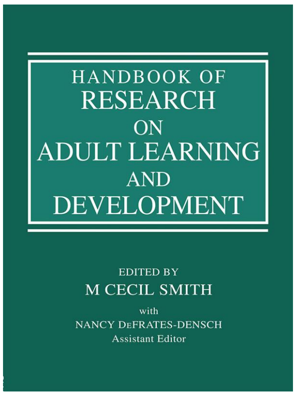

Handbook of Research on Adult Learning and Development

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Expertise and the Adult Learner

Publication details
https://www.routledgehandbooks.com/doi/10.4324/9780203887882.ch17
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Published online on: 07 Nov 2008

HANDBOOK OF RESEARCH ON ADULT LEARNING AND DEVELOPMENT

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First published 2009
by Routledge
270 Madison Ave, New York, NY 10016

Simultaneously published in the UK
by Routledge
2 Park Square, Milton Park, Abingdon, Oxon OX14 4RN

This edition published in the Taylor & Francis e-Library, 2008.

Routledge is an imprint of the Taylor & Francis Group, an informa business

Library of Congress Cataloging in Publication Data
Handbook of research on adult learning and development / edited by M Cecil Smith with Nancy DeFrates-Densch.
p. cm.
Includes bibliographical references and index.
1. Adult learning—Research—Handbooks, manuals, etc. 2. Adult education—Research—Handbooks, manuals, etc. I. Smith, M Cecil. II, DeFrates-Densch, Nancy.

ISBN 0-203-88788-3 Master e-book ISBN

ISBN 10: 0-8058-5819-9 (hbk)
ISBN 10: 0-8058-5820-2 (pbk)
ISBN 10: 0-203-88788-3 (ebk)

ISBN 13: 978-0-8058-5819-8 (hbk)
ISBN 13: 978-0-8058-5820-4 (pbk)
ISBN 13: 978-0-203-88788-2 (ebk)

Chapter 17

Expertise and the Adult Learner

A Historical, Psychological, and Methodological Exploration

Patricia A. Alexander, P. Karen Murphy, and Jonna M. Kulikowich

Throughout history, whether chronicled in primitive cave drawings, the annals of past cultures or societies, contemporary biographies, or web blogs, humans have been captivated by remarkable performance. Likewise, humans have remained fascinated by those capable of exceptional feats and unparalleled visions—whether the bravery of the unnamed hunters seen on the cave walls of Lascaux, France; the military genius of Alexander the Great; or the astonishing physical prowess of Lance Armstrong. Expertise is a term that has been applied to those who attain the pinnacle of human performance in specific domains or areas of pursuit; from art to athletics or from physics to politics. Experts are, in effect, the paragons that people have celebrated throughout the ages and the models to which they aspire.

In this chapter we will consider many questions that have been addressed by researchers in their study of expertise. Some questions pertain to the roots of expertise, be they heritable factors (i.e., genes) or those acquired though life experiences (i.e., schooling or professional opportunities). Other questions pertain to the distinctions between experts and novices both in terms of the traits they possess (e.g., intelligence or prior knowledge) and the procedures they execute (e.g., problem-solving strategies). These distinctions are important. By knowing what experts in contrast to non-experts have and can do, researchers have been able to plot potential developmental trajectories that can help guide movement toward expertise in domains (e.g., Ackerman, 2003a; Alexander, 2003b; Lajoie, 2003).

With our eyes toward the emergence of expertise, we undertake a historical, psychological, and methodological analysis of expertise literature. For the historical segment, exploration will be centered on the question: How has expertise been conceptualized in the distant and near past? One of the issues examined in this discussion relates to who, historically, has garnered the label of expert and what evidence has been applied to confirm the authenticity of such determinations. We will demonstrate that two lines of inquiry have directed our understanding of outstanding performance in fields of study. From the late 1800s to the early 1900s, researchers such as Galton and Terman focused extensively on intelligence and the role of heredity factors in the study of exceptional performance, administering a variety of tasks representing a host of domains. This approach planted the seeds of the large-scale testing movement in vogue today.

While the study of intelligence, testing, and the analysis of test scores continued throughout the mid 1900s, scholars began questioning the underlying mechanisms for how learning occurs. During this period, behavioral accounts of learning (e.g., Skinner) were commonplace. Many theorists posited that internal mental mechanisms for thinking and performing were not relevant in the explanation of learning. Instead, behavior and activity described in relation to external, environmental stimuli could account for human performance. Therefore, expertise as a formal study was not of primary interest to behaviorists for their central premises were not tied to variables like reasoning, memory capacity, or problem solving.

However by the late 1960s, views of learning dramatically changed and the study of expertise soon emerged as a dedicated area of investigation. As a metaphor for knowledge storage and retrieval, the computer, became a powerful force in the rebirth of domain-specific expertise. Initially, as we will show, the focus on performance, specifically problem-solving performance, was more closely linked to early turn-of-the-century views on intelligence. As such, problems were highly contrived (Gick, 1986), ensuring that domain-specific knowledge contributed little to correct solutions. Initially, strategic knowledge that was domain independent was of primary interest to scholars. Gradually, this focus changed as problem-solving tasks became tied to domains (e.g., chess and physics) and fields of practice (e.g., medicine and engineering) from which they were sampled. The interaction between domain knowledge and strategies established this nucleus for the study of expertise (Alexander & Judy, 1988). This nucleus still characterizes the central focus of research activity in contemporary research. However, as we will show, the history of research on intelligence continues to move in concert with this cognitive tradition. Additionally, modern programs of research have introduced other variables that play roles in the development of expertise such as beliefs, motivation, and personality factors.

In fact, contemporary views of expertise are significantly more multidimensional than views adopted throughout the majority of the history on expertise. As a result, these programs of research also offer much more complex accounts for examining differences between experts and non-experts, as well as generating explanations for how individuals may potentially become experts in time. Therefore, in the second section of our chapter, we turn to a more detailed analysis of the psychological research on expertise conducted within the last decade. The findings from select programs of expertise research will be scrutinized, along with the relative strengths and seeming shortcomings of this literature for adults working within academic and non-academic arenas.

Our goal is to offer a comparison that can inform research and practice pertaining to adult development. For this analysis, we review four programs of research that have reflected the history of the study of advanced to elite performance in one or more domains that draws on both the research traditions on intelligence and problem solving. Two of these traditions arguably have more narrow foci in that they examine the multidimensional nature of singular variables. For Sternberg and colleagues, the variable is intelligence. In contrast, for Lajoie and colleagues the variable is domain-specific processes and problem solving. The other two traditions explore the relations among complexes or sets of variables that define expertise and describe its developmental trajectory. For Ackerman and colleagues, the histories of intelligence and domain-specific problem solving are brought together in addition to the roles of personality factors. For Alexander and colleagues, the domain-specific lens focuses on the complex interplay of knowledge, strategies, and motivational factors as learners begin their journey toward expertise. Because the Ackerman and Alexander frameworks have many similarities but unique differences that help provide a more robust account of expertise and its development, we attend specifically to these two programs of research in section two of our chapter.

In the third section, we explore the methodological history in the study of expertise. Indeed, the methodologies employed and developed by researchers have been numerous and varied, spanning the gamut from qualitative to quantitative approaches. Aligning to the history of research on intelligence and its impact on the study of expertise, we review how the factor-analytic tradition was born and how it continues to be a mainstay in contemporary research in all of the social sciences. By comparison, as we revisit the historical path of domain-specific, problem-solving research, we will observe that the methodologies have been more qualitative in nature, resting heavily on think-aloud and verbal protocol analyses, as individuals attempt to describe the processing that coincides with performance. We will close this section by discussing how macro-analytic (i.e., intelligence) and micro-analytic (i.e., problem solving) platforms frame a more comprehensive system of methodological approaches that can chart the movement toward expertise.

Finally, we close our chapter by speculating on future developments in the study of expertise. Again, to match each of our three sections (i.e., historical, psychological, and methodological) we envision: a) what expertise research is likely to look like in the next decade; b) what variables (psychological as well as environmental) assume more central roles in describing expertise development; and, c) what types of methodologies must emerge to capture the essence of expertise as well as the landscape and roadmap that led to its development.

Historical Perspective on Experts and Expertise

Through the ages, humankind has recognized and lauded high levels of achievement. Through their writings and experimentation, various historical personages, among them Plato, Galton, and Terman, helped lay the groundwork for 20th- and 21st-century investigations of expertise. Here, we look briefly at the ideas forwarded by those brilliant scholars for clues to the perspectives and procedures adopted by psychological researchers of the late 20th and early 21st centuries. In this brief retrospective, we seek to understand how genetics and effort are intertwined in views of expertise. Historically, genetics has been tied to the study of intelligence, while effort is a key variable in more recent accounts of expertise as a domain-specific phenomenon where deliberate practice (Ericsson, 1996; Ericsson & Kintsch, 1995; Ericsson, Patel, & Kintsch, 2000) and years of training are hallmarks of exceptional performance (Ericsson & Staszewski, 1989). The interplay of intelligence and effort were evidenced in philosophical thinking that dates back to Plato, as we will demonstrate.

Historical Taproots in the Study of Expertise

In his dialogue, *The Republic,* Plato describes the ideal State where "kings are philosophers" and "philosophers are kings" and where humankind strives for justice through the pursuit of knowledge and the logic of science that contemplates "all truth and all existence." Plato railed against an aristocracy ("aristos" meaning best) or a government ruled by those whose powers were derived solely by virtue of their social status or noble birth. Rather, Plato argued for a government where power fell to those who merited the right to rule by the manifestation of their higher states of knowledge and knowing; that is, a meritocracy. Merit, as conceived in this way, was based not only on individuals' intelligence or inherent mental capability, but also on the effortful striving for the ideal. Plato also held that societies, as organic wholes, functioned best when those who excelled at particular roles were free to take on those roles. In essence, Plato's ideal republic was a place where individuals who displayed emerging expertise were supported and encouraged to assume their place of honor and to hone their particular talents through the continued pursuit of knowledge.

Francis Galton, as with Plato, was absorbed in understanding human excellence and in using whatever knowledge of human excellence he might garner to improve social order. However, where Plato began his quest from a philosophical ideal, Galton's pursuit started from a perplexing observation. Specifically, Galton became intrigued when he realized that many of the students achieving honors at Cambridge University, his alma mater, were the sons or brothers of other high achievers. This led Galton to question whether specific factors passed from farther to son, termed *eminence*, could explain this perplexing pattern of exceptional performance. While Plato's contemplation of human performance remained purely philosophical, Galton's moved into the realm of scientific inquiry—inquiry that became the foundation for modern studies of individual differences.

Specifically, Galton (1874/1970) set about testing the hypothesis that eminence begets excellence by amassing incredible amounts of data on hundreds of men and their offspring. His thousands of measurements included meticulous physical data (e.g., height, weight, or strength), as well as academic data (e.g., honors or professions). In order to deal meaningfully with such massive information, Galton ultimately borrowed a mathematical idea from the Belgian astronomer Adolphe Quételet, himself quite knowledgeable in mathematics. That little idea would serve as a fundamental tool in the study of individual differences, which is still alive and well. Specifically, when data are plotted to show how a population differs with regard to a variable of interest such as height or weight, the resulting graph appears bell-shaped. Formally, this bell-shaped curve is called the normal distribution, and its properties work as well in the descriptions of intelligence and expertise as they did in Galton's presentations of height, weight, strength, and academic honors. Without the ability to quantify human variability, researchers would be thwarted in their attempts to systematically study expertise via statistical means.

