar, Quackenbush, Schwartz, & Aerts, 2018). Despite the wide range of opportunities, these systems have not yet been implemented in clinical radiology practice. The earliest applications can be expected in areas where abundant high-quality-labeled data are available and concern tasks that currently overload human experts (such as in the detection of tumors in radiographs).

It is becoming clear that the introduction of this type of AI automation will not replace humans, but rather will lead to new workflows and create new roles for humans, requiring different human expertise. We can expect the following types of task-changes in an AI-assisted radiology workflow:

AI-replacement tasks that are completely taken over by the AI. These are subtasks in the radiology workflow at which the AI consistently performs as well as or better than humans. Examples are the visual interpretation of radiology images by deep learning image classifiers. This will result in deskilling of existing radiology personnel and relieve training requirements of new radiologists from having to acquire this skill.

AI-augmentation tasks where the AI system augments humans. These are tasks for which the AI (e.g., due to brittleness) sometimes makes mistakes that can be repaired by humans. An example of this is planning a patient's treatment. Whereas AI can help in monitoring the effects of past treatments, it is highly unlikely that a treatment plan is finalized without any human oversight. For these tasks humans are needed to recognize and deal with abnormal and rare cases. This requires that humans maintain the expertise of this task and acquire additional expertise on how to use the AI support system. Also, the AI support system must be capable of explaining its advice to humans such that they can judge its trustworthiness.

AI-maintenance tasks are added to the radiology workflow that did not exist before. These have to do with maintaining the AI systems, and require a whole new set of skills. Examples of these are (re-)training the AI system, understanding the complications of introducing new hardware on the AI performance, training human personnel to use the AI system, and so on.

Despite the fact that humans will not be fully replaced, the efficiency (in terms of human labor) of radiology practice will undoubtedly increase due to the introduction of AI. However, these efficiency gains may well be compensated by a higher standard of healthcare, such as requiring more frequent health checkups.

Summarizing the trends in radiology, we can see that the hybrid AI principle, where different forms of AI work together with experts is the most appropriate vision. These different forms of collaboration will require different skills. Daugherty and Wilson (2018) refer to these skills as fusion skills, as they draw on the fusion of human and machine talents within a business process to create better outcomes than working independently. For instance, *rehumanizing time* is a fusion skill that allows people to skillfully redirect their time toward more human activities. Particularly in medicine, physicians could greatly benefit from AI taking over visual interpretation of radiology images, as it would give them more time to see their patients or coordinate with other physicians. Other fusion skills involve knowing how best to ask questions of AI to get the insights you need, the ability to develop robust mental models of AI agents to improve process outcomes, and the ability to decide a course of action when a machine is uncertain about what to do.

Conclusion

Our review of the history of expertise studies with the history of AI has converged on a number of common themes. First, expertise is currently viewed as a skilled adaptation to complexity and novelty. This is not to diminish the importance of pattern-recognition capabilities amassed during extensive periods of deliberate practice. Rather, it is recognized that adaptation to complexity and novelty can only be skilled as a result of extensive practice. Second, although the current interest in AI largely focuses on machine learning capabilities there are a number of problems associated with that approach. First, machine learning approaches using deep neural networks cannot explain themselves to humans. This is crucial, particularly when experts need to work with these systems. Second, these approaches result in brittle systems that can easily be attacked or that do not work in unforeseen scenarios.

The history of joint cognitive systems has shown that viewing machines as prostheses results in breakdowns in performance, whereas viewing machines as tools or instruments aids in adapting to unanticipated variability. We have argued for a future of Hybrid AI in which expertise will be distributed across experts and AI in various ways. The example of radiology has shown that the introduction of AI capabilities may have various consequences, ranging from replacement, to augmentation, to maintenance of human expertise. It may well be the case that pattern recognition capabilities of AI systems will exceed human expertise (they already do so in restricted task domains). Yet, in order to be able to effectively collaborate with human experts, AI will need collaborative skills, such as being able to explain itself to human experts. This is an area that is still being researched. Simultaneously, human flexibility and adaptation will increasingly be required to deal with unanticipated variability and surprise situations. Human expertise will be needed to close the gap between the demonstration and the real thing (Woods, 2016). This is in line with recent views on expertise that stress skilled adaptation to complexity and novelty.

Finally, the introduction of AI will also result in a whole series of new skills that human experts need to develop in order to deal with AI. We have discussed a few of these fusion skills (Daugherty & Wilson, 2018), but there are likely to be many more that we cannot foresee. AI systems will hardly ever stand alone in a work process and will therefore need intricate tuning to human demands at various points in time. Such systems will need to be trained, validated, understood, explained, assisted, and overruled if experts want to accept them and be able to effectively work with them.

This chapter has shown that it is a gross oversimplification to consider AI systems and human expertise as two mutually exclusive entities, with one taking over the other without changing anything in the work process. Rather, we need to view this from a joint cognitive systems perspective, at a systems level and as dynamically changing over time. Only then will we be able to see the intricacies of the mutual dependencies between humans and AI, and the constantly evolving distribution of skill sets that are required from an organizational perspective. There is a bright future for experts working jointly and collaboratively with AI systems in organizations.

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9

The Impact of Changing Workforce Demographics and Dependency on Technology on Employers' Need for Expert Skills

Marie-Line Germain

This chapter examines how workforce demographics and technology are impacting how human expertise is perceived and defined. First, it focuses on the changing composition of the U.S. workforce, which is increasingly more diverse compared to previous decades (in educational attainment, age, gender, and race). It looks at how this diversity has changed the typical profile of today's CEOs and entrepreneurs. Second, it explains how the digital revolution and the exponential use of artificial intelligence in the workplace have created new demands in labor needs and employee skills in for-profit and nonprofit organizations. The author posits that the combination of these changes is reshaping how human expertise is perceived and defined, especially in technology fields.

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Workforce demographics, needs, and employer expectations have changed considerably since the 1990s. This continued change results from an evolving economy, globalization, rapid technological development, and a generational mix of Baby Boomers, Generation X, Millennials, and Generation Z. In 2020, for the first time in history, the global population of adults over the age of 65 is going to surpass that of children under the age of 5 (Friend, 2017) and in only 16 years' time (2014–2030), it is expected to grow by 300 million (United Nations, 2020). Such trends can be attributed to a decreased fertility rate and an increased life expectancy. In the U.S., the workforce profile has also changed significantly. The total number of participants in the labor force has continued to increase due to a growth in population; however, according to the U.S. Bureau of Labor Statistics (2019), the labor force participation rate has decreased since 2015 and it is estimated that, by 2026, it will decline to 60% (US BLS, 2019). Also, today's workforce is generationally diverse in workers' gender, race, education, and age. Most organizations have three generations on staff, each with its own set of work values and skills: Baby Boomers, Gen Xers, Millennials, and Gen Zs (see Table 9.1), with women representing about half of the workforce. The changes in workers' race reflect those of the general U.S. population, with an increasing representation of Hispanic and Asian workers. Finally, the workforce is more educated. More people complete secondary education than ever before, attend universities, and take advantage of mid-career reskilling or credentialing (Buckley & Bachman, 2017). In 1992, only 25% of Americans held a bachelor's degree versus 40% in 2017 and it is expected that by 2025, two-thirds of the U.S. labor force will have post-high school education (Buckley & Bachman, 2017).

The workforce demographic changes are seen at all levels of the organization, including in the corporate suite (C-suite). Yet, in 2019, top executives continued to be less diverse than the rest of the labor force (Roberts & Mayo, 2019). In the 1990s, 50% of CEOs had a bachelor's degree (versus 97% today), and 49% had obtained a master's or doctoral degree (versus 74% today). Between 1995 and 1999, women CEOs represented an average of 0.28% of CEOs versus 6% today (Pew Research Center, 2018). In 2004, 27 of the top companies had a racial minority CEO compared to 62 companies in 2019 (Statista, 2019). Also, in the

Table 9.1 Work values and skills by generation

Baby Boomers (1946–1964)	Generation X (1965–1980)	Millennials (1981–1995)	Generation Z (1996–)
Lived to work	Worked to live	Means to an end	Money and salary matter a great deal but want personalized career experiences. Gen Z prioritizes diversity, tech, and the greater good
Developed skills to enhance work at one company	Gained skills that would lead them to the next job	Gain skills that would make them more of an asset, better contributor, more well-rounded worker	Organizations need to tailor work around the curated skill set of a Gen Z worker. Organizations should invest in learning and skill/capability development. Gen Z proactively seeks out learning opportunities to enhance skills and prefers to learn independently via online platforms, such as online tutorials
Work ethic was valued as more important than acquiring new skills	Skills were more important than work ethic. They gained more skills through education and experiences within and outside of the company	Creativity and passion, along with job satisfaction remain of high importance. Skills could be obtained from a diverse arena	Draw on skill sets from diverging fields. Consider a traditional four-year college education more important than ever before.

(*continued*)

Table 9.1 (continued)

Baby Boomers (1946–1964)	Generation X (1965–1980)	Millennials (1981–1995)	Generation Z (1996–)
Loyal to the company	More loyal to themselves	Loyal to their cause	Expects to stay at a company for less time than Millennials. Want to work at organizations whose values align with their own. Want diverse and entrepreneurial opportunities with the safety of stable employment, and they may offer more loyalty to companies that can offer this.
Skills are an ingredient to success but they are not as important as work ethic and "in-person" time	Accumulation of skills will lead to the next job; the more they know the better. Work ethic is important, but not as much as skills	Training is important and new skills will ease stressful situations. Motivated by learning / want to see immediate results	Most diverse and highly educated generation. Want to gather a variety of different skill sets, rather than declaring a singular specialization (marketing majors want coding and data analytic skills; computer programmers want literature and creative skills).

Adapted from "Generational Differences Chart", (n.d.). *West Midland Family Center and* "Welcome to Generation Z" (Gomez, Mawhinney, & Bett, 2020)

1990s, the average age of chief executive officers was 56.4, with a tenure of 8.3 years. According to a Crist Kolder and Associates' Volatility Report, in 2019, over half of CEOs in Fortune 500 and S&P 500 companies were between the ages of 54 and 61.

These changes directly affect the stereotypical image of CEOs and entrepreneurs of a white, educated male above the age of 40 (Entrepreneur, 2018). Based on U.S. Census Bureau data, the Harvard Business Review (HBR) found that the average founding age of entrepreneurs is 42

(Azoulay, Jones, Kim, & Miranda, 2018). In the tech industry, starters are often younger, reflecting their tendency to be more tech-savvy consumers (Azoulay et al., 2018). In fact, common stereotypes surrounding modern entrepreneurship, especially among successful and high-tech businesses, revolve around youth. Surveying a decade of *TechCrunch* award winners revealed that the average age of a founder of a tech company is 31, and the Inc. Magazine's 2015 fastest growing startup list presented an average founder age of only 29 (Azoulay et al., 2018). A 2017 article from *The New Yorker* describes this market as one that "discourage(s) a 'stale degree' and demand(s) a 'digital native' who's a 'culture fit' – sift(ing) for youth" (Friend, 2017, para. 4). This is widely believed, in part because of a cultural phenomenon drawn from buzzworthy quotes from young founders and accolades which seemingly reward youth. On the other hand, in non-tech fields such as hospitality or manufacturing, research points to an older, mid-career average age for founders. In fields such as engineering or biotechnology, the average founder age is 47 (Azoulay et al., 2018). University of Chicago economist David Galeson posits that "experimental geniuses" need more time for research, trial and error, and highly advanced degrees while "conceptual geniuses" may succeed earlier (Freedman, 2012).

