Modeling Domain Learning: Profiles From the Field of Special Education

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The authors examined knowledge, interest, and strategic processing profiles within special education for 4 educational communities. Participants included undergraduates not majoring in special education and undergraduates, graduate students, and faculty from special education. Cluster analysis tested whether participants would exhibit the knowledge, interest, and strategic processing profiles expected for individuals at various stages of expertise. The Model of Domain Learning (MDL) was the theoretical framework for data interpretation. Results provided strong support for the MDL. Specifically, 4 clusters emerged from the data. Clusters (i.e., Acclimation, Early Competence, Mid-Competence, and Proficiency) were statistically distinct with regard to the external criterion, domain-specific analogical reasoning, and in relation to clustering variables. Implications for developmental models of expertise and for educational practice are considered.

Educational researchers have long sought to understand the marked differences between experts and novices (Chi, Glaser, & Farr, 1988). They have attempted to unravel the mystery of why some individuals grow and flourish in a complex field, becoming acknowledged authorities, while others falter or fail to thrive, remaining virtual neophytes (Ericsson & Smith, 1991). The theoretical and practical motives for investigating the differences between experts and novices are varied and compelling. For one, there are researchers who believe that by isolating the components or processes that most clearly separate experts from novices, an identification of emergent expertise can be undertaken a priori, before the expertise has become fully formed or clearly manifest (Kilpatrick & Wagner, 1983; Salthouse, 1991; Stanley, 1974). In addition, there are those who see the merits of the expert/novice research as extending beyond identification. They perceive the findings of the expert/novice research as a means of stimulating the development of expertise in all learners. In effect, these theorists and researchers hold that it is possible to introduce critical experiences or essential elements into the learning environment that will advance students along the road to expertise (Bereiter & Scardamalia, 1993; Bransford & Schwartz, 2001).

Such reasoning has been a catalyst for decades of expert/novice research and for associated educational interventions (Bransford, Brown, & Cocking, 1999). Typical of this methodology, the cognitive and noncognitive abilities, personalities, motivations, and backgrounds of recognized experts are quantitatively or qualitatively documented (Ackerman, 1996). The abilities, personalities, motivations, and backgrounds of novices are similarly chronicled. The resulting profiles of experts and novices are then contrasted, and their points of distinction become the basis for academic initiatives or curricular interventions (Alexander & Murphy, 1998; Wineburg, 1998).

The early research on expertise framed within cognitive science was fruitful in establishing rich profiles of experts in very diverse areas. Those areas include both academic (e.g., physics, computer programming, and mathematics) and nonacademic (e.g., typing, sports, and waiting tables) fields (e.g., Allard & Burnett, 1985; Anzai, 1991; Charness, 1991; Ericsson & Polson, 1988; Gentner, 1988). Among the key and consistent findings from those past decades of research was the recognition that experts

- have extensive and highly integrated bodies of domain knowledge,
- are effective at identifying underlying problem structures,
- select appropriate solution strategies for domain-specific problems, and
- can retrieve pertinent content knowledge with minimal cognitive effort (Ericsson & Smith, 1991; Glaser & Chi, 1988).
These identifying characteristics of experts have served as the basis for various educational models, instructional programs, and professional development activities intended to move individuals toward expertise. For instance, efforts to promote students’ general problem solving (Bransford & Stein, 1993; Hayes, 1988), historical thinking (Leinhardt & Young, 1996; VanSledright, 2002; Wineburg, 2001), literacy (Harris & Graham, 1992; Pressley & Wharton-McDonald, 1997), and mathematical/scientific problem solving (Clement, 1991; Sternberg, 1996) have drawn from the research on expertise. Similarly, the decades of expertise research have helped to change conceptions of learning and teaching by illuminating what successful learners look like (see, e.g., Pellegrino, Chudowsky, & Glaser, 2001).

Despite these laudable achievements, prior expert/novice research has not translated well or easily into effective educational programs. Potentially, there are several reasons for this transfer difficulty. For one, it is questionable whether expertise in academic domains is either within the grasp or among the goals of K–12 students (Alexander, 1997; Bransford et al., 1999). Rather, it would seem that the best that can be achieved within the years of mandatory education is the establishment of foundational knowledge, strategies, and motivations that might ultimately lead to expertise.

Two additional sources of difficulty in translating expert models into effective educational practices are the lack of a developmental progression between novices and experts (Ackerman, 1996, 1998) and an overreliance on “coldly cognitive” aspects of academic growth (Pintrich, Marx, & Boyle, 1993, p. 167). Specifically, early insights into expertise were largely based on sharp contrasts between experts and novices with little consideration of the systematic or intermediate changes that must occur between those extreme positions (Patel & Groen, 1991). Moreover, little, if any, consideration has been given to the shifts in motivational or affective factors that might propel or mitigate changes in the knowledge or strategic performance central to expertise (Ackerman, 1999).