One side-effect of Galton's quantification of human differences was his founding of the field of eugenics. For Galton, so much of human accomplishment was derived from inherited factors—in contrast to Plato who gave great weight to human striving. In fact, in his well-known work, *Hereditary Genius* (1869/1979), Galton set out to prove that genius is virtually the consequence of ancestry. The determinations he made in his examination of eminence led him to argue that societies should encourage selective breeding so that the desired traits associated with eminence could be encouraged while less desirable factors or conditions could be bred out of society. Even though many others toyed with ideas of selective breeding, including Plato, it was Galton who grounded his arguments in a wealth of "scientific" data. Although Galton's articulation of eugenics was well-intentioned, the negative ramifications of selective breeding or genetic engineering has become only too apparent to those familiar with the horrors of genocide or the infamous Nazi experiments on genetic engineering (Selden, 1999).

One individual who carried some of the premises of eugenics forward into the 20th century was Louis Terman (with Oden, 1947). Terman, drawn into the eugenic movement during its waning years, wanted to investigate what would become of those who showed exceptional intellectual promise early in life. As such, Terman was invested much more into issues pertaining to schooling like curriculum and testing practices than was Galton (Keating, 1990). In 1921, he launched a longitudinal study of children who scored at an exceptional level on a measure of cognitive ability. This approach differed from that of Galton, who worked backward from demonstrated accomplishments among adults to judgments about expertise.

Among Terman's goals was determining whether the *gifted*, as he called them, would be more or less disposed to psychological or physical disorders in the years to come or whether they would naturally emerge as society's leaders? A belief that genius and madness were two sides of the same coin had been a common conception that Terman, himself a precocious youth, hoped to dispel. As with Plato and Galton before him, Terman hoped that his efforts would have positive social consequences. In effect, Terman not only wanted the knowledge he garnered about the highly gifted to put the genius-as-madness belief to rest, but also to contribute to programs that might nurture these children of promise. The outcome, he trusted, would be an improved society.

In order to find his pool of highly gifted children, Terman and associates tested thousands of children in California. The initial basis for identification was exceptional performance on a translated and adapted version of the intelligence test created by Alfred Binet and Theodore Simon (1905). The resulting test, called the Stanford-Binet, remains a mainstay of intelligence testing in the United States. From this extensive pool, Terman (with Oden, 1947) identified 857 boys and 671 girls between the ages 3 and 19 who scored 135 or above on the Stanford-Binet. Extensive psychological, physiological, and academic achievement data were gathered on these "Termites," as they were affectionately called. These individuals were tracked for more than 80 years; more than four decades after Terman's death (Leslie, 2000).

Even though the design of Terman's longitudinal study has repeatedly been questioned, there is no doubt that this momentous study was a landmark in the exploration of exceptionality and served to define contemporary investigations of expertise. Perhaps the major contribution of Terman's (with Oden, 1947) multifaceted, longitudinal study was the realization that those who are intellectually advanced are also more likely than their non-identified peers to be physically and socially capable as well. It is almost inconceivable that present-day researchers could amass such intricate and lifelong portraits of human performance—portraits that span up to eight decades of participants' lives.

Psychological Studies of Expertise: Three Generations and Three Perspectives

The three forerunners to modern-day studies of expertise just considered had certain attributes in common. For one, Plato, Galton, and Terman believed that there were undeniable differences among human beings and that some individuals, whether as a consequence of their genetic endowments or through their own pursuit of ideals, were superior or advanced. Further, they held that those exceptional individuals should be nurtured and lauded by society. Finally, Plato, Galton, and Terman engaged in the philosophical or scientific study of exceptionality, in part, to advance society. Although contemporary researchers share some of the same characteristics as their historic forerunners, they have typically engaged in their studies for more pragmatic reasons.

Specifically, there was a resurgence of interest in eminent or gifted performance beginning in the late 1960s that has carried forward into contemporary research (Gick, 1986; Keating, 1990). In fact, it is helpful to consider this extant literature in terms of generations of psychological inquiry (Holyoak, 1991)—generations that were initially spawned by the notion of Alan Turing and others that machines (i.e., computers) could be made to think. The introduction of the computer had a tremendous impact on the history of the study of expertise. With the computer, scholars recognized that information could be stored and retrieved in a specific location. For cognitive psychologists studying human learning, that location was the brain. The theory of information-processing (IPT) emerged as a result of mapping human knowledge acquisition and use to that of computer storage and retrieval. Information-processing researchers and theorists are therefore cognitivists dedicated to understanding how the mind perceives, internalizes, interprets, stores, structures, and uses information (Anderson, 1983; Patel & Groen, 1986; Simon, 1989). Indeed, much is owed to IPT scholars like Chi (1978, 1997), Ericsson (with Polson, 1988), Glaser (Chi, Feltovich, & Glaser, 1981), and their contemporaries whose programs of research left their indelible mark on expertise research in the 20th century and paved the way for others invested in this line of inquiry.

Not only did the idea of the computer present a rich metaphor to describe human learning, but also the availability of computers as industrial tools allowed for social advances where seemingly innumerable bytes of information could be stored, organized, and accessed for human consumption as challenging problems arose in society (e.g., breaking codes in wartime, detecting submarines, and flying planes). However, to unlock the potential of computers to accomplish multi-step tasks, it was necessary to enhance the programming that directed their actions. Here, the human mind with its potential to be planful and to execute strategies to reach goals served as a means by which computer programmers could learn more about configuring their codes. As a result, researchers set out to discern the characteristics of expert performance (i.e., what do experts do or how do they reason/think?) and to validate them over a variety of problem-solving tasks so that those characteristics could be programmed into non-human systems or "smart" machines that approximated effective human thinking and actions (Alexander, 2003b; Ericsson & Smith, 1991).

Another goal of these researchers was to ascertain the cognitive attributes that would distinguish experts from novices so that those attributes could be trained in non-expert human populations (Chi, Glaser, & Farr, 1988)—a goal that is reflective of the individual difference theory and research of Francis Galton. In this chapter, we look across three generations of contemporary expertise research, comparing them with regard to their purposes, nature of tasks, target populations, and primary findings (see Table 17.1). We focus our discussion in the next section on the first two generations of this work, leaving more detailed treatment of the third and current generation of expertise research for later.

Table 17.1 A Cross-Generational Examination of Contemporary Expertise Theory and Research

	GENERATIONS		
PARAMETERS	*First*	*Second*	*Third*
Purpose	Study experts at generic problem solving	Investigate domain experts engaged in problem solving	Examine the developing and multidimensional nature of expertise
Theoretical Frames	Artificial intelligence and individual differences	Information-processing and individual differences	Information-processing and social constructivism
Structure	Expert/novice dichotomy	Expert/novice dichotomy	Novice to expert development
Tasks	Knowledge-lean, generic problems	Knowledge-rich domain-specific problems	Well-defined and ill-defined tasks
Participants	Identified adult experts and assumed adult novices	Identified experts and assumed novices; primarily adults	Range of novice, competent, and expert performers of varying ages

First Generation: Expertise as Generic Problem Solving

As noted, computers were a particularly powerful influence in the onset of psychological studies of expertise. A bidirectional relation emerged between research on computers and human learning. Computers served as a metaphor to describe memory and how knowledge is structured in memory. In turn, humans' abilities to solve problems provided programmers with the means to make computers "intelligent" machines that could complete cognitive tasks. This influence is evident in various ways within the first generation. Researchers of this generation such as Newell, Simon, and Chase (e.g., Chase & Simon, 1973; Newell & Simon, 1972) hypothesized that the in-depth study of the cognitive processes and mental structures of expert problem solvers would be a key to the effective programming of more intelligent machines. These cognitive-science researchers who were at the vanguard of artificial intelligence (AI) conceptualized expertise as the efficient and effective solution of generic problems; that is, problems for which all critical information was thought to be part of the given problem space. The first generation researchers also relied on computer simulations and computer modeling to test their assumptions about expert problem solving.

The isolation of the specific strategies or solution techniques employed by expert problem solvers required these first generation researchers to create or to select experimental tasks that would maximize cognitive processing data while controlling for the influence of background or content knowledge. Gick (1986), in her review of problem-solving strategies, refers to these as artificial puzzles or problems. Because of the lack of domain specificity, other scholars such as Holyoak (1991) refer to these tasks as knowledge-lean (Holyoak, 1991). The classic cannibal/missionary conundrum is representative of such knowledge-lean problems:

> There are three missionaries and three cannibals on a river bank. The missionaries and cannibals need to cross over to the other side of the river. For this purpose, they have a small rowboat that holds just two people. There is one problem, however. If the number of cannibals on either river bank exceeds the number of missionaries, the cannibals will eat the missionaries. How can all six get across to the other side of the river in a way that guarantees that they all arrive alive and uneaten? (Sternberg, 1986, p. 57)

In addition to these generic problem sets, it was essential for first generation researchers to ensure that the processes and structures they uncovered were indeed unique to experts, for the code used to program computers had to result in not only accurate task completion but also highly efficient performance. Therefore, they contrasted data from presumed or known experts to those considered to be novices. These expert-novice comparisons became a hallmark of this generation and lead to significant characterizations of expert problem solvers (versus novices) as those who:

- Perceive the underlying structure of problems and are not distracted by more surface-level features;
- Have a richer repertoire of heuristic strategies;
- Engage in problem analysis and planning;
- Employ a means-end problem solving strategy in which they combine aspects of forward and backward reasoning during solution, instead of moving forward in a step-by-step process (e.g., Bransford, Brown, & Cocking, 1999; Chi, 1978).

Despite these remarkable advancements in understanding, there remained critical shortcomings to the first generation approach to expertise. Most notable was the inability to acknowledge the structures of knowledge held in memory by experts and how this knowledge base interacted with strategies during problem solving. Thus, it became apparent that generic problem-solving expertise had limited relevance to exceptional problem-solving performance in specific domains (Gick, 1986). What followed, therefore, was a subsequent generation of researchers who wanted to understand the mental processing with the structures of knowledge of those who demonstrated expertise in specific problem-solving domains (Holyoak, 1991).

Second Generation: Expertise as Knowledge-Rich Problem Solving

As with its predecessor, the second generation of expertise researchers continued to focus on problem solving as the mechanism for operationalizing expertise and retained the expert-novice dichotomization indicative of the prior generation. However, the second-generation researchers were no longer interested in general search strategies or generic knowledge-lean problems. Rather, these researchers—many of whom had been part of the initial generation—targeted tasks drawn from particular fields or problem-solving contexts (e.g., chess, typing, waiting tables, or physics) for which knowledge of the domain was perceived as essential (Anderson, 1983; Chi, 1978; Chi et al., 1981).

In effect, their problems of choice were not self-contained, generic problems, but were problems expected to trigger the infusion of domain-specific knowledge and strategies, as well as general problem-solving heuristics. Careful task selection thus allowed second-generation researchers to document that knowledge and strategies were significant determiners of expert performance in selected domains (Ericsson & Smith, 1991). One such problem used in the domain of political science was:

> Assume you are the head of the Soviet Ministry of Agriculture and assume that crop productivity has been low over the past several years. You now have the responsibility of increasing crop production. How would you go about doing this? (Voss, Tyler, & Yengo, 1983, p. 212)

The pioneering research of de Groot (1978/1946) and Chase and Simon (1973; Simon & Chase, 1973) in the domain of chess serves as an illustrative case of early second-generation research. These researchers wanted to uncover the nature and characteristics of expert chess players. Chess was an ideal domain for this research because it is a game with limited but well defined rules yet with incredible variability in the way experts and novices execute those rules. What also made chess appealing as a domain of study was the fact that the strategic moves of players are transparent as pieces move on the gameboard. Therefore, researchers could readily record those moves. Through the use of think-aloud techniques or stimulated recalls, researchers could then prompt the players to verbalize the reasoning behind particular moves, adding to the problem-solving data. Finally, the procedural nature of chess and similar domains allowed researchers like de Groot to create simulations or laboratory versions of these problem-solving tasks. The benefit of these simulations was that the thinking and moves of experts and novices could be investigated in more controlled conditions, without the extraneous influences that might exist in everyday settings (Ericsson & Smith, 1991).