In addition to entrepreneurs, senior leadership is also seeing a shift to younger individuals (Pressentin, 2017). As large swaths of Baby Boomers retire, organizations are seeking Millennials and Gen Zs to fill key leadership roles, including CEO positions. Both younger entrepreneurs and CEOs are more educated than their older counterparts, highly skilled, globally focused, and able to balance their use of technological and human skills. If CEOs are considered at the top of their profession, as are experts, the question of whether expertise is changing, too, is legitimate.

New Demands for Employee Skills in Profit Versus Nonprofit Organizations

The Institute for the Future (2011) has identified ten skills for the future workforce: sense-making, social-intelligence, novel and adaptive thinking, cross-cultural competency, computation thinking, new-media literacy, transdisciplinary, design mindset, cognitive load management, and virtual collaboration. Additionally, advancements in artificial intelligence and robotics will require that employees be increasingly technologically savvy. Ongoing new advancements in technology continue to lead to drastic changes in the skills organizations need from employees (Pilenzo, 1989, p. 94). Before the internet age of the 2000s, employers did not expect employees to be digitally literate, creative everywhere and anytime, or excel in soft skills. They sought employees who mastered writing skills, communication, and teamwork. Today, some of the employability skills include soft skills such as a good work ethic, appropriate social behavior, reliability, and individuals with a good attitude (Indeed, 2020). Soft skills also include adaptability, communication, teamwork, decision making, time management, flexibility, problem-solving, and critical thinking (The Balance Careers, 2019). The five most important soft skills companies need the most in 2020 are creativity, persuasion, collaboration, adaptability, and emotional intelligence. Skills such as ethics, effective communication, time management, problem-solving skills, leadership, customer service, and decision making outweighed hard skills such as grant writing and marketing. According to a LinkedIn survey, creativity and persuasion were the top two needed soft skills in 2019 (Petrone, 2019). Furthermore, recruiters seek candidates with specific knowledge and hard skills. Hard skills are skills required to perform a job and are typically gained through formal education and training or from past work experience.

Both the for-profit and nonprofit sectors seem to follow these trends in needed skills. The differences in employability skills between for-profit and nonprofit organizations are shown in Table 9.2.

Although both for-profit and nonprofit organizations value employees who have hard and soft skills, nonprofits place less emphasis on hard skills such as grant writing, online marketing, and branding expertise (Rodriguez, n.d.). Indeed, in 2013, Hoefer, Watson, and Preble studied the preferred skills and educational degrees of executive directors (ED) and chief executive officers (CEO) in nonprofit human services. Their findings indicate that soft skills are rated higher than hard skills for EDs and CEOs (Indeed, 2020). In a 2019 global trend report, LinkedIn also found that 92% of companies surveyed believed that soft skills mattered

Table 9.2 Employability skills in for-profit and nonprofit organizations

For profit	Nonprofit
Hard skills (emphasis on software management, foreign languages, and operation of machinery)	Hard skills (emphasis on grant writing and direct service skills, such as teaching, counseling, and medical care)
Soft skills (communication, time management, problem-solving, and leadership are most desired)	More soft skills (i.e., fundraising and campaigning, communication and time management and desirable along with creativity, flexibility, and the ability to work with diverse groups)
Education and work experience	Leadership and ethics
People skills	Less emphasis on hard skills
Adaptability and time management	Budgeting

the same as, or more than, hard skills, with 80% believing that soft skills are important to a company's success.

The findings of Campbell & Company, an organization dedicated to helping nonprofits, challenge those of Hoefer, Watson, and Preble (2013). In December 2017, while the company claimed that hard skills such as campaigning, fundraising experience, and strategic and financial planning were in demand for the positions of chief development officers (CDO) and chief executive officers (CEO) in 2018, they considered emotional intelligence and empathy essential skills to create the right conditions for creativity and innovation (McFeely, 2017).

When corrected for the size of organizations, only one hard skill is tied with the desired characteristic of decision making: budgeting (Petrone, 2019). As more nonprofits continue to see an increase in corporate to nonprofit crossovers (C&C, 2019), emotional intelligence will not outweigh heavy fundraising experience (C&C, 2019). Such findings further confirmed the importance of soft skills such as communication, relationship development, management, leadership development, and integrity (Hoefer et al., 2013). This means that candidates who are "flexible, innovative, and [enjoy] meaningful work" (Rodriguez, n.d.) are highly sought after in the nonprofit sector. Surveys have also shown that the "Millennial advantage" can be extremely beneficial for nonprofit organizations. As shown in Fig. 9.1, behavioral skills such as flexibility, agility, ability to prioritize, working well with others and communication are the most

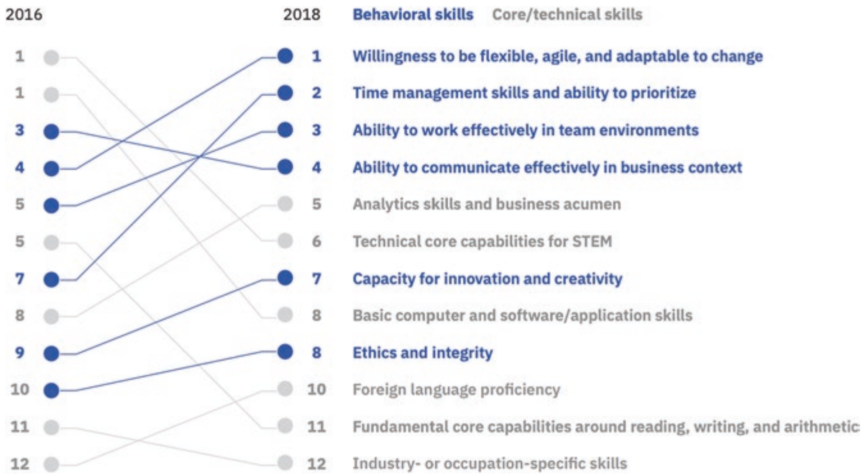

Fig. 9.1 Behavioral skills as most critical for today's workforce members. (Source: 2016 IBM Institute for Business Value Global Skills Survey; 2018 IBM Institute for Business Value Global Country Survey. (Used with permission))

critical for members of the workforce (LaPrade, Mertens, Moore, & Wright, 2019).

In today's competitive market, both for-profit and nonprofit organizations must find people who can make their company stand out. Candidates for employment should expect to "wear a lot of hats instead of doing the same tasks day-after-day" (Anderson, 2020).Overall, hard skills may remain essential in both the for-profit and nonprofit sectors, but there is strong evidence to support an upward trend in soft skills as 92% of employers deemed soft skills as growing in importance (CareerBuilder, 2019). Additionally, the ability to be trained is critical, as CareerBuilder found in 2019. Fifty-nine percent of the employers surveyed were willing to hire underqualified candidates that showed potential.

While the labor force is becoming more educated, we are also seeing a decline in the value of education attained. A 2019 study from economists at UCLA and the Pontificia Universidad Católica de Chile claims that the average income of high school graduates has declined 12% during the past 40 years and that the value of a high school degree has declined along with a loss of manufacturing jobs and an increase in low-wage service jobs (Fuentes & Leamer, 2019). Some sectors such as technology have seen education devalue rapidly in the years after graduation (Charette, 2013) and the speed at which professional skills become obsolete is increasing. The half-life of professional skills was once estimated at 10 to 15 years, meaning that the value of those skills would decline by half—or half the knowledge associated with the skills would become irrelevant—in a decade or so. Today, the half-life of a learned skill is estimated to be five years and even shorter for technical skills, meaning that a skill learned today will be about half as valuable in just five years or less (LaPrade et al., 2019). The knowledge half-life of software engineers is even shorter, with an estimated three years (Friend, 2017). This very short knowledge life change may impact how we define the knowledge component of human expertise, especially in the tech field.

The impact of the demographic changes and the half-life knowledge findings on the construct of expertise is three-fold: First, employee experience may not be as valuable as it was a few decades ago. As aforementioned, entrepreneurs and those employed in tech-related fields are much younger than in previous generations. What seems to be valuable to tech companies are specific skills and the desire to grow as an employee, not the "10,000 hours" of experience rule that has defined expertise (Ericsson, Krampe, & Tesch-Römer, 1993). Second, education is seen as a more negotiable qualification for some jobs. Rather, organizations value employees who are creative, adaptable to swift changes, and who are able to learn quickly. This may impact the knowledge dimension of expertise. Finally, the pace at which tech companies evolve organically excludes those with accrued knowledge in one specific domain. Also, because products and services encompass more than one domain, employers seek individuals who are curious about various subjects. Gen Z employees respond well to this requirement as they want to gather a variety of different skill sets rather than declaring a single subject (Gomez et al., 2020). This represents a significant shift for the definition of human expertise, especially for the longstanding belief that it is domain-specific.

1990 to 2025: A Changing Definition of Expertise

The changes in workforce demographics, the increasing use of technology, and the subsequent changes in the employee skills organizations need to remain competitive have influenced how expertise has been perceived and defined over the past three decades. Table 9.3 presents some changes in how expertise has been defined since the 1990s.

Artificial Intelligence and Employee Expertise

In this chapter, I have defined the construct of expertise as a combination of knowledge, experience, problem-solving skills, and behaviors. Artificial intelligence is defined as an intelligence demonstrated by machines, unlike the natural intelligence of humans. As artificial intelligence continues to change the nature of work, the question of whether or not the capabilities of AI will surpass that of humans and negate the need for human expertise becomes relevant. This section compares each dimension of expertise to artificial intelligence.

Table 9.3 Changes in expertise

	1990s	2020–2025
Knowledge	Depth Developed slowly Long half-life ~ 10 years	Depth and breadth of knowledge Constant upskill Short half-life ~ 3 years
Level of education	Bachelor's degrees: 17.2% Advanced degrees: 9.3%	Bachelor's degrees: 24.2% Advanced degrees: 14.7% (expected increase to 22% in 2026)
Number of jobs	1 or 2	4 to 5
Type of role and skills	Single discipline Functional skills	Multidisciplinary Hybrid functional skills
Organizational structure	Hierarchical	Flattened, with a focus on cross-functional teams and networks

Knowledge

Humans possess many types of knowledge: implicit, explicit, formal, informal, deep and shallow knowledge, along with the ability to multitask (Swanson & Holton, 2009). The algorithms necessary for AI analyze human-generated datasets and have the capability to retain unbiased knowledge in high volumes (SAS, 2020), but it is only through data. Although AI may outperform human knowledge in capacity and processing speed, at its core, AI systems are reliant on humans for knowledge through the input of data.