Even though the road to translating past cognitive models of expertise into educational practice has been rocky, the need for viable theories and models remains strong. If educators are to be effective in guiding learners’ journeys toward competence in academic domains, they should have a grasp of how expertise takes shape, as well as detailed pictures of what the end point of that development looks like. Moreover, educators require models that work within the complex and dynamic environment of the classroom. It is conceivable that the factors or experiences that contribute to expertise in typing or waiting tables may have little bearing on the development of expertise in biology, history, or other academic domains.

In recent years, a new generation of theories and models of expertise has emerged, building on prior findings from cognitive science but seeking to circumvent the limitations of those earlier conceptualizations (e.g., Ackerman, Kanfer, & Goff, 1995; Alexander, 2003). The goal of these new theories and models is to contribute to the formulation of educational programs that have a greater likelihood of success in fostering the knowledge, strategies, and motivations indicative of increasing expertise (Alexander, 2000). This new generation of expertise models is, thus, identifiable by its consideration of cognitive and noncognitive dimensions, its focus on the interactions among essential factors, and its attention to the transitions and trajectories across varying levels of competence (Lajoie, 2003). In addition, these new models investigate both the domain-specific and the generalizable character of expertise. In other words, these new perspectives not only acknowledge the domain-specific nature of developing expertise but also seek to be applicable to a range of content domains as varied as reading, history, and biology (Patel & Groen, 1991).

One of these new conceptions of expertise is the Model of Domain Learning, or MDL (Alexander, 1997). The MDL adopts a developmental perspective on expertise and considers knowledge, interest, and strategic processing as critical components in that progression. Specifically, the MDL portrays the progression toward expertise as unfolding in three stages: acclimation, competency, and proficiency or expertise. Different associations between the knowledge, interest, and strategic processing factors mark each of these stages. Although the MDL is a generalizable model of expertise in that it proposes that these three stages of development occur for any academic domain, it is also domain specific. That is, the interrelations of knowledge, interest, and strategic processing are examined within academic domains, such as history, physics, or biology. Further, it is assumed that any given individual is at varied points in his or her development depending on the domain under examination.

We adopted the MDL as the framework for this investigation with the intention of contributing to the literature on expertise in our choice of domain and participants. In particular, we concentrated on knowledge, interest, and strategic processing in the field of special education for four educational groups: undergraduate non-special-education majors, undergraduate special-education majors, graduate students in special education, and university faculty in special education. We judged special education to be an important and informative domain of assessment for several reasons. First, this investigation represents the first study of the MDL in special education, which has been a fairly neglected domain of study within the expertise literature (Stough & Palmer, 2003). The importance of this domain to educational practice is evidenced by the fact that approximately five and a half million students between the ages of 6 and 21 years old receive special-education services (Council for Exceptional Children, 2001). Moreover, with the movement toward inclusion of students with special needs in regular classrooms, general education teachers are increasingly becoming more responsible for these students’ learning. Thus, the development of expertise in special education is an important issue in teacher education.

Second, from a methodological standpoint, special education is a promising venue for study. First, the formal study of special education rarely occurs before the college years. This situation permitted us to secure a population of learners in acclimation who could process the same domain-specific tasks and texts as more experienced, advanced individuals. Further, personal involvement in special education can take many forms that reach beyond classroom tasks and educational experiences. This fact afforded us the unique opportunity to examine the nature of individual interest across diverse educational groups, as well as the relation of that interest to participants’ demonstrated knowledge and their strategic processing.

Not only does special education represent a unique arena for
inquiry but the inclusion of the four select groups also represents the most comprehensive test of model predictions to date. Our expectation was that members of those four educational groups would be at different points in the developmental journey from novice to expert in the target domain. As a result, we hypothesized that the knowledge, interest, and strategic processing of those educational groups would differ in ways consistent with MDL predictions. For instance, on the basis of the theoretical premises of the MDL and related research, we expected the undergraduate, non-special-education majors to represent learners in early acclimation. As such, these students would be expected to demonstrate limited and fragmented special-education knowledge and to report low levels of personal commitment or deep-seated interest (i.e., individual interest) in the field. In addition, we hypothesized that when confronted with a domain-specific text-processing task and given the state of their domain knowledge, these non-special-education majors would, by necessity, rely on strategies that would permit them to make sense of the written content (i.e., text-based strategies). Within the MDL, strategies are defined as intentional and effortful actions taken when individuals perceive some problem or gap in understanding. Of course, the degree to which these students would be willing to exert the cognitive effort required for strategic processing remained at issue because it was also assumed that their individual interest in the domain would be limited and likely to mitigate against such strategic processing.