As with their predecessors, these second-generation researchers were able to document clear and significant differences between experts in particular domains and those new to those domains. These differences, it was hoped, could signal the changes that should be prompted in novices in order to transform them into domain experts. For example, these programs of inquiry gave strong evidence that experts possess the following desirable traits:

- Have devoted much time and effort to the target domain and its relevant tasks;
- Possess an extensive body of domain knowledge that is coherently and efficiently organized;
- Rely on their rich prior experiences to analyze the problem at hand deeply and effectively;
- Select and execute domain-specific, as well as general, strategies that are well-matched to the target problem (e.g., Bransford et al., 1999; Byrnes, 2001; Chi et al., 1988; Ericsson & Smith, 1991).

Through this list, one can again see the intertwining of intelligence and effort. Time is essential to expertise as individuals must have multiple and repeated opportunities to interact with bodies of information. This is a domain-specific principle that relates directly to the fact that one hallmark of expertise is principled understanding (Alexander, Murphy, & Woods, 1996) or the ability of experts to organize information around the few central concepts of their domain. However, experts must also have keen perceptual skills that allow them to sift and sort through information and separate problems into classes. These types of pattern finding and detection skills are commonly measured by intelligence tests (e.g., Wechsler 1981).

Despite the many contributions of the second generation, there remained serious limitations to this body of research, particularly in terms of translating its findings to the development of expertise in and out of school. In effect, it was one thing to document how true experts differed from real novices when confronted with prototypic domain problems, but it was quite another to use that knowledge to stimulate the development of expertise. There have certainly been efforts to translate such consistent and significant findings about experts into instructional metaphors, models, and programs intent on facilitating expertise development (Bereiter & Scardamalia, 1993; Brown, Collins, & Duguid, 1989). Still, these efforts have not been particularly easy or readily apparent (Sternberg, 2003).

We must acknowledge that some of the translational difficulties faced by second generation researchers may be attributable to the social/political and academic climates that surround educational or professional development efforts (Alexander et al., 1996; Berliner & Biddle, 1995). Nonetheless, it was the limitations of the first and second generation research on expertise that gave rise to the current and third generation. As a way to introduce the third generation, we will consider several of those limitations and the manner in which current programs of expertise theory and research have sought to counter them.

Third Generation: Expertise as a Multidimensional, Developmental Process

Many within the third generation of expertise research share a commitment to the development of expertise. It is not simply the sharp contrasts between those at the extremes of expertise that matter; it is also all the places in-between. Further, it is the array of forces and experiences that seem necessary to move one along the trajectory from novice to expert that warrants attention. This developmental versus dichotomous orientation toward expertise is thus a hallmark of the third generation.

Another distinguishing feature of this generation of theory and research is the acknowledgment or embracing of non-cognitive or motivational/affective factors as part of expertise development. It has been argued that prior generations of research held to a "coldly cognitive" view of expertise (Pintrich, Marx, & Boyle, 1993). That is to say, these earlier generations did not expressly consider the personality, social, or motivational factors that seem inherent in the attainment of expertise. These motivational/affective dimensions do not supplant or eradicate the significance of cognitive forces, such as knowledge and strategic processing, but have been treated as complementary and integrated elements of expertise development. Growing competence or established expertise in complex domains also entails persistence, interests, curiosities, and other such forces (Ainley, 1998; Reio & Wiswell, 2000).

For example, in the prior generations of expertise research, the conation (will) or intentionality of the learner did not enter strongly into discussions (Sinatra & Pintrich, 2002; Snow, Corno, & Jackson, 1996). Any willful or goal-directed aspects of the transformation of novices to experts were not systematically incorporated into research designs or empirical measures of past generations (Ackerman, Kyllonen, & Roberts, 1999). Third generation researchers do not work under the assumption that individuals not already acknowledged as experts have a voiced or unvoiced goal of becoming experts in any domain, or any intention of committing the requisite time and energy to achieving expertise, even in those cases where the requisite cognitive abilities exist (Bransford et al., 1996; Meece, Blumenfeld, & Hoyle, 1988).

Over the years, there have been attempts to relate expert/novice research to education or professional development (e.g., Bransford et al., 1999), but little of the foundational research in those years considered schools or education as the primary context for research. As we discussed, the experimental tasks from the first and second generations were carefully crafted or contrived to be knowledge-lean or knowledge-rich (Allard & Starkes, 1991; Ericsson & Polson, 1988; Gentner, 1983, 1988; Patel & Groen, 1986). Those actions were perhaps critical to establishing the parameters for expertise research (e.g., Anzai & Yokoyama, 1984). But, those of the third generation have chosen to look explicitly at schools or academic domains as legitimate venues for study or to investigate expertise in everyday, dynamic settings or with complex, less well-structured tasks. As a result, the subject-matter areas represented in expertise research span the continuum from domains that rely heavily on algorithms (e.g., mathematics or physics) to those that rely heavily on heuristics and case-based reasoning (e.g., history, medicine, or psychology).

Even for domains that tend to be algorithmic, such as mathematics, expertise researchers have looked at both well-defined (i.e., correct solutions) and ill-defined (i.e., plausible solutions) tasks to gain insights as to how those who are more knowledgeable regulate deductive and inductive reasoning strategies (Kulikowich & DeFranco, 2003). Finally, even though domain-specific expertise assumes proficiency in one domain, no domain acts in isolation of other subject-matter areas or fields of study. Therefore, cognitive psychologists have paid significantly more attention to interdomain transfer during problem solving (e.g., Bassok & Holyoak, 1989) and crossdisciplinary thinking (e.g., Spiro & Jehng, 1990).

In the section that follows, we take a harder and more detailed look at this third generation of expertise researchers and consider the strengths, limitations, and contributions of this ongoing work for understanding expertise and its development.

Contemporary Programs of Research on Expertise

Research from the early 1900s on intelligence and the 1960s on problem solving (Chi, 1978; Chi et al., 1981; Ericsson & Smith, 1991) laid the foundation for current theories and models of expertise (e.g., Alexander, 1997). Indeed, ongoing programs of research are girded by a number of presuppositions gleaned from previous research. For example, the research programs reviewed herein assume that experts possess both a breadth and depth of knowledge that is highly integrated or principled (Alexander, 1997; Alexander & Murphy, 1998). When solving problems, experts effectively induce or deduce the underlying structure of the set of problems, and are adept at selecting and applying appropriate problem-solving procedures accordingly. Finally, experts proficiently draw on domain knowledge and strategies with limited cognitive effort (Alexander, 2003a). In essence, current models assume that experts are astute cognitively and metacognitively (i.e., the ability to monitor their thinking and reasoning). Of course, implicit within those presuppositions is the understanding that few individuals will achieve expertise in even one domain.

However, as might be expected, current research programs contribute uniquely to understandings about the emergence of expertise within individuals and the instructional and environmental/contextual conditions under which such emergence is more or less likely to occur. Consequently, there remains no grand theory of expertise. The purpose of this section will be to provide an overview of four empirically supported, contemporary programs of research on expertise and to compare and contrast their articulated theories/models along a number of parameters (e.g., theoretical frame/source or intended populations). Following that comparison, we will offer a more comprehensive overview of one theory and one model emerging from these programs of research. Specifically, we detail the Intelligence-as-Process, Personality, Interests, and Knowledge Theory (PPIK; Ackerman, 1996) and the Model of Domain Learning (MDL; Alexander, 1997). It is important to note that we have selected to review models that lend themselves most easily to adult education and expertise.

We have chosen to discuss the PPIK and the MDL because they are highly complementary, and together offer a more comprehensive picture of expertise in adults. Ackerman's (1996, 2000, 2003b) theory draws on the literature bases of intelligence research, personality theory, and domain-specific knowledge acquisition. He posits a developmental trajectory that has many similarities to the historical outline we described earlier. Intelligence factors contribute to personality and interest factors that in turn direct how individuals excel in one or more domains. Alexander also espouses a developmental trajectory. Unlike Ackerman, her model does not explore the roles of intelligence and personality factors on expertise. Instead, she pays attention to interactions among domain knowledge, strategy use, and interest within one subject-matter area (e.g., human biology or physics), even though her model is espoused to generalize variable relations and temporal patterns across domains. As such, the tenets of the MDL can be applied in diverse domains, under varied conditions, and with individuals of varying ages. As we will explain, these details make the MDL a highly versatile model that could be particularly useful for adults in workplace settings.

A Comparison of Contemporary Programs of Research on Expertise

Within the extant research literature, there are several researchers focused on developing and testing models or theories of expertise. Here, we will discuss the research programs of four contemporary scholars (i.e., Ackerman, Alexander, Lajoie, and Sternberg). These four programs were selected because they extend prior expertise research in critical historical, theoretical, methodological, and instructional ways and inform understandings regarding adult development, learning, and expertise. Specifically, three criteria were employed in the selection of these research programs. First, the perspectives offered by these researchers have been subjected to multiple empirical investigations in varied domains, albeit differentially so. Second, to varying degrees, each of these approaches has implications for adult learners. Finally, the perspectives forwarded in these theories and models have direct implications for learning and instruction within complex domains like those that might be found in the workplace.

Specifically, we will compare the various programs of research on nine parameters (see Table 17.2). In selecting the various parameters, our goal was to provide mooring points upon which we could compare the various strengths of the theories and models of expertise proposed within a given research program. As might be expected, we begin

Table 17.2 Comparison Between Current Programs of Expertise Research

	CURRENT PROGRAMS OF RESEARCH			
Parameters	*Ackerman*	*Alexander*	*Lajoie*	*Sternberg*
Focus (Learning/ Instruction)	Learning	Learning	Learning/ Instruction	Instruction
Theoretical Frame/Sources				
Primary	Information processing	Information processing, Vygotsky	Information processing, Vygotsky	Information processing
Secondary	Cattell, Snow	Piaget, Dewey	Cattell, Chi, Glaser	Gardner
Context (Academic/ Nonacademic)	Academic/ Nonacademic	Academic	Academic/ NonAcademic	Academic
Intended Population (School Age/Adults)	Adults	School Age/Adults	School Age/ Adults	School Age
Dimensions				
Cognitive	Fluid Intel., Crystal Intel., Domain Knowledge, Ability	Subject-Matter, Domain, Topic Knowledge, Strategic Processing	Knowledge, Skill	Analytic, Creative, Practical Abilities, Knowledge
Affective	Interest	Individual, Situational Interest	Confidence	—
Personality	Extroversion, Social Potency, Control[1]	—	—	—
Trajectory (Y/N)	N	Y	N	N
Problem-Based	N	N	Y	N
Domain Specific (Y/N)	Y	Y	N[2]	N

Note 1: Much of Ackerman's work has focused on trait complexes, rather than individual variables. See Ackerman and Heggestad (1997) for a meta-analysis of trait complexes.

Note 2: Lajoie's work has been more focused on problem-solving within particular domains as opposed to the acquisition of principled domain-specific knowledge.

with an overview of the *focus* and supporting *theoretical frame*. In discussing the focus, we also compare the various models in terms of the *context* (i.e., academic or nonacademic) and whether the *intended population* for the theory or model is school age or adults. We also felt that it was important to compare the *individual difference dimensions* incorporated. Certainly one of the shortcomings of previous research on expertise was the lack of a developmental trajectory for the fostering of expertise. As such, we also compared the theories and models on whether the authors present a *developmental trajectory*. Prior generations have considered a domain-general versus domain-specific orientation to problem-solving (Keating, 1990). Thus, we contrast the various theories and models on whether they have a domain-general, domain-specific, or blend of approaches.