Experience

Humans and AI gain experience in different ways. Human experience is gathered over time, throughout a person's life. It is dependent on the type, the quality, and the quantity of events experienced by an individual. According to Swanson and Holton (2009), "When specifically related to the development of human expertise, experience is an interactive component that is heavily dependent upon the type and quality, as well as the quantity, of the events experienced by the individual" (2009, p. 263). In contrast, AI gathers experience through the analysis of vast amounts of data (SAS, 2020) and is dependent on the analysis of input of human-generated data.

Problem-Solving

The ability to solve problems has been identified as a key component of human expertise (Swanson & Holton, 2009). Wertheimer (as cited in Swanson & Holton, 2009) believes that experts must have a real understanding of the environment in which the problem is framed to develop insightful solutions. Additionally, problems may require a variety of skills and approaches, which human experts possess, such as deliberative reasoning, expertise-based intuition, creativity and innovation (Salas, Rosen, & DiazGranados, 2010). In comparison, AI analyzes vast amounts of human-generated data to see relationships and recognize patterns in those data. The analysis of data allows AI to derive meaning and extract insights, which can be used to make decisions (SAS, 2020). While AI is capable of making decisions based on data, it still requires an initial human inquiry to set up the system and ask the right questions. Therefore, it is likely to just confirm its solution or finding. Therefore, one major limitation of AI lies in the way it makes decisions. Its intuitive ability is only as good as the dataset available for that system. Also, AI systems are largely focused on a single task. The relevant dataset is highly specific and the sole driving influence for solutions proposed by AI (SAS, 2020).

Behaviors

In 1999, Swanson and Holton defined expertise as “human behaviors, acquired through study and experience within a specialized domain” that have effective results and optimal efficiency (p. 26). Two decades later, the definition evolved to include behavioral traits, as Germain’s (2006) Generalized Expertise Measure (GEM) suggests. Germain defines expertise as a combination of knowledge, problem-solving skills, years of experience, and behavioral traits. Human experts have the ability to rely on intuition to help fill gaps in information while making decisions (Anderson & Rainie, 2018). Experts can also draw analogies to experiences in different areas to assist their decision-making process, while also bringing the human element to decisions, which require soft skills and emotion. Although AI systems can mimic human behavior, they are still far from thinking and behaving like humans (Rutschman, 2019). Table 9.4 compares the main variables of artificial intelligence and human expertise. Although they are beyond what defines expertise, accuracy and speed/processing are included in the table as their contrast is stark and helps in further understanding how AI and human expertise might be complementary.

Scholars are in agreement with the idea that the best use of artificial intelligence and human expertise lies in collaboration. Human expertise and AI are complementary, not substitutes (Evans-Greenwood, Lewis, & Guszcza, 2017). AI’s strengths in speed, scalability, and quantitative

Table 9.4 Comparison of artificial intelligence and human expertise

	Artificial intelligence	Human expertise
Knowledge	Variety of learning through algorithms' analysis of vast human-generated datasets Retention in high volumes Focused on a single task Unbiased	Deep learning through experience and education Vast amounts of domain-specific knowledge Many types of knowledge Possess sensory information
Experience	Dependent on the analysis of input human-generated data	Gathered over time Dependent on type, quality, and quantity of events experienced by an individual
Problem-Solving	Requires human inquiry to set up the system and ask the right questions Sees relationships and patterns through data Analysis of data allows AI to extract insights and make decisions	Understands the problem and the environment in which the problem was framed May use deliberate reasoning, expertise-based intuition, creativity, and/or innovation to solve problems and make decisions
Behavior	Far from thinking and behaving like a human	Soft skills, emotion, empathy
Accuracy	Increases accuracy with frequency of use and amount of data	Variable
Speed/Processing	Extremely fast processing capability Less ability to process nuance and ambiguity	Superior processing for multitasking Potential for fatigue

capabilities can enhance human expertise when solving problems in their roles as leaders (Wilson & Daugherty, 2018). Both are essential for superior organizational performance. Humans may define problems, machines may help find solutions, and humans may verify the acceptability of those solutions (Evans-Greenwood et al., 2017). Jesuthasan (2017) surmises that humans will still play an integral role in work, with more mundane aspects of work being relegated to machines, while the non-routine components of work may be managed and conducted by people. Studies by Schwartz, Collins, Stockton, Wagner, and Walsh (2017), Andra's (2017), and Jesuthasan's (2017) research support the claim that, while an "old rule" may be that "machines and artificial intelligence are taking over jobs" and replacing people, most companies (up to 77% of them) would either retrain people to use technology or redesign jobs to better utilize human skills. As such, Schwartz et al. (2017) suggest a "new rule" where jobs and tasks are being redesigned to use more essential human skills and are augmented by technology. These human characteristics of work include a variety of skills and abilities, such as problem-solving, decision making, communication, and empathy (Schwartz et al., 2017).

Furthermore, Jesuthasan (2017) contends that traditional jobs will be "deconstructed" into component tasks and competencies, which may or may not be performed as distinct jobs. He notes that talent platforms, such as Upwork, which connects specialized professionals/freelancers with businesses, unlike traditional staffing agencies, will alter the relationship between organizations and workers, including those with expertise. Seeking workers such as contractors, freelancers, outsourced employees, and contingent workers, in addition to machines or artificial intelligence, will enable organizations to be more adaptable as it pertains to cost, risk, speed, and capability.

Rather than hiring consultants who are often experts in a specific domain, organizations may seek a web of on-demand specialists who don't necessarily have the four pillars of expertise (knowledge, problem-solving skills, experience, and behavioral traits (Germain, 2006)). Freelancers, for instance, may develop a tailored digital solution for an organization, one that only requires a specific talent. The years of experience and the level of education become secondary to the ability to solve a problem for a client (problem-solving) and to communicate effectively (behavioral trait).

This chapter has drawn attention to how the changing employee demographics and the increasing use of technology and AI are changing the skills sought by employers and the traditional expertise-related dimensions. First, I suggested a shift in the importance of employee experience. As suggested earlier, entrepreneurs and those employed in tech-related fields are much younger than in previous generations. What seems to be important to tech companies are specific skills and the desire to grow as an employee, not the 10,000 hours of practice rule that has traditionally defined expertise (Ericsson et al., 1993). Second, it appears that education is a more negotiable qualification for some jobs, especially in tech fields where knowledge has a life of about three to five years, after which it becomes obsolete. The pace at which tech companies evolve organically excludes those with accrued knowledge in one specific domain. Additionally, organizations value employees who are creative, adaptable to swift changes, and who are able to learn quickly, rather than being in the form of a formal degree, that learning may occur via internal networks, certifications, Massive Open Online Courses (MOOCs), or other short-term training programs. Third, because consumer products and services tend to encompass more than one domain, employers seek individuals who are curious about various subjects and who value multidisciplinary knowledge. Gen Z employees respond well to this requirement as they want to gather a variety of different skill sets rather than embracing one specialization (Gomez et al., 2020). This multidisciplinary approach contrasts with the traditional domain-specificity and narrow focus of expertise (Swanson & Holton, 2009).

The past decades have been marked by significant investments in technical skills. Data science and machine learning have saturated almost every industry. It is expected that the application of intelligent automation will continue to have a deep and urgent impact on skills requirements. As LaPrade et al. (2019) suggest, executives' views regarding the priority of critical skills have taken a turn from digital and technical to behavioral. Navigating this new landscape requires individuals who can communicate effectively, apply problem-solving and critical-thinking skills to drive innovation using new technologies, and draw and act on insights from large amounts of data. It also calls for creativity and empathy, an ability to change course quickly, and a propensity to seek out personal growth. Going a step further, Ginni Rometty, President and CEO of IBM, predicts that AI will change 100% of jobs in the next five to ten years (Ioane, 2019) and 67% of executives expect that advancements in automation technology will require roles and skills that do not even exist today (LaPrade et al., 2019). If their predictions hold, it is unclear how the definition of human expertise will shift. Perhaps organizations will call on on-demand industry expertise networks rather than on individual experts. And these networks might only include tech-savvy, diverse, communicative, and creative individuals whose knowledge is multidisciplinary.

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10

Preparing for the Future of Work and the Development of Expertise

Jason Moats

Throughout this volume, expertise has largely been defined for the world as it is today. We can see that the central themes of expertise are plentiful and varied, but indicate that it is a process resulting in a display of mastery of the highest skills, knowledge, and abilities of a given domain. In his book *Outliers: The Story of Success*, Malcolm Gladwell (2008) tackles the phenomenon of "men and women who do things that are out of the ordinary" (p. 17) by telling stories of people far exceeding normal levels of performance. Gladwell uses the stories to explore the science of how experts are developed. He does this through the work of Ericsson (2008), Levitin (2006), and M. J. Howe (1999). These scholars have laid the foundation to our understanding of how expertise is developed. Collectively, their work tells us that an individual becomes an expert by engaging in an extraordinary amount of targeted efforts resulting in specific experiences. It is a *process* that requires thousands of hours of acquired experience and *deliberate practice*.

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As this volume concludes and our minds turn to what's next, it is imperative that the discussion moves to how expertise might be developed for organizations in the future. The modern competitive landscape is too volatile to allow organizations to remain sustainable by continuing to consume thousands of hours of focused effort to develop expertise beyond a pedestrian level. It calls for exploring ways in which expertise can be rapidly developed without compromising the requisite level of mastery. Additionally, there is a need for more competent and viable ways to equip humans to perform well in a digitally transformed workplace; a workplace that will most certainly include symbiotic relationships with machines to establish and sustain an organization's competitive advantage.

This chapter begins by briefly contemplating what serves as a catalyst rapid for expertise development in organizations. From there, we look at the need for workplaces to be both adaptable and agile if they are to effectively respond to the need for rapid expertise development. Next, some of the anticipated challenges facing workplaces of the future are presented. Then, to better envision what rapid expertise development might look like in an agile and adaptive organization a case of a national manufacturing facility is present. Finally, the chapter concludes with strategies and techniques that could (and should) be employed to lay the foundation for developing expertise in organizations including implementing adaptive learning, upskilling and re-skilling, and ensuring technology adoption.

Catalyst for Rapid Expertise Development

The amount of time and effort needed to develop individuals' expertise provides a daunting conundrum for workers and organizations alike**,** especially as we consider the amount of change expected to organizations in the near future. In particular, unexpected, world-wide events and the influence of innovation will require quick responses and create changes in organizations as they identify new needs for survival or for attaining a competitive advantage in the marketplace. For instance, as organizations sought to continue working in the face of the COVID-19 pandemic, employees were in great need of timely re-skilling to collaborate in the now virtual or hybrid settings. Employees were often required to work from home or isolated in an office, sometimes in different time zones, and even different countries. Sasangohar, Moats, Mehta, & Peres (2020) provide an example of the impacts created by COVID-19 for disaster managers. Disaster managers are, by definition, required to rapidly and efficiently adapt to the unique demands of each disaster in high stress complex environments. Disaster managers typically maintain close contact to establish and sustain shared mental models for rapid decision making—a key aspect of their work. However, social distancing requirements made the processes these individuals used in previous disasters inadequate. New processes were required to provide the same levels of performance. Unforunately, developing theses needed models to enable better decision making is "time consuming, inefficient, perilous, and in some cases, not possible" (Sasangohar, et al., 2020, p. 1064). Organizations responsible for disaster management quickly realized that there was a need for a new mindset created by the new ecosystem in which their work occurred.