In contrast, we predicted that undergraduate special-education majors would fall at either late acclimation or early competence in the MDL. Given that these individuals have taken undergraduate courses in their major, we believed that they would have some foundational knowledge of special education. Moreover, having chosen this field as their major, those undergraduates would likely exhibit some personal interest in the field. In addition, according to the MDL, learners at this stage should use a combination of strategies. Some of those strategies (e.g., rereading parts of the passage) pertain to the encoding or comprehension of the textual content (i.e., text-based strategies). Other strategies (e.g., reflecting on or critiquing the reading) involve a more extensive manipulation or evaluation of that text (i.e., deep-processing strategies). Such a strategic combination would allow these learners not only to garner meaning from the informational text but also to construct a deeper, more personally relevant interpretation.

Because of their educational and professional experiences, we expected the graduate students in special education to fall within competence, as described in the MDL. That is, we thought that these learners would possess a range of knowledge in this academic field. In addition, we believed that they would manifest a sustained individual interest in special education as a result of their vocational pursuits. Also, these individuals should rely more on deep-processing strategies than text-based strategies in dealing with domain-specific problems.

Finally, special-education faculty were hypothesized to be in the stage of expertise or proficiency. As recognized authorities in the field, these participants were expected to display both depth and breadth of domain knowledge, as well as a significant and abiding interest in the field. Also, we hypothesized that these experts would rely heavily on deep-processing strategies versus text-based strategies when reading domain-specific text because of their rich base of knowledge and correlated interest in the field.

Participants

Participants in this investigation included general-education undergraduates (n = 111), special-education undergraduates (n = 56), special-education graduate students (n = 21), and special-education faculty (n = 20). As stated, our purpose was to select from groups who would be at varied points in their expertise development for the domain of special education, an important but understudied field within the expertise literature (Stough & Palmer, 2003). Because of the disproportionate number of undergraduates in this initial pool and because cluster analysis is sensitive to such group differences, we randomly selected 20 general-education and 20 special-education students for inclusion in subsequent analyses. In this way, resulting profiles would be more equitable, and outcomes would not be unduly influenced by group numbers.

All undergraduates and graduates were enrolled in a large land-grant university in the mid-Atlantic region. The demographics of the general-education and special-education majors were comparable. Collectively, the undergraduate group consisted of 13% male and 87% female students. The ethnic breakdown of this group was 80% European American, 10% African American, 4% Asian/Pacific Islander American, 2% Hispanic American, and 2% Other. These students were mainly juniors and seniors.

Because of teacher certification requirements, both the general-education and special-education students had certain curricular experiences in common. For example, teacher certification mandates a number of methods courses in reading/language arts, mathematics, science, and social studies oriented toward the populations these preservice teachers will eventually serve (e.g., early childhood or middle school/secondary students). Moreover, instructors in these foundational courses are encouraged to present information relative to diverse and special-needs populations as it relates to their content. Thus, for the general-education majors, there was a likelihood of exposure to the domain of special education but no detailed treatment of the domain.

For the special-education undergraduates, the certification program is expected to provide an initial foundation in generic special education, followed by a period of specialization at either the early childhood, elementary, or middle school/secondary level. The program also specifies that students at each of these three education levels should be prepared to teach students across disability categories manifesting mild to severe disabilities.

We drew the graduate-student respondents from several special-education classes that included both master’s and doctoral students. Although there are core courses within the master’s and doctorate programs intended to provide an overview of the research in the domain, those pursuing advanced degrees in special education increasingly specialize during their studies. That specialization can be focused on specific high-incidence (e.g., learning disabilities) or low-incidence (e.g., autism) disabilities and can address a range of research topics, including reading/writing, inclusion, and school-to-work transitions. Among our respondents, 81% of whom were female, the ethnic composition was 71% European American, 10% Asian/Pacific Islander American, 5% African American, 5% Hispanic American, and 10% Other.

The 20 faculty members who took part in this investigation were members of nationally ranked programs in special education from six universities in the United States. Two criteria guided our selection of academic programs. First, we targeted special-education departments that had repeatedly been highly ranked by U.S. News and World Report. Second, we wanted to have a geographically representative sample. Therefore, we contacted programs in the mid-Atlantic, northeastern, midwestern, southeastern, and southwestern regions of the United States. To secure these respondents, we directly contacted faculty from the final six institutions. The response rate for the faculty we initially contacted was approximately 65%. Faculty participants were predominantly female (75%) and
almost exclusively European American (95%), with one African American female respondent.

On the basis of our direct knowledge of their research or from our perusal of curricula vitae, we determined that these 20 faculty members represented a range of research specializations within the domain of special education. Approximately 60% focused their research around high-incidence disabilities, most notably learning disabilities, whereas the research of the remaining 40% focused on low-incidence disabilities such as autism. In addition, the writings and scholarly presentations of these participants addressed an array of topics including reading, writing, the identification of learning disabilities, assessment practices, and the communication and social skills of children with moderate to severe disabilities.