Ackerman

Ackerman has spearheaded a program of research on the role of intellectual investment and trait complexes in the development of expertise (Ackerman, 2000; Ackerman & Rolfhus, 1999; Rolfhus & Ackerman, 1999). Ackerman's work, similar to the other theories or models discussed herein, draws on various cognitive learning theories as a theoretical frame. Among the cognitive researchers most influential in his work were Snow and Cattell. As will be discussed, his research has been instrumental in presenting an understanding that expertise is far more complex than a composite of novel and traditional indicators of intelligence. Specifically, the clustering of various cognitive and affective variables (i.e., trait complexes) identified in his research have been repeatedly shown to correlate differentially with specific academic domains (Ackerman & Heggestad, 1997).

Arguably, the most important implications of this line of research for individuals working with adults in various settings were that (a) middle-aged adults often outperform their young adults in domain knowledge, and (b) trait complexes are linked to domain expertise. As the name would suggest, the strength of Ackerman's (1996) theory, Intelligence-as-Process, Personality, Interests, and Knowledge (PPIK), is that it incorporates a number of cognitive (e.g., fluid and crystallized intelligence or domain knowledge), affective (e.g., interest), and personality (e.g., social potency or control) factors in explorations of expertise in adults. A concomitant area for continued research, however, pertains to the role of these particular factors in the development of expertise.

Alexander

Alexander's MDL was derived from extensive research in knowledge acquisition, motivation, and strategic processing (e.g., Pintrich et al., 1993; Pressley, Goodchild, Fleet, Zajchowski, & Evans, 1989). Thus, she draws her theoretical frame from both information processing and more affective classes of learning theory (e.g., social constructivism). In effect, Alexander's work sketches the nature of and changes in the relations among selected cognitive and affective variables as individuals develop expertise in a domain. Unlike prior expertise research, Alexander has considered the interplay among knowledge, interest, and strategic processing at three stages (i.e., acclimation, competence, and proficiency) in the journey toward expertise.

Alexander and colleagues (e.g., Alexander & Jetton, 2000; Alexander, Jetton, & Kulikowich, 1995; Alexander, Sperl, Buehl, Fives, & Chiu, 2004) have found support for the predictions of the MDL in a multitude of domains (e.g., astrophysics, human biology, or special education) and with varying ages (i.e., elementary through adult). The strength of this program of research is that it is one of the first attempts to model the developmental trajectory of expertise. In fact, this is the only model reviewed that forwards a trajectory for expertise. In addition, the domain-specific nature of the model lends versatility to its application in diverse settings like those commonly found in the workplace. More longitudinal research is needed validating the relations among these factors in individuals over time within varied domains.

Lajoie

The programs of research by Lajoie and Sternberg focus on instructional systems and approaches requisite for enhancing the development of expertise. These two programs of research, however, are quite different. Lajoie's research is heavily rooted in the early expertise research by Chi and colleagues (e.g., Chi et al., 1988). One of the primary contentions gleaned from this line of research was that one could study the actions, skills, abilities, and knowledge of experts as a mechanism for creating instructional interventions for novices. Such a premise clearly underlies the creative instructional environments designed by Lajoie and colleagues. In essence, Lajoie has created a series of computer-based learning environments in which she attempts to foster expertise through knowledge scaffolding, deliberate practice, and creative, dynamic assessments.

A major contribution of this work to the expertise literature is the incorporation of dynamic assessments (Lajoie & Lesgold, 1992). Lajoie has been quite successful at creating learning environments in which cognitive tutors (i.e., computers) continually monitor problem-solving as the process is taking place. Given the dynamic nature of this process, the computer can offer direct in-the-moment feedback allowing the novices to make subtle corrections as needed. It is important to note that Lajoie and her colleagues hold to the understanding that there is no ideal solution path, but that the use of cognitive task analysis can aid in revealing similarities in terms of the planning, strategies, actions, and interpretations that experts make and the ways in which they differ from novices (Lajoie, 2003).

Moreover, Lajoie and her colleagues have been successful at fostering expertise in problem-solving within a number of domains including biology (Lajoie, Lavigne, Guerrera, & Munsie, 2001), surgical intensive care (Lajoie, Azevedo, & Fleiszer, 1998), statistics (Lajoie, Lavigne, Munsie, & Wilkie, 1998), and personal finance (Ahmad & Lajoie, 2001). It is important to note that this is the only program of research that we reviewed that continues to take a problem-based approach to learning where transfer of problem-solving expertise within a domain is of primary interest. For this reason, Lajoie's work is characterized in Table 17.2 as being domain general as compared to other lines of research (e.g., Alexander) in which the primary interest is the acquisition of principled, domain-specific knowledge. For example, if adults in the workforce participate in a computer-based learning experience, like those being created by Lajoie, would they be able to transfer the skills and abilities they acquired during the problem-solving environment to other situations? This is certainly a vital question for both teachers and individuals in the work force.

Sternberg

Like Lajoie and colleagues, Sternberg has forwarded an instructional approach aimed at what he has termed *successful intelligence* (Sternberg, 2003). In effect, Sternberg's premise is that current pedagogical approaches in schools are aimed almost exclusively at fostering technical knowledge in given domains. The problem with such an approach is that it does not foster the kind of *real world* thinking requisite to function as an expert in the world beyond school (Sternberg, 2003). Successful intelligence describes a kind of intelligence in which an expert possesses requisite technical knowledge that he or she can apply in flexible ways. This is similar to and supported by Hatano's (1982; Hatano & Oura, 2003) differentiation between adaptive and routine experts. What varies from the work of Hatano are the conditions requisite for the fostering of adaptive expertise. While Hatano and colleagues (e.g., Hatano & Inagaki, 1992) have pointed to the motivational context of adaptive expertise, Sternberg has focused on fostering expertise by tapping novices cognitive aptitudes. He argues that schools have primarily focused on analytic thinking which is most closely aligned to traditional intelligence measures, and as a consequence, have fostered technical rather than adaptive expertise.

Within Sternberg's (2003) *Theory of Successful Intelligence*, instruction in schools would be refocused to develop students' analytical (e.g., analyze, critique, or evaluate), creative (e.g., invent, discover, or predict), and practical (e.g., apply, use, or implement) thinking abilities. Additionally, Sternberg suggests that such thinking skills should be developed by solving real world problems, perhaps similar to those created by Lajoie. Sternberg and colleagues (e.g., Sternberg & Clinkenbeard, 1995; Sternberg, Grigorenko, Ferrari, & Clinkenbeard, 1999) have found support for the theory in a number of empirical, intervention studies in varied domains and settings. Among those studies was an aptitude treatment-interaction intervention. That is to say, when students received instruction paralleling their strength (e.g., creative thinking), then they performed better than when instruction was mismatched to their strengths. This finding is reminiscent of Gardner's (1999) notion of teaching to students' unique intelligences. Another major finding was that students taught in accordance with his model outperformed students taught through traditional instruction (Grigorenko, Jarvin, & Sternberg, 2002). The difficulty, of course, is that these results have not been replicated. Such replication opens a vast area for future research. Moreover, it is not clear what implications this instructional program will have for adults in the workforce.

In the sections that follow, we offer a more detailed discussion of one theory and one model emerging from these four lines of research. It is important to note that the use of the terms theory versus model in no way implies greater predictive abilities or stronger empirical support. Rather, in the case of Ackerman and Alexander, the variability in the use of terms is likely more attributable to differences in field of training (i.e., cognitive psychology versus educational psychology). The comprehensive picture of expertise offered across Ackerman's (1996) Intelligence-as-Process, Personality, Interests, and Knowledge (PPIK) and Alexander's (1997) Model of Domain Learning for adult learners is quite impressive in both breadth and depth.

Intelligence-as-Process, Personality, Interests, and Knowledge

Much of Ackerman's research has had intellectual investment as its central focus. Rooted in Cattell's (1971/1987) investment theory, Ackerman has proposed that domain expertise results from the investment of intellectual resources over time. Unlike Cattell, however, Ackerman's (1996) theory PPIK moves beyond the sole reliance on intelligence and includes other variables to account for how individuals move toward expertise. Specifically, the theory includes: a) two different kinds of intelligence (i.e., fluid intelligence [Gf] and crystallized intelligence [Gc]); b) a set of cognitive, affective, and conative trait complexes; and, c) domain knowledge in multiple subject-matter areas (Ackerman, 2003b). Ackerman has defined Gf and Gc traditionally, based on Cattell's work

(1971/1987), in that he views Gf as the psychological capabilities involving in short-term memory (e.g., pattern recognition, induction, or abstract reasoning) that are fairly stable for a substantive portion of the lifespan. By comparison, Ackerman (2003a), again like Cattell, defines Gc as the psychological capabilities based in formal and informal experiences. As such Gf is highly influenced by heredity and peaks in early adulthood, whereas Gc is highly influenced by learning in various settings (e.g., family, schools, or jobs). In contrast to the development of Gf, Gc is heavily influenced by the investment of Gf, and has the potential to mature into middle-age.

Ackerman's trait complexes are conceptually similar to Snow's (1989) aptitude complexes. In a meta-analysis, Ackerman and Heggestad (1997) determined that a moderate number of traits relating to abilities, personality, and interests appear to cluster in the prediction of domain knowledge. The traits identified by these researchers include Science/Math, Intellectual/Cultural, Clerical/Conventional, and Social. As Ackerman (2003b) suggested: "The inference from the overlapping complexes is that individual differences in trait complexes may have useful properties in determining the direction and level of cognitive investment in the acquisition of expertise" (p. 16). Trait complexes such as Clerical/Conventional or Social seem to have a broader range of influence on expertise across domains, whereas the Science/Math complex more heavily influences expertise within a limited set of domains.

Perhaps the most pertinent finding relative to adult learning is that middle-aged adults generally outperform young adults on domain knowledge assessments even in the context of lower Gf scores or slightly higher Gc scores (e.g., Ackerman, 2000; Ackerman & Rolfhus, 1999; Rolfhus & Ackerman, 1999). These results have been replicated in 20 different domains of expertise (Ackerman, 2003a). Traditional investigations of these populations have compared performance primarily using measures of Gf. Given that Gf peaks in early adulthood, this younger group had the advantage:

> These investigations succeeded in showing that a broader representation of adult intellect as including assessment of the breadth and depth of domain knowledge beyond traditional measures of Gc yielded an overall assessment of middle-aged adults as more capable than younger adults. (Ackerman, 2003b, p. 19)

This finding lends support to the fact that expertise development takes time. Older adults, more so than younger adults, may have opportunities to immerse themselves in one academic area with one set of vocational responsibilities. In contrast, younger adults may still have to negotiate shifting interests and investments among domains as they are likely still acquiring the skills necessary for their eventual professions. As a result, they are exposed to numerous subject-matter areas.

Also of importance in various studies by Ackerman are the consistent findings linking trait complexes with particular domains of expertise. For example, knowledge in the Physical Sciences and Technology domains and Gf have been found to be highly correlated with the Science/Math trait complex. Knowledge across Humanities, Civics, and Business/Law domains was highly positively correlated to Intellectual/Cultural trait complex scores. Finally, scores on the social trait complex have been negatively correlated with knowledge across the domains. Such findings could have tremendous implications for career counseling and guidance, as well as workforce placement, since social trait complexes, which include the personality factors, are hypothesized as mediating forces between intelligence and knowledge.