Another catalyst driving expertise development is the desire to push the boundaries defined by the limitations of human performance through gains in technology and innovation. Technologists are often inspired by opportunities to improve and enhance human health and well-being (Simone, Zenobia, & Richard, 2018) as well as the performance of the individual, team, and organization. For example, within the field of healthcare, invasive abdominal surgical procedures often resulted in prolonged recovery times and greater risks of complications, including infection. However, technologists, specifically roboticists, created the DaVinci robot, which enables surgeons to operate through small holes in the skin with high levels of dexterity and near perfect accuracy. Consequently, patients have a reduced risk of surgical complications, less pain, and they heal faster (Kwartowitz, Herrell, & Galloway, 2007). As organizations continue to push the envelope of human performance, workers are constantly being exposed to new tools that are touted to improve performance at a seemingly frenetic pace. However, this rapid and relentless pace demands correlating changes in the knowledge, skills, and abilities of the workforce. As technology continues to emerge in the ever-transforming workplace it will require workers to develop and implement new knowledge and skills (i.e., expertise) at a higher frequency than ever before; and in some cases even before mastery is attained.

As large-scale, unprecedented events disrupt organizational or employment practices or technology such as artificial intelligence (AI) becomes more prevalent in the workplace and unknown human augmentation technologies continue to emerge, workers and organizations must be prepared for rapid re-skilling to stay competitive. Unfortunately, the unyielding pace of change presents an immediate challenge to developing expertise. This is because of the lengthy amount of time and dedication it takes to develop expertise in tension with rapidly changing conditions. In addition, the high operational tempo of top organizations provides little time for the development of expertise while on the job, requiring workers to often cross over the work-life boundaries. Ultimately, this crossing of boundaries often leads some workers to leave the organization for greener pastures. Therefore, the need for rapidly developing expertise to adequately prepare the workforce to perform beyond a pedestrian level of operational proficiency while keeping pace with the evolving workplace is critical.

Organizational Response for Rapid Expertise Development

Organizations are in the midst of a digital transformation. Kaplan and Haenlein (2019) propose that organizations and societies across the globe continue to engage in "novel use[s] of technology to solve traditional problems" (p. 679). For example, work is being transformed into *digital work,* a reconfiguration of practices and operations that adapt to emerging technology being employed into the workplace (Dittes, Richter, Richter, & Smolnik, 2019). To be competitive, the workplaces of the future will need to be adaptable and agile (Gerwitz, 2016; Holbeche, 2019) in response to the catalysts described previously. This is because the consequences of maintaining the status quo are dire: either the organization is replaced or the workers are. Processes are needed that enable workers to seize strategic opportunities as they arise, mitigate threats to their learning, and ensure that changes are sustainable over the longer term. This means the standard of 10,000 hours of deliberate practice (Ericsson, Krampe, & Tesch-Römer, 1993) to build a master level of expertise must be challenged in a way that doesn't compromise rigor. The workplace will need to be adaptable, with the capacity to effectively implement change, and also agile. This will require organizations to go beyond being adaptable to gaining a competitive advantage by strategically capturing opportunities, mitigating threats, and making *sustainable* changes (Holbeche, 2019, p. 669).

Let's return for a moment to the example of a disaster management organization during the COVID-19 pandemic. An *adaptive* organization meets the prescribed objective. In this case, the organization created a safe, socially distanced workplace by increasing the distance between work centers. Unfortunately, that adaptation required more space for the same number of employees resulting in increased long-term costs, challenges to the interactions of working teams, and even a change to operations. However, by also being an *agile* organization, they can go beyond the prescriptive and focus on a performance-based objective that adapts to the changing environment by creating a safe, social distanced workplace with solutions that do not significantly increase costs or team interaction. For example, the organization not only erected safe screens that reconfigured the space, but also provided an aesthetically pleasing environment that allowed teams to interact with few limitations. Most importantly, the organization strove to communicate the rationale behind the changes and employed the workforce in a collaborative relationship that ensured cooperation. Similarly, the workforce embraced the changes and looked for and communicated innovative implementation of the changes back to the organization. The workers adopted attitudes that supported the changes, thus aiding in the efficient and rapid development of new expertise.

Adaptive organizations are those organizations able to effectively and efficiently adjust to the changes in their ecosystem (Fulmer, 2000; Takahashi, 1987). These organizations are intentional in building their adaptiveness. They focus on strategic planning processes that build corporate culture and an enhanced sense of community within the organization. Adaptive organizations build community by placing high emphasis on the individuals' personal satisfaction and happiness, integrity, and a clear understanding of the meaningful contribution of their work (Tanklevska, Kyrylov, & Zaitseva, 2017).

Agile organizations are those organizations able to proactively and rapidly transform to seize opportunities, mitigate potential threats to create a competitive edge (Holbeche, 2019). Agile organizations are adaptive by nature. These organizations anticipate changes in the ecosystem by watching for and reacting responsibly to trends, anomalies, changes in the behavior of customers and competitors. The reaction time of agile organizations is faster than the competition because there is a willingness and ability to implement changes, even when it is not a sure thing (Holbeche, 2019). Agile organizations are focused on innovation and finding the "right balance between standardizing operations and pursuing (sometimes risky) *sic.* innovations" (Rigby, Elk, & Berez, 2020, p. 67). Agile organizations can be interdisciplinary meaning they are created when two or more disciplines blur their boundaries, join forces, and interweave their knowledge to create a product or service. However, agile organizations are best when they are transdisciplinary. Transdisciplinary organizations are interdisciplinary, but the organizations transcend the traditional discipline structure resulting in a wholly new organizational structure absent of the pretense of boundaries (Choi & Pak, 2006). Transdisciplinarity enables and empowers organizations to react swiftly and intentionally without the encumbrances of alternate identities or loyalties that can undermine the change processes (i.e., transformation) (Gromb & Martimort, 2007). Ultimately, transdisciplinary organizations are the ultimate agile organizations because they are wholly focused on the mission and equipped with the *right* expertise yet lack the extraneous baggage of being mired in the *home discipline*.

Challenges to the Future of Work

One significant challenge is the enhanced risk of failure that is present when an organization does not prepare their workforce for success in the transformed environment (Moore, 2018; SHRM, 2016). The workforce is the foundation of an organization's growth and success (Grenier &

Germain, 2014) and training and development are foundational to creating and maintaining that workforce. Despite these facts, a survey of HR professionals conducted by the Society for Human Resource Management SHRM (2016) revealed that 31% of responding organizations did not have a training budget in the 12 months prior to the study. Moreover, an additional 11% reported their training budgets decreased in the same 12 months. Not having a skilled workforce is clearly a concern for CEOs around the globe. A 2019 global survey of 3200 CEOs revealed that nearly 80% are concerned about the availability (or lack thereof) of workers with key skills for their organizations (Stubbings, Sethi, & Brown, 2019). Additionally, more than half of these respondents understand the derogatory impact that a lack of workers with the *right* skills has on their organization's growth. It is most perplexing that despite the recognized impact on organizational growth, only 46% of these CEOs have made re-skilling/upskilling a top priority for their organization. Upskilling is enhancing and refining current skills to keep one in the same job. Re-skilling is developing new skills and abilities for a different job (Gratton, 2019).

A second challenge occurs as new technology is integrated into the workplace resulting in some employees fearing that they will lose their jobs (Peters, 2017; Pol & Reveley, 2017). As the transformation of the workplace unfolds, many observe that the technology provides a clear advantage for the organization by providing greater accuracy and improved consistency in operational performance. As machines and automation are utilized to do more in the transforming workplace, the need for employees with certain skills decreases, as organizational efficiency and profitability increase (Pol & Reveley, 2017). As employees observe the changing nature of the work required, they may deduce that the skills they possess are no longer relevant to their organization (Peters, 2017; Pol & Reveley, 2017) and that they need to change if they are to remain in the workforce (Schwab, 2016).

Inevitably, some of the workforce will be among the *technologically unemployed* (Frey & Osborne, 2016; McCarthy, 2014; Pol & Reveley, 2017). Technological unemployment is not a new concept. The term dates back to the early nineteenth century and refers to when the increase in the number of jobs assumed by technology in a given time is more than the number of jobs taken by humans in the same time (Pol & Reveley, 2017). The challenge for the organization is to best determine who needs re-skilling versus upskilling and how to do it without disrupting the competitive advantage. In other words, the organization must not only transform the *workplace*—but also the *workforce*—by determining the expertise needed, how to develop it, maintain, and sustain it. This is important since, although 18% of the CEOs feel they can hire the expertise needed from the outside, recruiting costs about six to nine months of an employee's salary and the organization has little productivity impact to show for the effort and expense (Tah, 2018).

A third challenge, labeled by one scholar as "the Luddite strategy" (Peters, 2017), occurs when employees reject using the technology. Korn Ferry's Global Technology President, Werner Penk**,** describes the organizational impact of this phenomenon**:** "No value will be created from technology unless people embrace it" (Moore, 2018, p. 9) which is a challenge when employees harbor resentment toward the use of technology for one reason or another (Moats, 2013). For example, many workers struggle to adapt to new, innovative tools because they struggle to understand the usefulness of the technology when they compare it to what is already in place. Or, some employees may feel the technology is too intrusive, too demanding, or even unethical (Schwab, 2016).

A final challenge will be how organizations adapt to the needs of employees as the transformation unfolds. For example, some workers will be very comfortable in a less structured environment, where work-life boundaries are blurred or removed. On the other hand, other workers will need or want the structure provided by an office and the nine to five work day (Dittes et al., 2019). Failing to adapt to changing workforce needs could result in the inability to recruit and/or retain the expertise needed to maintain a competitive advantage (Schwab, 2015).

Envisioning the Future: The Workplace Transformed

Workplaces of the future will reveal a very different landscape compared to the ones we work in today. De Bruyne and Gerritse (2018) tap into the future forum study to provide insights into what might be expected in future workplaces. They note that workplaces will be highly digitized, collaborative, and agile. Many futurists describe empowering and encouraging environments where cross-functional teams are enabled to be adaptable and autonomous (De Bruyne & Gerritse, 2018; Guinan, Parise, & Langowitz, 2019); places where access to knowledge, the ability to store data, and the power to process that data will be unprecedented (Schwab, 2015).

Workers in these transformed workplaces will be expected to be more innovative, creative, and entrepreneurial than in any previous time, as they work within reconceptualized structures that see the current eight–five workday replaced by a focus "… on the efficient completion of work" (Dittes et al., 2019, p. 650). This new structure will enhance the ability of teams to collaborate, even when they are miles—or even continents apart. This also means the potential for the boundaries of work and personal times to become increasingly blurred (De Bruyne & Gerritse, 2018; Dittes et al., 2019; Kaplan & Haenlein, 2019).

The tools that workers will use in the future will be different as well. Guinan et al. (2019) explains that the continued development of digital applications provides a powerful energy to the ongoing digital transformation. The speed of the expansion of the Internet of Things (IoT); the widespread implementation of neural interfaces to join human and machine; and integration of artificial intelligence will be used to make the organization's performance faster, more efficient, and to improve accuracy. The use of collaborative robots, powered exoskeletons, and other to-be-determined technologies will augment human capacity and improve workers' individual performance beyond the current limitations of human capability. Furthermore, the future will likely see machines learning from humans, who are learning from machines to create a symbiotic relationship. What follows is an imaginative case study. It sees how the workplace of the future responds in the face of catalysts to expertise development in an adaptive and agile environment and provides a means of considering the anticipated challenges facing the transformed workplace of the future, along with strategies to mitigate their effects.

Expertise on a Manufacturing Floor

Imagine for a moment that you work in a durable goods (e.g., air conditioner, home appliance, etc.) manufacturing facility. You applied for the job four years ago after graduating from college with a bachelors in history. The opportunity appealed to you because the organization was known to be a proactive corporate citizen in their communities and had an outstanding reputation as a company that cares about their employees and families. You had no manufacturing experience, so in addition to the attractive starting salary and benefits package, you were drawn to a career development path that enabled advancement in a low-tech industry using high-tech tools that would transfer to other parts of the organization. Once hired, you took part in a one-day classroom-based course addressing administrative issues and basic safety and from there you were placed in an onboarding program to prepare you for working on the manufacturing floor. From that point on, you advanced through the organization's development program with its blend of coaching, mentoring, counseling, and training. Although over the last four years you have been constantly learning, you have not been in a classroom training session since your first day with the company. Today you are considered a master technician, performing with the highest level of expertise within the organization.

Currently, your position on the line is responsible for creating a housing component by fabricating a large box from six 750-pound steel panels. More specifically, you work as a manufacturing technician responsible for overseeing the manufacturing processes, including maintaining the fabrication machines (i.e., robots) and ensuring the quality of the assembled components. Carrying out this job means that you will interact with the artificial intelligence system, use powered human augmentation technologies (e.g., augmented reality, powered and non-powered exoskeletons etc.) and collaborative robots, as well as many other technologies. Training and professional development happen in many forms, but always on the job. More importantly, the training you receive is often created by an AI training module that is observing your performance, identifying your strengths and deficiencies, and then creating and scheduling learning opportunities through an array of media that are tailored to your needs and learning styles.

On any given day as you and your colleagues enter the building, facial recognition automatically identifies you and checks you in to officially start your workday. At the entrance you are greeted by a personalized virtual dashboard. It displays your schedule for the day and other critical information specific to you (e.g., leave balance, days worked, etc.), as well as the performance metrics from the previous shift and organization-wide reminders such as available development opportunities. After reading it and moving ahead, the display screen changes for the next employee. Walking through another entryway, your equipment bag arrives via a chute. The bag contains your personal protective equipment and the tools you will need to complete the scheduled tasks for the shift**.** This includes your biometric wrist sensor and safety glasses with integrated eye-tracking, augmented reality (AR) and your personal assistant interface that is connected to the company's artificial intelligence (AI) system. As you don the safety glasses, the system automatically activates and in the lens you see a display confirming that you are connected, and your equipment is functioning properly. You are also greeted by your personal assistant, an audio-based, AI-driven system that communicates through your headset with a professional, yet relaxed voice. The personal assistant recaps the performance metrics from the previous shift and throughout the day it provides important personalized messages needed to complete your work. The personal assistant and the augmented reality function of your safety glasses have eliminated the need for emails and going to most meetings. These tools now enable the meeting to come to you wherever you are.

As you arrive in the physical space of your workstation, you and every employee in the area are provided a virtual *employee roll call*. When you look around the manufacturing floor, a yellow symbol highlights an empty workstation. The system recognizes where you are looking and provides information indicating that the absent employee checked into the company infirmary after his wrist sensor detected an elevated body temperature. The system provides everyone on the manufacturing floor a short list of signs and symptoms that may indicate the spread of an illness with suggested protective actions to minimize it. The system also confirms that all employees present in the work area have normal body temperatures.

The work area is clean, but cavernous, and is maintained by a small fleet of automated sweepers (similar to industrial "Rumbas"). As you walk to your personal workstation, you notice a line of robots adjacent to the main thoroughfare moving as it fabricates steel panels into a large box weighing approximately 1500 pounds. The system senses welding slag as it flies into the pathway and immediately identifies a hazard you should avoid. You and others walking with you are guided away from the hazard with a series of green arrows superimposed on an adjacent walkway. You safely arrive at your workstation.

Your personal assistant announces that the collaborative robots are ready to start shift. As the massive robots begin to move, the system constantly updates the status of each machine and you see the startup process checklist in your AR display. As your eyes move to each item on the checklist, a blue circle highlights the specific area of the machine you must inspect, and if needed, also calibrate. As you complete each step of the startup procedure the AI evaluates the accuracy of the assessment and if completed to pre-set standards, a green check is displayed and the next item on the list appears.

As the first of several components passes your workstation, the system announces that you will need to lubricate several joints on the machines. In previous years, this task would have been performed by a technician and production would have stopped for three to four hours. However, the maintenance schedule is optimized by the cloud-based AI system to avoid disruptions in the production flow. Although you have never performed this maintenance task and it is scheduled for a very tight window, you are confident that you will be able to complete the task in the time given. About 90 minutes later, you receive a notification to start a short two-minute video that demonstrates the procedure. The video plays in your lenses and you complete a summative evaluation called a knowledge check by correctly answering five questions. The training advances from a knowledge component to the psychomotor skills development module. The safety gloves you donned as you entered the facility are equipped with haptic devices. The next part of the video plays in your AR headset and you are now able to imitate the motions shown in the video. As the AR superimposes a *virtual* grease gun in your hands, the haptic feedback gives you the sensation of holding it. To the passerby, your training looks like a form of Tai Chi; however, to you, it feels like you are doing the actual task with the tools.

The system initiates a timer. As you acknowledge the timer by looking at it, a small wheeled robot arrives at the workstation with a grease gun identical to the one in the training video. When you grab the grease gun, a sensor activates the display of the greasing procedures in your AR display. The first grease port is highlighted in red, indicating it is not yet safe to start the procedure. As a few seconds pass, the highlight changes to yellow and then green indicating it is safe to begin the maintenance. Your personal assistant provides reminders from the training video ensuring that you have accurately and adequately completed the task. The system also provides verbal reinforcement by indicating common problems associated with the task. As each grease application is completed, the AR directs you to the next grease port. Simultaneously, the small camera in the frame of the safety glasses snaps a photo of the completed work and archives the picture. The system is autonomously assessing your performance based on a set of parameters, including time, accuracy, and visual evidence from the photos. This information is used to adapt your training and will be used in your personal performance evaluation.

Six hours into your workday, the system announces that a robot is malfunctioning and requires emergency maintenance. To complete the task, the procedure will require a passive upper body exoskeleton. This is needed to prevent strain injuries that can result from extending your arms as you use a 20-pound motorized driver for more than 30 minutes. Ten minutes before the task is to begin, a wheeled robot, about the size of a vending machine stops next to you and opens automatically to reveal the exoskeleton. After suiting up, the procedure, as before, is displayed in the AR glasses. Ten minutes before your workday ends you complete the task. Sensing the task is over, the vending machine reappears at your workstation to collect the tools. As you and your co-workers exit the building, you drop your personal safety equipment in a tray to be disinfected for the next day, and you are automatically clocked out for the day.

A Way Forward

Ericsson and others have noted that developing someone to an expert level in the modern workplace requires a significant investment of time and effort (Ericsson, 2008; Ericsson et al., 1993; Gladwell, 2008; Levitin, 2006). However, as we can see, the workplace is going to change in significant ways in response to technology and the types of knowledge and skills needed by the workforce changes. These factors conspire to challenge the validity of the current views of expertise. As the workplace continues to transform, so should the ways in which expertise is defined and developed.

Take for instance the learning that happens in organizations. The massively inefficient classroom methods used by many of today's training departments must yield to in-situ learning that integrates emerging and innovative technologies in meaningful activities. The need for rapid expertise development means that pedagogical methods of instruction should instead be andragogical approaches (Knowles & Associates, 1984). This means that instructional design methods which produce one-size-fits-all curricula must instead offer personalized curricula capable of being adapted to the specific learner in real time. Moreover, long classroom sessions with limited and / or iterative application activities will need to transform to short bursts of just-in-time learning using techniques such as microlearning (Kapp & Defelice, 2019; Zhang & West, 2020) and simulation-supported learning experiences (Cabanero-Johnson & Berge, 2009; Marlow, Lacerenza, Reyes, & Salas, 2017; Oblinger, 2003). In addition, as the case illustrates, learning experiences will be less formal and include repeated, but purposeful interactions with technologies such as AI, Augmented Reality (AR), and Virtual Reality (VR) (Merriam & Bierema, 2014; Messmann, Segers, & Dochy, 2018). Although the integration of informal learning into work is not a new concept (Marsick & Watkins, 1997; Marsick, Watkins, Callahan, &

Volpe, 2006), it has not been used significantly by organizations as a primary means of developing occupational expertise.

Current training is typically designed as a one-size-fits-all solution for building skills, increasing knowledge, and refining abilities. The significant investments of time and effort to gain mastery will, in the future, render this approach grossly inefficient**.** Yet, it is efficient and, more important, cost-effective for the organization as they develop learning opportunities. It is also well accepted that people start their respective learning journeys from different points, with different levels of knowledge and different skills mastered (Knowles & Associates, 1984). Moreover, research has shown that one-on-one instruction is the most effective learning style (Howe & Barrow, 2020). However, creating tailored learning experiences scaled for an organization's workforce is costly and time-consuming. HRD professionals need to identify and develop solutions that balance the power of customization with the speed of mass production of learning, including implementing adaptive learning, upskilling and re-skilling, and ensuring technology adoption.

Adaptive Learning

The pace of changes in technology necessitates developing and implementing learning opportunities within days not weeks or months. HRD professionals will need to understand and expand the value of enhancing the knowledge, skills, and abilities of the organization's workforce, especially since recruiting can take longer as the competition for attracting the *right* expertise can take months. A likely strategy to address this involves implementing *adaptive learning*. Adaptive learning can be explained as a data-driven learning tool that tailors the content and interactions to the individual's specific needs (Cavanagh, Chen, Lahcen, & Paradiso, 2020). There are several ways in which this customization can occur, including the use of a machine-learning system. In machine-learning systems, the computer observes and records interactions with the learner and adapts the content and delivery based on algorithms. Perhaps the most important factor in adaptive learning is detecting and identifying essential data points about the individual learner to determine what content he or she requires (Mwambe, Tan, & Kamioka, 2020).