The Model of Domain Learning

The MDL depicts the journey toward expertise in a domain in terms of select cognitive and affective components (i.e., subject-matter knowledge, learner interest, and general strategic processing). These components are positioned within a framework that addresses both stages and phases of domain learning. Long-term characterizations that arise from the interplay of knowledge, interest, and strategies are referred to as *stages*. Similar to other stage-like theories of development and learning, the stages predicted in the MDL are essentially non-regressive and non-recursive (Karmiloff-Smith, 1986; Shuell, 1990). With the exception of a life-changing event or a dramatic change in the domain itself, the tenets of the MDL posit that it is improbable that an individual will easily regress to a lower stage once a particular stage has been reached. One differentiating feature of the MDL is that the stages are not strictly aligned with chronological age. Rather, the stages in the MDL are much more aligned with the experiences, schooling, and work that tends to be age-associated. The stages of the MDL are acclimation, competence, and proficiency/expertise.

The model also addresses the interplay of knowledge, interest, and strategies at a more immediate and situation-specific level. *Phases* refer to the more recurrent, iterative aspects of domain learning and development (Karmiloff-Smith, 1986, 1986; Shuell, 1990) and are derived from the state of knowledge, interest, and strategies at any given moment or with any given task. As would be expected, the situational factors are always in flux. Consequently, there is a constant interplay, perhaps even tension, between the forces that shape, form, or transform one's state within a field of learning. The phases of learning are meant to capture the fluidity within the learning process. It is the recurring patterns emerging from the phases that give rise to the profiles indicative of a particular stage of domain learning.

Components

Transformations in the components of subject-matter knowledge, interest, and strategic processing serve to define domain learning in the MDL. *Subject-matter knowledge* refers to the knowledge an individual possesses relative to a specific field of study (e.g., biology, algebra, or agronomy; Alexander, Schallert, & Hare, 1991). Two forms of subject-matter knowledge are distinguished in the MDL: domain and topic knowledge. *Domain knowledge* represents the breadth or generality of knowledge including all the declarative, procedural, and conditional knowledge relative to a designated field (e.g., genetics or psychology). By comparison, *topic knowledge* characterizes depth of understanding about a topic (e.g., photosynthesis or the battle of the Alamo; Alexander et al., 1991).

As will be discussed in more detail, the MDL depicts domain knowledge and topic knowledge as working in concert. That is, the more topic knowledge learners have, the more domain knowledge they are projected to have. However, these two forms of subject-matter knowledge have also been shown to operate independently in certain learner groups. For example, Alexander, Kulikowich, and Schulze (1994) found that learners with more fragmented knowledge bases could provide information about domain-related topics (e.g., black holes) but were unable to associate those concepts with their associated domains (e.g., astrophysics). In contrast, they identified certain learners with moderate levels of knowledge in a certain domain (e.g., human immunology/human biology), but who were unfamiliar with selected topics drawn from that domain (e.g., bacteriophages). Thus, the correspondence between domain knowledge and topic knowledge, while understandably high, is not perfect and undergoes hypothesized changes over the course of one's domain learning.

The MDL also speaks to the role of affective or motivational variables in the movement toward expertise. *Interest* connotes the processes by which the underlying needs or desires of learners are energized (Ames & Ames, 1989; Dewey, 1913; Murphy & Alexander, 2000). Within the MDL, two forms of interest have been plotted (i.e., individual interest and situational interest). *Individual interest* refers to more long-term investment or deep-seated involvement in a pursuit (Hidi, 1990; Schiefele, 1991). In recent research, Alexander and colleagues have identified two forms of individual interest evident in expertise: general and professional (VanSledright & Alexander, 2002). *General interest* gives energy to pursuits in which an individual might engage in their everyday experience (e.g., watching historical documentaries). *Professional interest*, by comparison, is a more specialized, goal-oriented interest aligned with vocational or career activities (e.g., attending a psychology conference; Alexander, 2003b).

By comparison, *situational interest* represents more temporary arousal or attention and often tied to conditions within the immediate context (Schiefele, 1991). Hidi (1990) has suggested that this type of interest is necessarily fleeting because it is tied to the environment. Despite links to context, there appear to be some universals that appear to generally pique situational interest (e.g., sex or violence; Schank, 1979).

The third primary component in the MDL is strategic processing. Within the MDL, *strategic processing* denotes a form of procedural knowledge purposefully invoked to overcome perceived deficits in understanding or to circumvent potential barriers to learning. Strategic knowledge entails both surface-level strategies (e.g., rereading) and deep-processing strategies (e.g., elaboration). Specifically, surface-level strategies are defined as processes individuals use to make sense of a text. By comparison, deep-processing strategies involve delving into a given text to make meaning. So defined, the general strategy component of the MDL encompasses tools critical in the acquisition, transformation, and transfer of information (Pintrich et al., 1993).

Stages of the Model

As with several other developmental models or learning theories (e.g., Shuell, 1990; Spiro & Jehng, 1990), the MDL entails three stages. Woven through these three stages are the critical forces of subject-matter knowledge, interest, and strategic processing that serve as catalysts for structuring and restructuring within and across each stage. Thus, it is the configuration of these components that bridges the stages and gives them identifiable characteristics.

Acclimation. The initial stage of development toward expertise is referred to as acclimation. This stage is representative of that point when individuals are confronted with a domain for which they possess little if any relevant knowledge. As novices to the domain, individuals must acclimate or orient themselves to the domain by establishing a base of relevant knowledge and skills. During this stage of acclimation, individuals will begin to acquire knowledge but it will be fragmented and unprincipled (Gelman & Greeno, 1989). Due to this fragmentation, acclimated learners may demonstrate difficulties in differentiating relevant form irrelevant knowledge (Alexander, Jetton, Kulikowich, & Woehler, 1994), and experience difficulty associating information within a domain.

While students are acclimating to a domain, interest necessarily has a situation-dependency to it. That is, individuals within the acclimation stage are more apt to be influenced by transitory and short-lived conditions within the immediate context. In other words, they will be guided more by their situational interests than by any individual interest in the domain. Even if students will eventually possess an individual interest in the domain that interest needs time to take root and grow as the individual's knowledge grows. In addition, few deep-level procedures are specified since most of the tasks are novel and challenging (Alexander et al., 1996). Rather, acclimated learners must rely on their surface-level strategic knowledge if they are to build a relevant knowledge base. Overall, individuals in the acclimation stage demonstrate limited and fragmented knowledge of the subject, rely heavily on surface-level strategies, and report relatively higher levels of situational interest than individual interest.

Competence. A number of changes take place during the phases of acclimation on the road to competence. For example, individuals evidence more principled, coherent subject-matter knowledge. Moreover, they are facile at applying this information in novel ways, and can more easily differentiate between relevant and irrelevant information.

A substantive increase in individual interest is predicted for competent learners. In essence, the rise in domain knowledge is correlated with a growth in individual interest (i.e., a personal investment in the field) and a decreased reliance on situational interest (e.g., Alexander, Kulikowich, & Schulze, 1994; Renninger, Hidi, & Krapp, 1992). In terms of strategic processing, more competent learners are focusing on expanding and elaborating the knowledge base, and necessarily require a period of optimal interplay between surface-level and deep-level. Specifically, there is a reduction in the need for surface-level processing due to prior knowledge acquired by the individual within a given domain. Concomitantly, competent learners have enough domain knowledge to employ deep-level strategies in effective and efficient ways. Moreover, the additional effort required for deep-level processing aligns with the substantive increases in individual interest and the decreasing reliance on situational interest during competence. Thus, the indicators of competence within a domain include a distinct increase in the breadth and depth of subject-matter knowledge, a deeper personal investment in the domain combined with decreased reliance on situationally interesting conditions, and finally a willingness to exert the effort necessary to employ deep-level processing strategies.

Proficiency. The highest stage in the MDL is proficiency or expertise. Unlike the first stage change in which any one variable could move an individual forward, the change from competence to proficiency requires a synergy among subject-matter knowledge, interest, and strategic processing (Alexander, 2003a). Perhaps understandably, one of the only components, besides surface-level strategies, that do not exhibit a rise to at least a moderate level of intensity during the proficiency stage is situational interest. Rather, situational interest appears to exert a low-to-moderate influence on learning outcomes. The basis for this prediction is the determination that those judged as proficient or as an expert in a field can operate at a level of abstraction that makes them less bound to the conditions within the immediate environment. Thus, while experts may find particular facets of a situation intriguing, their attention or performance is not distracted from relevant goals or important content (Alexander, Jetton, et al., 1994).

Perhaps the most captivating component within the proficiency stage is that of subject-matter knowledge. The proficient or domain expert must go beyond the gradual acquisition of knowledge, and play a role in redefining the very base of knowledge that signifies a domain. In effect, these individuals are creating principled domain understandings. During the process of knowledge creation, subject-matter knowledge and individual interest become inextricably intertwined. Moreover, as the expert continues to generate new knowledge, they will also experience novel problems—problems for which they must also create strategies to solve. Thus, at this stage there is not necessarily an increase in strategy use, but the employment of deep-level strategies in novel ways.

Those individuals fortunate enough to achieve proficiency in a domain are distinguishable from competent learners in several ways. First, the subject-matter knowledge of an expert becomes increasingly dense and cohesive and proficient learners actually generate knowledge. In addition, individual interest and knowledge combine as a unified force. Finally, they may experience a slight rise in deeper strategic processing due to the knowledge generation and solving of novel domain problems, and a concomitant decrease in surface-level strategies.

In the next sections, we survey the vast variety of methodologies used by researchers to study expertise. As we will see, strategies have differed depending on: a) the theoretical framework of the investigators; b) the participants studied; c) the primary variables of interest; and, d) the contexts in which learning takes place (see Table 17.3). Focusing on the theoretical frameworks of Ackerman and Alexander, we compare and contrast the types of methodologies used to address their research questions. Our chapter closes with an overall look at unanswered questions about expertise. Through these questions, we

Table 17.3 Comparison among Methodologies Used by Psychological Sub-Disciplines in the Study of Adult Expertise

Parameters	*Intelligence*	*Cognitive Science*	*Educational Research*
Units of Analysis	Individuals	Individual Experts and Novices; Expert and Novice Teams	Individuals; Classrooms; Schools; Organizations
Sample Size	Large	Small	Small to Large
Variables	Single-/Multiple-Factor Intelligence; Second-/Third-Order Intelligence	Knowledge acquisition, Strategy Use, Problem Solving	Cognitive (e.g., achievement, aptitude); Intelligence (e.g., Crystallized, Fluid); Affective (e.g., Interest, Motivation), Personality (e.g., Introversion/Extroversion; Self-Concept); Beliefs
Tasks	Multiple-choice items, Short-answer items, Analogy problems, Block rotations, Puzzle completions	Think-alouds, Interviews, Group Discussions; Sorting Tasks, Graphical Constructions, Computerized Problem-based Learning Environments	Traditional to Performance Assessments; Rating Scales, Self-Report Inventories; Classroom Discussions/Internet Chatrooms; Hypermedia/Multimedia Tasks, Computerized Problem-based Learning Environments (e.g., Dynamic Assessments)
Methodological Approaches	Factor Analysis, Structural Equation Modeling	Proximity Analysis, General Linear Model (e.g., ANOVA)	Qualitative Methods; Proximity Analysis; General Linear Model (e.g., ANOVA); Latent Variable Modeling Procedures (e.g., IRT, SEM); Cognitive Psychometric Approaches (e.g., Error Analysis, Rule-space Analysis).

offer an agenda of research that may be adopted to not only understand expertise better but also to assist more individuals in reaching the pinnacles of success in their chosen domains of practice.