There are many delivery platforms for this kind of learning opportunity, including web-based, video-streaming, and face-to-face instruction (Cavanagh et al., 2020). However, augmented reality, virtual reality, and other immersive technologies provide opportunities to engross participants in the learning moment through adaptable scenarios where he or she can *play* through the learning experience (Chandramouli, Zahraee, & Winer, 2014). Scenario-based learning has long been a tool used to develop expertise (Chermack, 2003; Chermack & Walton, 2006; Moats, Chermack, & Dooley, 2008). The learning focus of immersive platforms such as virtual reality, combined with the customized content tailored by adaptive learning algorithms can provide a powerful tool to rapidly develop expertise.

The transformation of the workforce is a *process* that must be planned, implemented, evaluated, and constantly adjusted based on the environment. Swanson (2007) notes, "Developing expertise is not an event. It is a purposeful journey" (p.126). Moving forward on this journey, organizations must accept that developing expertise means developing learning opportunities that simultaneously demonstrate *valuable* impact to the organization and individual learner and is *tailored* to the individual's specific learning needs. However, the learning needs will vary based on each person's knowledge, skills, and abilities. Some will be general and permeate the entire organization, while other expertise will be highly technical and specialized, and needed by only a few. Learning opportunities based on pedagogical approaches to teaching that unfold in iterative, stepwise progressions in which all attendees get the same information, regardless of their existing experiences and cognitive abilities, is often the practice, regardless of the expertise needed. Learning that ignores the need for basic knowledge or complex cognitive system-based decision-making skills cannot remain in the future. Expertise development must adapt and be tailored not only to the learner, but also to the expertise that is needed for any given work scenario. For example, building the expertise to manage complex situations may best be accomplished with immersive, virtual reality supported, scenario-based experiential learning. However, building the expertise to perform a routine maintenance procedure, such as in the greasing task described in the case study is more suited for just-in-time microlearning.

Upskilling and Re-skilling

Upskilling, defined earlier as enhancing the *current* skills and abilities so there is a greater depth, is a vastly underutilized human resource development strategy. Failing to incorporate this as part of the workforce transformation of the future will be costly in terms of time and financial resources (Carnevale, Ridley, Cheah, Strohl, & Peltier Campbell, 2019; Modestino, Shoag, & Ballance, 2015). Providing for the employees' continued development as the organization changes can engender loyalty. Researchers (J. Y. Lee, Rocco, & Shuck, 2020; Shuck, Adelson, & Reio, 2017) have shown that when organizations invest in developing their employees, employees are likely to be more engaged in the organization. Consequently, upskilling can have a positive impact on the company's ability to recruit and retain the best and brightest employees (Marquardt, 2011).

Upskilling is rife with opportunities to provide micro-duration, high impact interventions delivered through a variety of modalities, including through an individual's mobile devices using video sharing platforms (e.g., YouTube), podcasts, and video games instead of the traditional face-to-face classroom (Gratton, 2019). Upskilling builds on an individual's existing expertise, or redevelop expertise, and helps them adapt to new technology (Tah, 2018). However, understanding the need for upskilling and more importantly, providing the motivation and support to incorporate it into the organization is a shared burden by both the employee and employer (Gratton, 2019).

Where upskilling is enhancing skills for the current job, re-skilling is developing new knowledge and skills for a different job (Gratton, 2019). Weber (2019) suggests that both re-skilling and upskilling are underutilized strategies for most organizations. Weber explains why organizations are reticent if not outright against re-skilling:

> Sometimes the required skills aren't easily taught to existing employees, experts say. It's also often because companies have only a hazy sense of what their internal talent is capable of, and migrating large numbers of employees into new positions requires time, money and commitment. (p. 1)

V. E. Davis and Minnis (2017) make a similar point about veterans who are transitioning from the military to the civilian workforce. Employers misjudge what the existing workforce is capable of when given an opportunity. Therefore, as with upskilling, re-skilling must be inextricably embedded within the core strategies of the organization. In doing this, organizations can effectively plan for the expertise they will need in the future and create strategic plans to plot a course for strengthening the workforce, developing the needed expertise, and retaining people. Attending to re-skilling means organizations are able to maintain their competitive advantage through a strong, viable, tenured workforce with organizational expertise. In other words, the organization that strategically plans and implements re-skilling for employees is closer to realizing true self-sufficiency. Failing to include re-skilling as part of the organization's transformation strategy is taking a great risk that will ultimately result in the organization's failure (Moore, 2018) and the loss of employee expertise.

Adoption and Acceptance of Technology

However, for any of this to be successful, organizations of the future must ensure that steps are taken to facilitate the adoption of innovation (Rogers, 2003) and technology (McGurn & Prevou, 2012; Pavera, Walkera, & Hunga, 2014). Research (Davis, F. D., 1989; Lee, Kozar, & Larsen, 2003; Moats, 2015; Venkatesh, Morris, Davis, & Davis, 2003; Yen, Wu, Cheng, & Huang, 2010; Yousafzai, Foxall, & Pallister, 2007) has shown that technology is more likely to be accepted by users when several criteria are met. First, one must understand how the technology will help him or her perform the job better. Second, he or she needs to realize that the technology is relatively easy to use (Davis, F. D., 1986, 1989; Lee et al., 2003; Yen et al., 2010). Third, the user needs to sense that others want them to use the technology**.** This is especially important when the opinions are from those who are important to the user (e.g., the boss, a trusted colleague, etc.) (Moats, 2015; Venkatesh et al., 2003). A final, but important criterion is that the user believes that the organization can support the implementation and the sustained use of the technology (Venkatesh et al., 2003). This final criterion is of great concern given the rapid pace of the evolving technology. Many business leaders openly question whether technology developers will be able to keep up with the demand as the digital transformation continues to permeate the workplace (De Bruyne & Gerritse, 2018; Schwab, 2015).

Rogers (2003) defines a four-component strategy that is essential for integrating an innovation throughout an organization and ensuring learning and development of employees; chief among these components is a social system. In technology adoption literature, the power of this component is strongly reinforced (Moats, 2015; Venkatesh et al., 2003). To that end, organizations must be ready to go beyond teaching individuals how to use the technology. Although this is vitally important, it is not enough. Organizations must also create, communicate, and explicitly support technology implementation strategies (Moats, 2015). Simply throwing technologies at workers with little or no guidance of how the technology will integrate into the organizational operation is likely to fail and hinder the application of employee expertise.

Building an adaptive capability within organizations will require the agility to innovate creative approaches to identifying the needs of the organization *and* the learners. As was the scenario in the case, processes will be completed in a small fraction of time compared to those used now (Moore, 2018; Schwab, 2015), which means the speed of designing and developing learning opportunities must be greatly improved. Plus, there needs to be a culture that welcomes change. All of which necessitates OD strategies and techniques that foster the adoption and acceptance of the new and innovative technology as it continues to appear in response to the ever-changing landscape (Moore, 2018). By doing this, new approaches to developing expertise are opened, allowing for the eventual reduction of the prolonged timeframes currently needed to create mastery. In other words, the development of expertise must be as agile and adaptable as the organizations (De Bruyne & Gerritse, 2018). However, keeping pace with transformation may not be adequate given the advancement of technological change. What is required is disruption (Christensen, Raynor, & McDonald, 2015) to the current training and development processes to rethink how individuals gain expertise and how the workforce is equipped for success. To create new ways of developing expertise, HRD professionals will need to expand their repertoire of training and development techniques and go beyond the *usual suspects* (i.e., instructional designers, content specific subject matter professionals, technical writers, and graphic designers). As Schwab (2015) writes, "The response to it [transformation] must be integrated and comprehensive, involving all stakeholders of the global polity, from the public and private sectors to academia and civil society" (p. 1). For expertise development this means having a transdisciplinary approach. Without this, organizations will struggle to be competitive (Moore, 2018).

Given the discussions in this chapter around and about technology, it is important that an individual's perceptions and decisions about the technology's value and the perceived investment of time and effort they will expend to learn it be given some attention. The decision to accept technology can potentially provide organizations the single greatest risk of failure with reference to developing expertise. For example, if an individual decides to not accept a technology, a couple of things could unfold that would cost the organization time, money, and other resources. First, the organization could possibly lose the employee and the expertise that employee possesses. Second, the organization's investment in the technology goes unreturned, or returned on a much lesser scale than expected. Or both could occur, resulting in incomplete staff and investments that go unrecovered. In a competitive environment in which minor adjustments often result in major impact, these losses are likely to be critical to maintaining a competitive advantage. Ultimately, if an individual rejects (i.e., does not accept) the technology, they are unable to develop the expertise needed to do the job. For example, in the case of the floor worker, the acceptance of augmented reality is vital. There would be risks to their safety as they moved around the manufacturing floor and repairs and maintenance would likely take hours or days, instead of a few minutes.

In the future, HRD professionals should consider a few points as they plot the course for engendering technology acceptance among employees to endure rapid development of expertise. First, an individual's perception of the innovative technology in context influences the decision to accept (or not accept) the technology. Often, an individual experiences a feeling of awe and amazement as they initially encounter the technology. However, this quickly changes to anxiety as they realize that their performance would be, at least in part, contingent on how well they used the unfamiliar, innovative technology. Yet, as the individual's exposure to the technology increased and they experienced successes with the technology in context, the anxiety typically wanes, and the individual's confidence grows, and they become more comfortable with the technology.

Second, anxiety is created and can be counter to a decision to accept the technology. Moats (2013) has shown that an individual's anxiety is intensified when using an unfamiliar technology. Therefore, organizations should anticipate the anxiety and employ OD strategies and learning opportunities that are specifically designed to mitigate anxiety that can slow expertise development.

Third, exposure to, and early success in using, an innovative technology is essential to the individual's continued use of it. An individual's first-hand experience with innovative technology is powerful in discovering the technology's ease of use since individuals are able to gauge difficulty. They can then weigh that against the level of investment they are willing to make to learn the technology, instead of relying on others' interpretations and explanations. Opportunities to use the technology in context and experiencing successes will continue to build comfort with it. These successes, although comparatively small, will serve as motivators for the individuals as they continue to use innovative technology and develop expertise. Experiencing the utility of innovative technology is also important for ensuring continued use. Therefore, the previously mentioned scenario-based opportunities are important. While some learning opportunities can be constructed around mastery of tasks, intrinsic motivation to engage in these is often absent, especially among the competing interests of the working environment and work-life balance. However, when the learning opportunity is built to provide a perception of a forward direction, it is meaningful and often more palatable for the individual to justify spending the time and effort to participate.

Finally, role models, whether formal or informal leaders within an organization, are influential to the acceptance and use of technology. These personnel are uniquely positioned to facilitate change, mitigate, and even alleviate anxiety, and help individuals identify the ease of use and utility of the innovative technology. This is a very powerful position and makes them critical to bolstering the probability of technology acceptance. Given this, organizations must ensure that role models are identified, and well prepared to use the technology.

Conclusion

This chapter asked you to take a journey into the future. From the outset, I have asserted that current methods used to develop expertise are inefficient, costly, and incongruent with the volatile environment of organizations found in the future. We must reconsider how we think about expertise and how we develop expertise. We must prepare for a very different workplace and ensure that we have the *right* expertise within an organization to provide a powerful competitive advantage (Grenier & Germain, 2014; Lee et al., 2020; Marquardt, 2011). This means that in workplaces that are continuously transforming and innovations continue to emerge, an investment of 10,000 hours of deliberate practice will likely be untenable and how we prepare and develop expertise now will be incompatible for establishing and maintaining competitive advantage in the future. HRD professionals must do more than push the boundaries to ensure expertise development. They must be disruptive by introducing learning as part of operations and push the organization to go beyond being an organization that learns when it needs to, to being a “learning organization”, an organization “that learns effectively and collectively and continually transforms itself for better management and use of knowledge; empowers people within and outside of the organization to learn as they work; utilizes technology to maximize learning and production” (Marquardt, 2011, p. 209).

The quick glimpse into the future that was provided in this chapter was an example of what that push can lead to, and it might be quite disorienting as it seems to bring science fiction to reality. Innovations such as artificial intelligence, exoskeletons, collaborative robots, and those yet to be discovered will continue to evolve, emerge, and transform the workplace and work processes. The result is a workplace that changes the requirements of *what* expertise *is needed* and *how* expertise *is implemented*. Likewise, the innovations in technology and processes and the speed at which they emerge will demand changes in *how* expertise *is developed*. The ubiquitous nature and the rapid evolution of workplace technology, as well as unforeseen world-wide events, such as the COVID-19 pandemic will continue to disrupt the competitive landscape, subsequently challenging organizations' performance in the future. As the global pandemic created by COVID-19 demonstrates, a disruptive event serves as a catalyst for furthering transformation and the need for rapid expertise development. It is very likely that many organizations who are unable to adapt will fail over the long term and employees too who do not redevelop their expertise may be made redundant. This illustrates the need for organizations to be adaptable and agile, and create and implement innovative approaches to develop and maintain occupational expertise.

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11

Conclusion

Marie-Line Germain and Robin S. Grenier

The goal for this book was to offer readers an overview of the construct of expertise at work: what it is, what it looks like in various organizational and work settings, and how some external factors such as artificial intelligence (AI), changing workforce demographics, and innovation are likely to reshape it. We did not attempt to offer an exhaustive research and practice book about expertise since there are numerous such resources already available. Rather, we sought to provide the reader with a cross-sectional snapshot that offers various views and contexts. We also wanted a culturally rich perspective on the topic. To achieve this, we brought together experts in countries as far away as South Korea and The Netherlands and from an array of academic disciplines. The final

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intention was to situate a discussion of what expertise might mean in the future as organizations integrate innovations such as AI.

As a conclusion, we wish to address some of the implications that scholars and scholar-practitioners alike might wish to consider as they explore and support expertise at work. In order to be able to support the development of expertise in organizations, it is critical that those in Human Resource Development (HRD) and in similar roles, as well as workers themselves, have a grasp of how expertise is defined and understood. The ability to build organizational supports that embrace such understandings is key to measuring and assessing expertise, ensuring opportunities for redevelopment of expertise when necessary, and respecting different expressions of expertise that demonstrate to workers their value and contribution to organizational success. Yet, as Kim makes clear in Chap. 2, defining expertise is not as simple as one might expect. We can say that experts pursue "exceptional performance" and that the developmental processes to expert status are applicable to almost all individuals, but that characterization is limiting unless there is a recognition of both the psychological and sociological perspectives of expertise in the workplace. This is because a traditional concept of expertise alone, described as a set of structured and decontextualized knowledge and skills, while important and helpful in understanding deliberate practice, is limiting because it overlooks subtle and other critical, but less known aspects of expertise found in today's dynamic organizations. Ideally, this more robust idea of what it means to have expertise is combined with a perspective that sees the role of adaptive expertise and flexible expertise as key for solving unpredictable and atypical problems. This means that organizations must recognize and encourage the continuous transformation of expertise. To do that, adaptive expertise needs to be understood and supported since it is important for performing successfully in novel situations. Today's organizations operate in increasingly dynamic environments, plus, with changes in workers' contexts: as they take part in the gig economy, are self-employed, or work as contingents that position them outside of a stable work environment, means individuals are exposed to novel situations more frequently. To be successful workers need to develop a deep conceptual understanding of their occupational domain. Through organizational development opportunities, professional societies, or self-study and application workers will be better able to navigate these dynamic environments.

With a firm grasp on what it means to have expertise, flexpertise, or adaptive expertise organizations can only then turn to instruments that may be useful for identifying and measuring expertise in employees. And although, as we see in Chap. 4, researchers and practitioners are beginning to demonstrate that expertise can be measured, elicited, transferred, and redeveloped, a strong, data-driven understanding of expertise remains underdeveloped. This is due in no small part to scholarship that is useful in characterizing expert processes in specific contexts, but offers little in addressing the complexity of expertise in ways that broaden our understanding of expertise in organizational contexts. When organizations seek measures for assessing expertise, they need to look to those derived from various business contexts, workplace leaders, and impression management techniques, as well as those that acknowledge the challenges to existing social power. This is no easy task for those like HRD professionals, and what is clear from the first section of this book is that organizations and scholar-practitioners must call on scholars to expand and challenge existing assumptions of expertise practice, including employees' critical thinking and problem-solving skills. It is also apparent that there is a need for clear delineation between the study of competence, proficiency, and expertise with measures that move beyond examining experts primarily in relation to novices.

The book also offered readers a chance to examine expertise in work and organizational settings. This provided an opportunity to consider the more practical aspect of expertise, which gives scholars and scholar-practitioners a way to situate the understanding gained in the first section of the text. In Chap. 5 readers were presented with the challenges and opportunities associated with military expertise as veterans' transition to non-military work. Although the context is quite specific, it is clear that workers (veterans or otherwise) can find it difficult to translate their expertise for potential employers to see how skills and knowledge found in one field or environment can transfer to another, for instance, the ability to effectively articulate expertise in soft and technical skills. In the case of veterans, doing so is important to their overall understanding of the value they bring to the workplace and a shift in confidence they may experience as they find new ways to use their skills. Equally important is how employers, too, might need to review how they write job descriptions and market openings. Considering how to more broadly conceptualize the expertise they seek will help get more qualified applicants in their hiring pool.

Another implication for scholars and scholar-practitioners that comes out of a specific look at expertise in context is the need to consider how self-regulation might be key to expertise development at work. As several authors in this book noted, deliberate practice is important, but without self-regulation, that practice might not be achieved. Those who master self-regulatory skills are well positioned to overcome psychological and physical challenges that stand in their way of attaining expertise. Liutkutė, Hettinga, and Elferink-Gemsera argued that self-regulation as a core component for enabling successful deliberate practice is the ultimate determinant for attainment and execution of expert performance. This means that individuals seeking to develop expertise might be wise to take a cue from elite athletes and be proactive and committed learners who use reflection, goal setting, planning, monitoring, and evaluation of their performance on a regular basis.

Readers also had the opportunity to consider the possibility of organizations as assemblages of knowledge—places that see all individuals, novice and expert alike, as having the potential to contribute in meaningful ways to the success of the organization, but as the last section of our book demonstrates, what it means to successfully identify, nurture, and retain expertise will shift significantly in the future. This will be due in no small part to the rise of artificial intelligence (AI) as an organizational tool. The chance to understand the history of AI and how AI and expertise converge is very useful as a way to envision our future work. But, as is pointed out in Chap. 8, we need to be aware that machine learning approaches using deep neural networks cannot explain themselves to humans. This is crucial, particularly when experts need to work with these systems. Moreover, these approaches result in brittle systems that can easily be attacked, or that do not work in unforeseen scenarios. AI capabilities can also have various consequences on workers, ranging from replacement, to augmentation, to maintenance of human expertise. It may well be the case that pattern recognition capabilities of AI systems will exceed human expertise. Yet, in order to be able to effectively collaborate with human experts, AI will need collaborative skills, such as being able to explain itself to humans. For those looking to harness human expertise and AI, organizations of the future will need to focus on Hybrid AI in which expertise is distributed across experts and AI in various ways. The understanding of new skills (fusion skills) that human experts need to develop in order to deal with AI will also be vital. This is because AI systems will hardly ever be stand-alone in a work process and therefore will need intricate tuning to human demands at various points in time. Such systems will need to be trained, validated, understood, explained, assisted, and overruled if experts want to accept them and be able to effectively work with them. Maarten Schraagen and van Diggelen emphasized an important point: it is a gross oversimplification to consider AI systems and human expertise as two mutually exclusive entities, with one taking over the other without changing anything in the work process. Rather, we need to view AI and humans from a joint cognitive systems perspective, at a systems level, and as dynamically changing over time. Only then will we be able to see the intricacies of the mutual dependencies between humans and AI, and the constantly evolving distribution of skill sets that are required from an organizational perspective.

As the author of Chap. 9 pointed out, the digital revolution and the increasing use of artificial intelligence in the workplace create new demands in labor needs and continual re-education. And when this is combined with changing demographics in the workforce, including more diversity than in previous decades in educational attainment, age, gender, and race, and the increased demand for soft skills, organizations may find that their existing notions of expertise no longer serve them. In fact, Germain suggested a shift in the importance of employee experience. What seems important to tech companies are specific skills and the desire to grow as an employee, not the 10,000 hours of practice rule that typically defines expertise. Second, the author claimed that, in some fields such as technology, education is a more negotiable qualification for some jobs. Indeed, in the tech industry, entrepreneurs are often young and tech-related knowledge has a life of about three to five years, after which it becomes obsolete. Additionally, organizations value employees who are creative, adaptable to swift changes, and who are able to learn quickly.

Third, because consumer products and services tend to increasingly encompass more than one domain, employers seek individuals who are curious about various subjects and who value multidisciplinary knowledge. Germain suggests that Gen Z employees respond well to this requirement as they want to gather a variety of different skill sets rather than embracing one specialization. This multidisciplinary approach contrasts with the traditional domain-specificity and narrow focus of expertise.

To explore the idea of the digital revolution and AI at work, the book concludes with an imagining of work in the not-too-distant future that calls into question developing expertise in light of shifts in technology and innovation. Scholars and scholar-practitioners must consider the possibility and likelihood that, while having the *right* expertise will remain a very powerful advantage, an investment of 10,000 hours of deliberate practice is untenable. They should also ask: are current methods for developing expertise incongruent for establishing and/or maintaining a competitive advantage in an accelerative environment driven by technology and innovation? As Moats contended, tools such as artificial intelligence, exoskeletons, and collaborative robots will continue to evolve, emerge, and transform the workplace—so work-process and the associated human expertise will need to reflect those changes. Likewise, the innovations in technology and processes and the speed at which they emerge and need to be implemented will demand changes in *how* expertise is developed. The ubiquitous nature and the rapid evolution of workplace technology, the ever-present transformation of the workplace, and the unrelenting fast pace of innovation will continue to disrupt the competitive landscape which subsequently challenges organizations' performance.