Methodological Threads in the Study of Expertise

In this section, we examine two methodological threads that have been influential in the study of expertise. First, the testing tradition that emerged from Galton's work on intelligence continues to thrive in research and practice. Starting with Binet's first test of general mental abilities, which Terman used in his study of youths identified with exceptional talent, to Sternberg's program of research, which incorporates principles of cognitive psychology into the study of various types of intelligence, assessment has been a key force in portraying the individual differences of students (Keating, 1990). Related to this point is that there has been no mathematical distribution more important than the normal distribution to depict how individuals' performance based on item and test scores stands relative to one another.

This strand of methodology is suited ideally to study multivariate relations based on performance, product, or self-report scores. Performance, product, or self-report scores such as those derived from intelligence and knowledge measures, interest scales, and self-concept inventories are often treated as outcome measures predicted by latent traits (Barrett, 2005; McGrath, 2005). Latent traits are unobservable psychology constructs like intelligence, creativity, motivation, and interest that predict response patterns on tests and measures (McDonald, 1999). Latent variable modeling (e.g., Item Response Theory [IRT]; Reise, Widaman, & Pugh, 1993; or Structural Equation Modeling [SEM]; Reise, Widaman, & Pugh, 1993), therefore, has been a primary means by which researchers test their hypotheses. These techniques are commonplace in the work of Sternberg, Ackerman, and Alexander.

However, these methods of task development and data analysis have not allowed researchers to study the processing that differentiates experts and novices or that leads to proficiency in any domain. Here, qualitative, descriptive tools such as think aloud and verbal protocol analyses have served as better means to explore individual differences than scores on tests or self-report inventories. The second thread of methodology we review finds its roots in cognitive science and can be seen in the work of Lajoie. Specifically, cognitive scientists were and continue to be interested in how individuals move through problem spaces (e.g., Bransford & Stein, 1993), and what the interaction between knowledge and strategies looks like as they attempt to complete domain-specific tasks. Lajoie has built an entire body of research around the use of dynamic assessments which are essentially computer platforms that capture individuals' movements through complex problem spaces. We now examine each of these threads in turn.

Methods in the Study of Intelligence

The methodologies used to study intelligence have looked quite different from those employed in the study of domain-specific expertise. Yet, both bodies of work contribute to an understanding of what characterizes adult proficiency. The primary difference in these approaches is that expert-novice researchers focused their attention on individuals whose performance characterized extremes of the normal distribution (i.e., the very low and the very high). By comparison, researchers who study intelligence often do so with an eye toward testing where resultant scores represent the complete continuum of performance. Standardized tests of intelligence must yield reliable and valid sets of scores.

Since the fundamental principles of reliability and validity rest on mathematical foundations of the normal distribution (e.g., Campbell & Fiske, 1959; Cattell, 1952; Spearman, 1904; Cronbach & Meehl, 1955), researchers who study intelligence must construct a broad array of verbal and performance tasks that can depict differences with adult populations (e.g., Wechsler, 1981). Because the need to sample a large variety of tasks becomes essential in terms of matching intelligence scores to tasks that incrementally vary in difficulty (Lord & Novick, 1968), intelligence theorists cannot readily afford administering a set of problem-space tasks like cognitive scientists. Simply, conducting think alouds, interviews, sorting tasks, or graph constructions, which we will discuss subsequently, is not a realistic undertaking. It would take too much time, and the scores are not as psychometrically trustworthy as what can be obtained using traditional measures like multiple-choice or short-answer items that can efficiently cover a broad array of topics drawn from multiple domains. Therefore, those who measure intelligence tend to keep their tasks simple. If they do include tasks in their battery, these exercises (e.g., block rotations or puzzle completion) can be assembled and administered quickly to cover the spectrum of abilities that define general views of intelligence (e.g, generalized intelligence, Spearman, 1904; crystallized and fluid intelligence, Cattell, 1941; verbal and performance intelligence, Wechsler, 1981).

The difficulty intelligence theorists soon encountered when faced with the administration a large set of items or tasks is how to reduce the responses to establish that a single set or small group of scores are reliable and valid. Fortunately, developments in theories of intelligence were concurrent with study of mathematical tools that could reduce correlated patterns of item scores. It was common, therefore, to find intelligence theorists such as Cattell (1952) or Thurstone (1938) to be as much an experts in mathematics/statistics as they were in psychology. Factor analysis became the means by which researchers established the underlying constructs that predicted responses to items/tasks (Carroll, 1993). To this day, it remains the primary mathematical tool among researchers in the social sciences to establish construct validity. Further, with ongoing developments in computer programming, factor-analytic methods have progressed to include measurement models with structural equations where dependent latent constructs can be regressed on a set of independent factors or variables. These types of tools have been useful to test theoretical models. As mentioned, these tools are nested in a family of latent variable modeling techniques that include Item Response Theory (IRT; Baker, 1992; Lord, 1980; Lord & Novick, 1968), Multilevel or Hierarchical Linear Modeling (HLM; Bryk & Raudenbush, 1992; Hox, 1995; Singer, 1998), and Structural Equation Modeling (SEM; Bollen, 1989, Browne, & Cudeck, 1993).

Cognitive Science and Task Analyses

When reviewing the types of methodologies utilized by researchers to study expertise from the perspective of cognitive science, one pattern emerges above all others: the methodologies differ significantly from those used by intelligence theorists. Specifically, the cognitive science tradition is one that does not rest on large-scale testing to the degree found in studies on intelligence. For cognitive scientists, many of whom were invested in pioneering work in artificial intelligence (Anderson, 1987; Chase & Simon, 1973; Clancey, 1985; Kolodner, 1983; Shanteau & Stewart, 1992), the primary goal was to compare problem-solving processes of experts and novices in an effort to inform the programming of computer systems that could be accessed for deep stores of knowledge and corresponding decision-making strategies useful for solving problems in a particular domain (e.g., avionics, economics, or medicine).

Cognitive science offered the first formal study of expertise by examining how people interacted with carefully constructed or selected problem spaces (Hoffman, Shadbolt, Burton, & Klein, 1995; Olson & Biolsi, 1991). Initially, these spaces were very artificial or knowledge-lean as in the missionary/cannibal problem. Methodologically, the steps required for solution were rather sequential as these problem spaces introduced much structure when presented to the problem solver.

In time, however, cognitive scientists came to appreciate that not all problems within a given domain are well-structured (e.g., algorithmic steps or correct solutions) and for some domains like economics and marketing (e.g., Cross, 1988), medicine (Arocha & Patel, 1995; Patel, Groen, & Arocha, 1990), and literacy (Scardamalia & Bereiter, 1991), the problem spaces are more ill-defined and ill-structured. As a result, experts employ heuristic strategies (i.e., guidelines). These strategies often result in more nonlinear movements through the space than linear sequences that result in correct or best solutions (Spiro, Vispoel, Schmitz, Samarapungavan, & Boerger, 1987). An entire subdiscipline of cognitive science is dedicated to the study of problem spaces. This realm of research is referred to as cognitive task analysis (e.g., Essens, Post, & Rasker, 2002; Schraagen, Chipman, & Shalin, 2000), and it classifies the various types of problem sets encountered by experts representing various domains.

For some problem spaces, individuals must troubleshoot (e.g., electronics and engineering). That is, the problem requires individuals to fix one or more operations that are not working properly such as in the case of a mechanic who replaces the transmission of an engine so that the vehicle accelerates and decelerates correctly on the road. Troubleshooting tasks, as a result, require individuals to use significant amounts of conditional knowledge (Alexander, 1997). Conditional knowledge is knowledge of when and why a particular concept or procedure would be facilitative. Experts have significantly more conditional knowledge than novices. Experts are not only able to detect why something is not working correctly, but they also possess the suitable strategies to fix the problem efficiently and effectively.

Troubleshooting tasks are not the only types of problem spaces studied by cognitive scientists. Other problem spaces are characterized as novel (e.g., locating submarines, Gray & Kirschenbaum, 2000; navigating the sea, Hutchins, 1996). In these instances, cognitive scientists have no preset notions as to how problem solvers will move toward solution. Hutchins (1996) refers to this type of problem-solving experience as *cognition in the wild*.

A final set of problem-solving spaces require experts to construct or create their problem environments as in the case of inventing or modeling (e.g., human factors engineering, Essens et al., 2000). This form of problem-solving activity allows for creativity, as in the case of architects who sketch blueprints for buildings and landscapes. And, more recently, these types of creative enterprises have been linked with developments in technology. For instance, investigators can study problem spaces that are dynamic and open, permitting one individual or a team of members to move in and out of activity as in the case of a business firm like Ford or General Motors working on new designs for cars and trucks (Gorman, Tweney, Gooding, & Kincannon, 2005). Here, experts who differ in terms of their areas of expertise (e.g., engineering, graphic design, marketing) work together to accomplish complex tasks.

Think-Alouds and Interviews

Independent of the types of problem spaces analyzed by cognitive scientists, two primary methodologies have been used to explore aspects of expertise and what makes experts' knowledge and performance profiles distinguishable from those of non-experts. Specifically, think-aloud protocol analyses and interviews have been the means by which researchers came to understand how memory capacity, strategy use, recovery from error, and storage of knowledge around principles are hallmarks of domain proficiency (Hoffman et al., 1995; Olson & Biolsi, 1991). So rich was the collection of studies on think-aloud methodology that Ericsson and Simon (1993) wrote a classic book entitled, *Protocol Analysis: Verbal Reports as Data* to offer guidelines for eliciting more reliable and valid data about knowledge and problem-solving strategies.

Although the think-aloud methods showcased knowledge and strategy use during the course of problem solving, interviews both for individuals and groups offered reflections on past performance or speculations on future performance (e.g., de Jong & Ferguson-Hessler, 1986). There are many types of interview procedures that can be used depending on the purposes of the researchers. Unstructured interviews are open-ended. Interviewers ask participants a general question such as; *tell me everything you know about the solar system* (Wood & Ford, 1993). The benefit of unstructured interviews is that participants can draw on a wide array of personal and professional experiences, including references to what interests them most, setbacks they have had in their careers, and sources of inspiration to pursue excellence. A limitation of unstructured interviews is that responses can be long or meander around a host of topics without any sense of cohesion. Alternatively, participants may have difficulty elaborating upon the knowledge and ideas they share. This is a common problem among experts as they try to draw from their rich and tightly networked structures of knowledge (Pressley & Afflerbach, 1995). Likewise, this is a common problem among novices who struggle in their attempts to describe fragmented parcels of knowledge that may be interspersed with misconceptions.

A variation on the open-ended interview is the structured interview. Here the researcher introduces more scaffolding into the questions asked of respondents. Questions can be domain-general, domain-specific, or topic-specific, but they are generally based on an inventory of concepts and procedures that are central to the domain of interest and the problems solved within it. Shadbolt and Burton (1990) extended the methods of structured interviews by establishing what are called *probe sets*. Probe sets are constructed around taxonomies. Interviewers begin with questions asked to get a respondent's overall sense of the domain and its scope (e.g., Can you tell me about the latest research projects completed by you and your colleagues?).

Based on the responses provided, the interviewer sets parameters around the next set of questions by focusing on concepts mentioned in the interview (e.g., Can you describe electromagnetism? Can you tell me the difference between the strong and weak nuclear forces?). After querying for concepts, the interviewer then probes for the types of procedures or mechanistic processes that are key to the domain's activity (e.g., How does a supercollider work? What does a Feynman diagram show you?). These procedures can relate to steps used to solve problems in the domain such as use of the scientific method or mathematical proof construction. These procedures can be associated with explanations for how models or tools of the domain work or operate (e.g., Doppler effect or standard model).