As demonstrated in this concluding chapter, understanding expertise at work is a complex enterprise, but one that is imperative for those seeking to identify, develop, and maintain expertise, both now and in the future. Although we attempted to present a book that is forward in its thinking on the topic, there is no doubt that there are conditions and events that will continue to shift the course of expertise research and the work of scholar-practitioners. For instance, the rise of the global pandemic, COVID-19, has led to a reimagining of work. With millions of people changing their work patterns (Davidson, 2020; Richter, 2020) and organizations rethinking their business models, adopting new technology, needing alternative work arrangements, and shifting to online services and new partnerships, the expertise that was necessary for success in 2019 is no longer the same in 2020. Unexpected changes faced by organizations and employees always have the potential to affect expertise and scholars and scholar-practitioners need to be prepared for that change.

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Index

A
Adaptability, 25, 43, 48, 49, 63, 162, 182
Adaptive expertise, 5, 18, 25–27, 31, 39–52, 62, 63, 160, 226, 227
Affect, 5, 8, 113–114, 119, 141, 180, 231
Agile, 198, 200–202, 205, 206, 215, 219
Anxiety, 8, 84, 107, 113–115, 119, 217, 218
Artificial General Intelligence (AGI), 149, 156, 161
Artificial intelligence (AI), 4, 8, 9, 39, 149–170, 177, 182, 186–192, 200, 205–208, 210, 219, 225, 226, 228–230
Assemblage theory, 8, 130, 142, 143
Athlete, 3, 7, 8, 100–102, 104–119, 228
Automation, 163–167, 191, 203

B
Behaviors, 5, 23, 26, 41, 44, 46, 58, 100, 101, 107–111, 113, 132, 151, 157, 162, 182, 186, 188–192, 202
Big data, 155–157

C
Career, 3, 17, 22, 27, 28, 63, 64, 77–79, 85, 88, 89, 91, 100, 106, 109, 206
Career transition, 79, 83–84, 89, 93, 94
Change, 8–10, 17, 25, 26, 39–41, 44–47, 49, 58, 79, 80, 83–86, 103, 110, 113, 116–118, 129, 131, 136, 138, 141, 163, 165, 177, 178, 180, 182, 185, 186, 191, 198–203, 209–211, 213, 215–219, 226, 229–231

M.-L. Germain, R. S. Grenier (eds.), *Expertise at Work*,
https://doi.org/10.1007/978-3-030-64371-3

Competency, 3, 6, 9, 22, 58, 75, 76, 83, 181, 190
Conceptual knowledge, 41, 44, 51
COVID-19, 10, 198, 199, 201, 219, 230
Culture, 2, 5, 80, 85, 86, 201, 215
Cycling, 7, 102–119

D

Deep learning, 155–157, 167, 168
Deep neural networks (DNN), 155–157, 169, 228
Deliberate practice, 8, 10, 17, 22–25, 29, 46, 61, 105–107, 111, 112, 118, 169, 197, 201, 218, 226, 228, 230
Demographics, 9, 73, 177–192, 225, 229
Development, 2, 4, 5, 8, 17–31, 40–51, 57–64, 74–76, 78–80, 86, 94, 95, 100, 102–104, 106, 107, 109–111, 118, 133, 149, 154–156, 178, 183, 187, 197–219, 226, 228
Digital revolution, 9, 177, 229, 230
Disaster management, 199, 201
Diversity, 9, 48, 177, 229
Domain knowledge, 19, 21, 42, 44, 47, 48, 153, 159

E

Education, 3, 23, 24, 29, 58, 74–76, 87–90, 93, 100, 129–131, 133, 139, 178, 182, 184, 185, 190, 191, 229
Employee, 2, 3, 6, 9, 10, 17, 18, 24, 25, 28, 29, 31, 39, 40, 50–52, 58–65, 76, 78, 82, 83, 90, 93, 94, 131, 177, 181–192, 198, 201, 203, 204, 206–208, 213–217, 219, 227, 229–231
Employment, 7, 27, 79, 84, 86–95, 184, 200
Environment, 2, 4–6, 10, 26, 29, 31, 39–52, 63, 75, 79–86, 93–95, 100, 103, 104, 108, 118, 130–132, 135, 136, 139, 143, 151, 162, 165, 187, 199, 201, 202, 204–206, 212, 216–218, 226, 227, 230
Expertise, 1–10, 17–31, 39–52, 57–65, 73–95, 99–119, 129–144, 149–170, 177, 181, 182, 185–192, 197–219, 225–231
Expert systems, 153–154, 159, 161, 162

F

Fatigue, 8, 107, 109, 112, 113, 116–119
Flexpertise, 5, 26, 27, 43, 227
For-profit, 81, 82, 177, 182–184
Future, 4, 8–10, 64, 77, 90, 92, 94, 110, 150, 152, 156, 157, 169, 170, 181, 197–219, 226, 228–230

G

Generalized Expertise Measure (GEM), 6, 61, 62, 188
Generation, 73, 87, 88, 140, 159, 178–180, 185, 190
Globalization, 64, 178

H
Healthcare, 29, 51, 75, 166, 168, 199
Higher education, 7, 8, 88, 129, 130, 135, 138, 142
Hiring, 6, 76, 89–91, 93, 95, 190, 228
History, 2, 19, 73, 106, 129, 142, 143, 149–170, 178, 206, 228
Human Resource Development (HRD), 2, 4–6, 10, 17, 18, 23, 25, 31, 57–59, 63–65, 78, 160, 211, 213, 216–218, 226, 227
Hybrid AI, 157, 168, 169, 229

I
Innovation, 10, 26, 27, 42, 50, 183, 187, 191, 198, 199, 202, 214, 215, 218, 219, 225, 226, 230

J
Jobs, 3, 17, 27, 50, 51, 63, 64, 75–78, 80, 81, 83, 85, 86, 88, 90–95, 131, 150, 182, 185, 190, 191, 200, 203, 204, 206, 207, 213, 214, 216, 228, 229
Joint cognitive systems, 9, 149, 161–166, 169, 170, 229

K
Knowledge, 1, 2, 5, 7, 8, 10, 17, 19, 21, 23–31, 40–43, 45, 47–49, 51, 52, 58–60, 62–64, 74, 75, 78–80, 83, 85, 87–92, 94, 100–102, 109, 115, 129–144, 150–155, 158–160, 162, 163, 167, 182, 185–188, 190–192, 197, 199, 200, 202, 205, 208–213, 218, 226–230

L
Learning, 2, 4, 5, 10, 17, 19, 22–24, 27–29, 41, 50, 52, 58, 59, 74, 75, 77, 79, 106, 108, 130–132, 135, 138–140, 142, 150, 155–157, 167–169, 191, 198, 201, 205–207, 210–213, 215, 217, 218, 228
Luddite strategy, 204

M
Machine, 136, 155, 161–166, 168, 169, 186, 189–191, 198, 203, 205, 206, 208, 209, 228
Mastery, 10, 47, 75, 197, 198, 200, 211, 215, 217
Measurement, 59–63, 65, 150
Military, 7, 73–95, 214, 227
Model of Expertise Redevelopment (MER), 7, 79, 80, 83, 84, 95
Mood, 8, 113, 115–116, 119
Multi-agent systems (MAS), 155

N
Non-profit, 9, 59, 81, 89, 177, 181–192
Novice, 8, 18, 19, 22, 23, 29, 30, 46, 49, 58, 59, 61, 65, 81, 110, 129–144, 159, 227, 228

O

Occupational expertise, 2–4, 211, 219
Organization, 1–10, 17–19, 21, 22, 25, 27, 28, 31, 39, 40, 50–52, 57–65, 74, 76, 77, 80–83, 85, 86, 89–95, 130, 170, 177, 178, 181–192, 198–206, 210–219, 226–231

P

Pain, 8, 102, 108, 109, 112, 113, 116–119, 199
Performance, 2, 7, 8, 10, 18, 19, 21–24, 26, 27, 29–31, 39–41, 43–47, 51, 52, 57–61, 64, 77, 82, 91, 100–106, 108–119, 133, 138, 150, 151, 153, 155, 156, 158, 161, 162, 167–169, 189, 197, 199, 203, 205, 207, 209, 217, 219, 226, 228, 230
Problem-solving, 1, 19, 23, 42, 48, 49, 57, 59, 65, 78, 100, 133, 159, 160, 162, 182, 186–188, 190, 191, 227
Procedural knowledge, 41, 44, 51, 132, 133
Proficiency, 18, 58, 65, 78, 200, 227

R

Radiology, 9, 150, 166–169
Rapid, 10, 135, 178, 198–202, 210, 215, 217, 219, 230
Redevelopment, 4, 7, 59, 78–95
Re-skilling, 178, 198, 200, 203, 204, 211, 213–214
Routine expertise, 5, 25, 26, 39–52, 160

S

Scholar-practitioner, 4, 10, 226–228, 230, 231
Scholars, 4, 10, 18, 30, 31, 59, 60, 65, 94, 95, 129, 136, 139, 143, 188, 197, 204, 226–228, 230, 231
Self-regulation, 7, 8, 43, 107–111, 118, 228
Semantic web, 155
Skills, 1, 3, 5, 7–10, 17, 21–27, 30, 31, 41–49, 57–60, 63–65, 74–81, 83–95, 100, 101, 105–107, 109–112, 118, 119, 133–135, 150, 159–161, 164, 166, 168–170, 177–192, 197, 199, 200, 203, 209–214, 226–230
Sport, 7, 8, 24, 99–119

T

Talent, 18, 89, 100, 102–107, 110, 118, 168, 190, 214
Technology, 1, 3, 9, 10, 39, 135, 143, 155, 163, 164, 167, 177–192, 198–200, 203–207, 210–219, 229–231
10,000 hours, 105, 106, 185, 190, 201, 218, 229, 230
Training, 2, 23, 24, 46, 51, 59, 64, 74–77, 80, 82, 86–90, 93, 102–106, 108–110, 112, 116–118, 138, 150, 156, 168, 182, 191, 203, 206, 207, 209–211, 216
Transfer, 25, 26, 30, 31, 43, 48, 49, 59, 94, 159, 206, 227
Transform, 10, 135, 155, 202, 204, 210, 218, 219, 230
Transition, 7, 30, 79–84, 86–89, 91–95, 105, 227

U

University, 8, 129–144, 178
Upskilling, 198, 203, 204, 211, 213–214

V

Veterans, 7, 73–95, 214, 227

W

Work, 1–10, 23, 24, 26–29, 42–44, 46–51, 58, 61, 62, 73–95, 103, 112, 137–143, 150, 151, 153–156, 158, 159, 161, 165–170, 178–180, 182, 183, 186, 189, 190, 197–210, 212, 218, 219, 225–231
Workers, 3, 6, 10, 27, 62, 178, 190, 198–201, 203–205, 215, 216, 226–228
Workplace, 3–5, 7, 9, 10, 18, 19, 22–31, 46, 50, 57, 60, 61, 63, 65, 74, 80–82, 84, 85, 87, 88, 90, 94, 139, 177, 198–201, 203–210, 215, 218, 219, 226, 227, 229, 230