Finally, the questions may pertain to the ways the field represents information or how the expert represents information in an effort to communicate concepts, principles, and procedures to others (e.g., diagrams, graphs, or equations). Rounding out the probe set are questions geared toward an understanding of unusual experiences or insights that have reshaped or restructured one's thinking about the field and representing problems within it (e.g., aha! experiences, anomalies in data, or novel discoveries).

Contrived Tasks

Sometimes researchers weave contrived tasks within protocol analysis or interview studies. Introduction of contrived tasks serves as another means to frame participants' responses so they do not roam all over the place. Usually, these contrived tasks are built around principles and procedures of the domain. For example, researchers interested in proficiency in physics may ask respondents to sort a set of word problems into piles dependent on important structural relations among fundamental principles of the domain (e.g., force-mass-acceleration or distance-rate-time). Similarly, investigators attempting to observe the interplay between knowledge and strategies in a domain that is characterized by high levels of motor performance (e.g., athletics or music) may ask participants to compare and contrast characteristics of those who are considered eminent in their fields (e.g., basketball: Larry Bird, Michael Jordan; classical music: Bach, Mozart) in an effort to reflect on the patterns of individual differences that contribute to hallmarks of excellence in their fields.

Ludwig (1995, 1998) and Martindale (1990) have conducted studies to describe how the interaction between knowledge/ingenuity and personality factors contributes to level of productivity in the domain and its quality. Participants rate the degree to which characteristics about an elite performer fall on a low-to-high continuum. Attributes selected to compare individuals might encompass sets related to: a) work patterns; b) styles of human interaction; c) medical histories (e.g., mental illness); d) impact on the field; and, e) onset and longevity of expertise.

What contrived tasks provide researchers that protocols and interviews may not is a way of coding characteristics efficiently so that they may be subjected to statistical analysis (Hoffman et al., 1995; Olson & Biolsi, 1991). Researchers can examine how many piles are sorted or profiles of ratings on various performance and personality factors using proximity analysis techniques. Proximity analyses are basically correlational analyses. Objects or people are examined for how similar or different they are from one another. For example, grapefruits and oranges would likely be related for high similarity of proximity for they are two types of citrus fruits. Grapefruits and lettuce, however, would likely be rated as highly dissimilar with low proximity as one is a citrus fruit and the other is a leafy vegetable.

When there is a large group of objects to be rated as pairs that are similar or dissimilar, the frequency of proximities can make detection of patterns of relation very difficult for investigators. As a result, these researchers subject a matrix of proximities to data reduction techniques that can mathematically determine the basic underlying patterns of similarity. Cluster analysis and multidimensional scaling are two common forms of data reduction techniques for proximity matrices (Olson & Biolsi, 1991). These data-analytic tools also permit investigators an opportunity to reduce the data into patterns that can be observed visually. So for the grapefruit, orange, and lettuce example, the results might show two general groupings of fruits and vegetables. A flexible feature of these quantitative tools is that data can be analyzed just for one individual or a large group of individuals, or for comparison between groups, such as experts and non-experts.

As early as 1974, Shavelson used proximity analysis methods to explore the memory structures of students in science. Following an information-processing model of memory structure (e.g., Badderly, 1992; Norman, 1969), Shavelson assigned participants to treatment and control conditions where each group was assigned two tasks: word associations and graph constructions. Proximity analyses were then used to explore the structural relations among objects and how they changed over time from those who received instruction in science and those who did not. Based on the data, Shavelson made conclusions about which participants were able to move incoming information through their working memory to long-term store where it could be structured in principled form. Not only did those receiving instruction acquire more concepts and procedures in time (based on the word-associations task), but they also made tighter connections among concepts and procedures (based on the graph constructions) than control counterparts. These types of data summaries, therefore, helped researchers in cognitive science support several of the conclusions noted in our introduction. Specifically, from the first generation of expertise studies, these researchers learned that: *Experts perceive the underlying structure of problems whereas novices are distracted by more surface-level features of problems*; and from the second generation: *Experts possess an extensive body of domain knowledge that is coherently and efficiently organized.*

Standard Statistical Procedures

Cognitive scientists have relied on simpler ways to study expertise differences. Comparing means on knowledge-acquisition outcome measures such as free recalls, reading tasks, and word problems using classical analysis of variance (ANOVA) techniques or multiple regression (e.g., Murphy & Alexander, 2002; Renkl, 1997) have been commonplace. These techniques afford researchers an opportunity to conduct meta-analyses (Glass, 1978; Hunter & Schmidt, 1990) to determine whether manipulations in the task environment (e.g., animation, multiple representations, or seductive details) alter differences between expert and non-experts performances.

Meta-analyses are reviews of the literature that gauge the magnitude of a statistical effect over a series of investigations. For example, the use of the worked example in algebra-based word problems has a long and extensive history (e.g., Mousavi, Low, & Sweller, 1995; Sweller & Cooper, 1985); thus there are many quantitative investigations to form a data pool for a meta-analysis (Renkl & Atkinson, 2003). What these analyses attempt to reveal is what amount and type of instructional intervention promote knowledge acquisition for non-experts. Renkl and Atkinson's summary demonstrated that the worked example facilitates problem solving for novices. Yet, for experts, the inclusion of problem solutions can be detrimental as knowledge structures become more tightly organized around principles. As a result, problem solving looks automatic. In short, the worked examples are excess parcels of information that draw knowledgeable individuals away from their solution path.

Educational Researchers: Weaving Together the Methodological Threads

Unlike researchers who study intelligence or cognitive scientists who address questions about problem spaces, educational researchers must weave together both theoretical and methodological traditions in an effort to help school-aged learners or adults in the workplace. Central to their programs of research, investigators in education must address primary questions related to instruction and assessment. As such, their frameworks for understanding adult expertise must include variables that are more common among cognitive scientists (e.g., conceptual change, knowledge acquisition, or strategy use), as well as those of intelligence theorists (e.g., general vocabulary knowledge, spatial reasoning, or speed-of-processing). In addition, educational researchers must include variables that tie more closely to lines of inquiry in motivation and personality, for students come to schools with a plethora of individual differences. As a result, these researchers connect their variables in a system in an effort to explain what contributes to, as well as derails, progress toward expertise. Only within these tests, can these researchers gain insights into instructional methods that can help those who struggle, as well as feed the roots of expertise. Additionally, educational researchers must be mindful of the assessments they use as those assessments serve not only as a means to measure achievement but also as a form of feedback for instruction that can correct errors, eliminate misconceptions (Alexander et al., 1998; Kulikowich & Alexander, 1994, 2003; Lajoie & Lesgold, 1992), or troubleshoot ineffective problem-solving routines (e.g., Lesgold, Lajoie, Bunzo, & Eggan, 1992).

Ackerman and Factor Analysis

To test the tenets of PPIK, Ackerman and colleagues use factor-analytic and correlational methods. Several instruments are used to assess aptitude, trait complexes, and knowledge structures, respectively. In the case of knowledge structures, for example, Ackerman (2003a) built 20 multiple-choice measures to cover the broad spectrum of science and social science subject-matter areas that depicted primary areas in which expertise is likely to become manifest. Scores on these 20 knowledge measures were subjected to factor analysis. Five primary factors emerged representing the knowledge structures (i.e., physical sciences/technology, civics, humanities, current events, and business) represented in his theoretical framework. Factor analyses have also been used to reduce trait measures so that complexes can be formed (Ackerman, Bowen, Beier, & Kanfer, 2001).

Once the factor analyses are used to reduce sets of scores into aptitude complexes, trait complexes, and knowledge structures, Ackerman and colleagues conduct correlation analyses to detect profiles of individual differences across the variable sets. This is how Ackerman is able to determine that individuals with a lot of fluid intelligence are likely to show dispositions toward study of science and mathematical topics that are likely, in turn, to lead to knowledge acquisition and vocational pursuits in the physical sciences and technology. By comparison, correlational patterns reveal that individuals who have significant amount of crystallized intelligence tend also to have strong proclivities to social and cultural affairs and, as a result, demonstrate achievement in civics, the humanities, and business arenas. These individuals are also likely to know much about current events.

Sternberg and Aptitude-Treatment Interactions

Sternberg's methodology is very similar to that of Ackerman. Relying extensively on factor analytic procedures, Sternberg and colleagues attempt to establish the reliability and validity of the various types of intelligence they study. To date, however, Sternberg has been able to study directly aptitude-treatment-interactions (Snow, 1989) using analysis of variance techniques to a greater extent than Ackerman. The ability to test instructional variables in relation to aptitude profiles is largely due to the fact that Sternberg's modeling framework does not include as many variable sets as in the PPIK framework of

Ackerman. Nonetheless, both scholars are interested in how instructional platforms can best be matched to aptitude and personality factors.

For example, Sternberg, Torff, and Grigorenko (1998a, 1998b) studied elementary- and middle-grade students as they learned about topics in science and social studies. They used experimental procedures and assigned students randomly to one of three conditions based on their intelligence theory framework. In condition one, students received regular classroom instruction. In condition two, instruction focused on critical and analytic thinking. In condition three, the intervention focused not only on analytic thinking but also creative and practical thinking. As such, this arm of the intervention represented the successful intelligence condition. Outcome measures included both multiple-choice knowledge measures as well as performance-based assessment tasks. As expected, results of ANOVA procedures supported the researchers' expectations. Students assigned to instruction where successful intelligence was prioritized as key to academic success outperformed peers on knowledge and aptitude outcomes. Similar results from ANOVA procedures have been found for high-school students who may be experiencing academic challenges similar to those one would expect for young adults beginning to choose one or more domains (e.g., biology, engineering, or history) in which they may eventually demonstrate expertise (Grigorenko et al., 2002).

Lajoie and Case Studies

Lajoie's methodologies rest on case studies of adults working through computerized problem spaces given a variety of tasks representing a variety of domains. As a result, Lajoie and her colleagues more so than Ackerman, Sternberg, and Alexander follow the classical cognitive science tradition in terms of their investigations on expertise. Still, like her contemporary colleagues, Lajoie recognizes the importance of both instruction and assessment in moving non-experts along so that they can begin to perform like experts. Her dynamic assessments are computerized problem spaces that evaluate the progress of individuals as they attempt completion of tasks. The assessment systems are also designed to provide feedback so that problem solvers can begin to detect solution paths that effectively and efficiently lead to solutions.

In using case study analyses, Lajoie's work is perhaps the most qualitative of the group of researchers who have espoused contemporary models of expertise. However, her procedures for analysis follow many of the design strategies evidenced in experimental research (Lajoie & Lesgold, 1992). For example, Lajoie and Lesgold built a computer-coaching tool called Sherlock I to teach troubleshooting skills in avionics. Each participant worked through the Sherlock system in a series of stages. First, the participants completed pretests to measure knowledge, strategies, and plans associated with avionics. Then, the participant progressed through a set of three tutorial exercises that incrementally increased in difficulty. The difficulty was determined through comparisons of expert and novice performance. So, when participants finally completed the last task, their performance began to exemplify the knowledge, strategies, and plans used by experts.

To achieve its desired ends, the dynamic assessment system constructed by Lajoie and colleagues is programmed as a smart tool (Bransford et al., 1996). Specifically, as participants interacted with each tutorial, there was a constant stream of feedback to correct misconceptions and provide suggestions for more efficient plans that resulted in problem solutions. After completion of the third tutorial, participants completed a posttest. Experts in avionics were enlisted to evaluate pretest to posttest performance.

As anticipated, there was a noticeable difference between final and initial scores on outcome measures. Initially, participants' strategies and plans were random and incomplete with minimal evidence on monitoring for more efficient solutions. At posttest, strategies were executed efficiently with evidence that both conditional and principled knowledge not only increased but was also used effectively to reach problem-solving goals (Lajoie & Lesgold, 1992).

Alexander and Cluster Analysis

Alexander and her colleagues have studied the developmental trajectory of expertise using tools like those employed by Ackerman, Sternberg, and Lajoie. In addition, cluster analysis and SEM models are prevalent in their work. As mentioned previously, cluster analysis is a data reduction tool. Like factor analysis, it can be used to study how scores on items and tasks fall into particular groupings, but it can also be used to demonstrate how profiles of individuals' response patterns across a set of variables reduce into prototypic cases. In this fashion, Alexander and her colleagues (Alexander et al. 1995; Alexander & Murphy, 1998) have used cluster analysis to characterize groups that emerge based on students' knowledge, strategies, and interest scores. As related examples, Lawless and Kulikowich (1996, 1998) ran cluster analyses to establish profiles among hypertext users. Their hypertext systems traced the paths of readers using time-stamped data collection methods that can be subjected to log-file analysis. Essentially, log files are just performance protocols that can be captured by a computer system (Young, Kulikowich, & Barab, 1997).

What distinguishes the work of Alexander and her colleagues from that of Ackerman and Sternberg is there is a greater emphasis on the types of knowledge students possess in one domain. This is similar to the work of Lajoie, but it is also different in important ways. Whereas Lajoie's work focuses on problem-solving outcomes, Alexander and her colleagues have invested considerable time look at reading-based outcomes. Simply, Alexander's MDL starts with knowledge and it ends with knowledge by means of acquisition of subject-matter information from texts. These types of text-based outcomes have ranged from simple recalls or retellings (Alexander, Kulikowich, & Schulze, 1994) to more complex comprehension exercises, as in the case of understanding arguments presented in persuasive texts (Murphy & Alexander, 2004). Because knowledge begins and ends at important starting and ending points to determine where individuals are located in stages, SEM models have also served as extremely useful tools to establish that students are moving along a trajectory and that variables specified in the MDL, such as strategy use and individual interest contribute to this movement (Alexander, Murphy, Woods, Duhon, & Parker, 1997).

Additionally, and as evidenced in the work of Lajoie, task and test construction for variables of the MDL has drawn extensively from developments in cognitive psychometric theory (e.g., Katz, Martinez, Sheehan, & Tatsuoka, 1998; Mislevy, 1993; Tatsuoka, 1983, 1985). Specifically, both Alexander and Lajoie have attended greatly to the types of errors students make and the misconceptions they hold. For example, Alexander and colleagues (Alexander, Murphy, & Kulikowich, 1998, Kulikowich & Alexander, 1994) built vocabulary multiple-choice items and analogy problems so that errors could be graded in terms of degree of accuracy. The results from this program of research were very informative. These findings showed that the majority of students' error patterns were nonrandom, meaning that a specific gap in knowledge or processing could be isolated. As a result, instruction could be geared toward filling the knowledge gap, providing remediation for misconceptions, or explicitly teaching strategies that could facilitate knowledge acquisition by means of reading and problem solving (Kulikowich, in press).

Finally, in many instances (e.g., Garner, Alexander, Gillingham, Kulikowich, & Brown, 1991; Judy, Alexander, Kulikowich, & Willson, 1998), Alexander and her colleagues have depended greatly on experimental procedures to test tenets tied to hypotheses about when and why knowledge acquisition or strategy use occurs or does not occur. For example, Alexander and her colleagues were among the first to demonstrate that analogical reasoning could be taught to very young children (e.g., White, Alexander, & Daugherty, 1998) in an effort to help them bridge domain knowledge and strategy use. Analogical reasoning remains a mainstay in Alexander's study of adults' developing expertise (e.g., Alexander & Murphy, 1998; Alexander et al., 1998).

While experimental procedures using ANOVA designs have helped to show that use of analogies can lead to knowledge acquisition, intervention studies using ANOVA procedures have also demonstrated that adults can be non-strategic. For instance, insertions of seductive details or highly salient but irrelevant sources of information often pertaining to death, power, or sex in texts can distract readers' attention away from information that should be comprehended as important (Alexander, Kulikowich, & Schulze, 1994). Specifically, mean recalls of students assigned to text conditions with seductive details compared to students assigned to conditions without seductive details showed that the first group recalled significantly less domain-relevant information than the second group which was very good at jotting down the very interesting, but unimportant bit of information (e.g., Stephen Hawking's wager with Kip Thorne for an issue of Penthouse magazine). Collectively, the cluster analysis, SEM, error analysis, and experimental design approaches have contributed to establishing the MDL as a viable framework for the study of developing expertise.

Final Prognostications: The Future of Expertise in Research and Practice

Throughout this chapter, we have explored the distant past of expertise theory and research and three more contemporary generations, each with its own perspective, goals, and methodologies. Our purpose was to understand the nature of expertise and to examine the forces that contribute to expertise development. While it is relatively easy to look back over the centuries and decades in an effort to describe the state of expertise research, it is far more risky to ask what will become. What will the next generation of expertise research bring? What particular trends will capture the foci and contributions of expertise research in the next 10 years? What research methodologies will surface as most useful or informative in that next iteration?

If we are to project forward based on current trends in expertise theory and research, we believe we can at least glimpse some of that future. Thus, we offer five prognostications related to expertise theory and to the influence of expertise research on everyday practice.

The Road to Expertise Will Become as Important as the Final Destination

As we have witnessed, there has been an increased attention to the trajectory or the path that individuals may follow as they progress toward competence or expertise. This emphasis was a distinguishing characteristic of the third and current generation of expertise theory and research. Nonetheless, the trajectories or paths that have been plotted to date remain largely sketchy and speculative, and the expert/non-expert contrasts still dominate the literature. In the future, the paths that mark expertise development will become more richly specified and the expert/non-expert distinctions will give way to a more developmental orientation—an orientation that stresses the process of *becoming* more competent or more expert.

Longitudinal Investigations Will Be Undertaken

Before the developmental orientation toward expertise becomes a reality, several related transformations must occur within subsequent generations. Among the most critical changes in the empirical landscape is that theory and research can no longer be based solely on cross-sectional investigations—regardless of how well conceived or how theoretically grounded. What are needed are longitudinal studies of expertise. We appreciate that extended longitudinal studies, like that conducted by Terman, are unlikely for a multitude of reasons (e.g., funding requirements and human subject guidelines). However, we still see studies that extend over several years as a hallmark of the next generation of expertise research, especially transitional periods (e.g., transition from school to the workplace). As expertise researchers track the specific cognitive and motivational changes that occur in individuals over time, it will be possible to more fully and completely profile individuals at different points in their journey toward expertise. These longitudinal studies will also contribute to more accurate mapping of the developmental paths individuals traverse.

Multidimensionality of Models and Theories Will Be Expanded

Despite the advancements in multidimensionality witnessed between the second and third generations of expertise research, the scope still remains somewhat limited with regard to the variables examined. Yet, several research trends gaining momentum in the literature may well find their way into future studies of expertise development. Among those trends are the growing interest in emotions and their role in human learning and development (e.g., Bell & Calkins, 2000; Bråten & Olauseen, 2005; Van Yperen & Janssen, 2002). Such emotional dimensions, foreshadowed by the trait complexes of Ackerman (2003b) could enrich current efforts to explore the “hot” side of cognition at work within expertise development.

It is also conceivable that the burgeoning studies in neurology, neuroscience, neuropsychology, and related fields will contribute new insights into the cognitive and noncognitive attributes of those at various points in their growth trajectories (e.g., Donald, 2001; Keating, 2004). Are there structural differences in the brains of those who achieve higher levels of expertise than those who do not, for example? What neurological correlates should be considered in the examination of expertise development? Neurological fields may also shed light on the real-time processing of those engaged in domain-specific tasks of varying complexity; thus shaping what we know about expertise development (Berninger & Corine, 1998; Berninger & Richards, 2002). For instance, what can neuroimaging studies reveal about the way that those new to a domain and those considered highly competent or proficient in that domain mentally engage with a given problem or task?

Further, it might be argued that the role of situation or context as a dimension of expertise development has had little place in past or contemporary models or theories. One of the most salient aspects of situation or context that would seem relevant to discussions of expertise development is culture. Are the expertise models and theories articulated to this point presumably generalizable across diverse cultures? Or, will it become essential for expertise researchers to nest the study of expertise within particular sociocultural contexts? There certainly appears to be sufficient sociocultural research that would cast some doubt over arguments for universality of expertise models and theories (Keating, 2004; Walker, Hill, Kaplan, & McMillan, 2002). At a minimum, those invested in furthering existing knowledge about expertise will want to consider the dimension of culture or cultural context in future programs of research.

Interventions Studies Will Become More Commonplace

Overwhelmingly, the patterns and findings reported in the literature on expertise, regardless of which generation, have been built on correlational or descriptive studies. What have been long missing within this literature are intervention investigations that actually seek to create the conditions that should propel individuals forward toward expertise in a given domain. The work of Alexander and colleagues, for example, would seem to lend itself to interventions framed in the tenets of the MDL. For instance, we would expect that interventions formulated around the knowledge principles of a given academic domain in which strategies are explicitly taught within the context of meaningful domain-specific problems and in which individual interest was intentionally nourished should fuel expertise development. We, therefore, predict that the next generation of expertise research will abandon its over-reliance on correlational and descriptive investigations and become known for interventional studies.

The Workplace Will Become a Relevant Context for Expertise Research

Across the contemporary generations of expertise research, we saw significant change in the context deemed suitable for investigation. Within the first and second generation the parameters for study were particular problem-solving contexts that either constrained or augmented the influence of the respondents' background knowledge. In the third generation that context widened to embrace academic domains like history or science. Ackerman's studies also considered the trait complexes associated with expertise in particular professions. It seems logical, therefore, that future investigations will pay greater attention to the workplace as yet another viable context for expertise development.

Expertise development continues across the lifespan—it does not end with the completion of formal schooling, whether one's schooling concludes with high school, college, or even graduate school. It is likely within the realm of work that the knowledge, strategies, and interests acquired through the educational process are extended and elaborated through meaningful application. Thus, our prognostication is that the next generation will represent an era of lifespan expertise development where the workplace is conceived as a relevant and nature venue for systematic investigation.

New Methodologies Will Be Applied or Will Be Devised To Permit More Sensitive Testing of Emergent Expertise

None of the predictions we have made to this point will come to fruition without concomitant developments in the methodologies associated with expertise research. Among the changes that we envision for the next generation will be the incorporation of innovative statistical procedures that will allow for both micro-analytic and macro-analytic studies.

As the questions about the nature and development of expertise become increasingly more complex and the context and tasks become more ill-structured and "messy," it will be critical to adopt and adapt the statistical tools that are plied. For example, one facet of the MDL that has been understudied is the phases—the dynamic interplay of knowledge, strategies, and interests that occurs with each task engagement. Devising the tasks that permit these phases to be evidenced and tracked over time will be a challenge for expertise methodologists, along with the identification of viable statistical procedures to analyze and interpret the resulting data. However, these are just the kind of challenges that will further energize studies of expertise development.

What we have offered are just five predictions about future theory and research that we anticipate within the next ten years. There are clearly other possibilities that could be forwarded for consideration. Yet, whether these particular outcomes are realized or not, we remain confident that the fascination with expertise and experts, evident throughout human history, will continue unabated. The more that we come to understand the nature of expertise and the more skilled we become at mapping its course across the lifespan, the better guides we become for those undertaking the journey toward expertise in schools and in the workplace.

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