**Clustering Measures**

**Knowledge measure.** A 25-item measure was developed to assess participants’ knowledge in the domain of special education. This measure, which was framed on content from a leading introductory special-education textbook (Hardman, Drew, & Egan, 1998), was organized in two sections that assessed somewhat different forms of domain-specific knowledge. As a means of expert validation, we shared an initial draft of cases and items with selected special-education professors and graduate students not included in the study sample and with two experts in measurement. Unclear cases and questionable items were reworded on the basis of the feedback received.

The first section of this measure consisted of 12 multiple-choice questions that surveyed participants’ factual knowledge about particular conditions, legal events and policies, and educational practices relevant to special education. We examined undergraduate and graduate volumes in special education to validate the appropriateness of these items and their centrality to the domain (e.g., Blanton, 1992; Bos & Vaughn, 1998; Swan & Sirvis, 1992). Two sample items from this portion of the knowledge measure follow:

Which landmark court case declared that a free public education be provided to all children with disabilities?

- (a) Mills v. District of Columbia
- (b) Brown v. Board of Education
- (c) PARC v. Commonwealth of Pennsylvania
- (d) Wyatt v. Stickney

The DSM-IV identifies autism within which of the major groups of disorders?

- (a) attention deficit and disruptive behaviors
- (b) anxiety disorder
- (c) pervasive developmental disorders
- (d) other disorders of infancy, childhood, and adolescence

For the second portion of the test, we wanted to explore pedagogical understanding and decision making. Therefore, we created four minicases that posed a particular pedagogical situation involving students with special needs followed by three or four questions related to each case. These resulting 13 items were presented in multiple-choice format. We built these pedagogical cases around two categories of high-incidence special needs (i.e., learning disability and attention-deficit/hyperactivity disorder) and two categories of low-incidence special needs (i.e., autism and cerebral palsy). The associated pedagogical questions were constructed to assess respondents’ ability to identify the described configuration of symptoms and to respond appropriately to the specific problem in terms of instructional strategies, placement, or support services.

One minicase scenario and two associated questions follow:

Juan is a third-grade student with an IQ of 105 who does well in most of his subjects, but his reading ability is two years below grade level.

**His reading is choppy and his comprehension is poor because he has to sound out most of the words.**

Juan could be described as:

- (a) mildly mentally retarded
- (b) mentally retarded
- (c) learning disabled
- (d) a remedial reader

Which strategy is likely to improve Juan’s reading performance the most?

- (a) have his parents read more to him
- (b) teach him letter-sound combinations
- (c) help him recognize more words on sight
- (d) read more books to the class

As the last sample item suggests, there may have been more than one option that would be seen as plausible from a general-education perspective (e.g., teaching sight words or reading more books). However, the target option was judged as more appropriate for the particular category of special needs on the basis of empirical research in the domain.

We scored both the declarative knowledge and pedagogical knowledge portions of the knowledge measure similarly. Specifically, each response was coded as 1 (correct) or 0 (incorrect). Thus, the maximum score for the knowledge measure was 25. The Cronbach’s alpha for entire knowledge measure across all groups was .69.

**Interest measure.** The 13-item interest measure focused on participants’ interest and involvement in a range of activities relevant to the field of special education. The participants indicated their level of involvement by placing an X on a continuum ranging from very rarely to very often for each of the listed activities. For example, participants were asked:

How often have you:

- Read articles related to special education?
  
<table>
<thead>
<tr>
<th>very rarely</th>
<th>very rarely</th>
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</table>

Volunteered for programs aimed at individuals with special needs?

<table>
<thead>
<tr>
<th>very rarely</th>
<th>very often</th>
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</table>

Respondents could also mark a not-applicable box to indicate that they had never participated in the named activity. We coded each response by giving the individual a score of 0 to 10 (maximum score = 130).

To examine the underlying structure of this measure, we submitted the data from the 13 interest items to a principal axis factor analysis. This form of factor analysis was chosen because of the latent nature of interest. Because we believed that the factors might be related, we used an oblimin rotation. This rotation technique should also have resulted in fewer double loadings than the varimax rotation, increasing the interpretability of the factors. However, the overall factor structure was similar for both oblimin and varimax rotations.

Two factors were extracted based on the eigenvalue-greater-than-1 criterion and examination of the scree plot. Loadings of .4 or above served as a criterion for retaining individual items. Specifically, one item (‘Made a donation/contribution to a charity serving the special needs population’) did not load on either factor. Eight items loaded solely on the first factor.

These items reflected more of a general interest in the field of special education (e.g., reading material related to special education or working with individuals with special needs; $\alpha = .89$). One item (‘Attended professional conferences/seminars/workshops related to individuals with special needs’) loaded on both factors, but its highest loading was on the second factor. We felt that this item was conceptually more related to the
three other items loading on the second factor (i.e., publishing work, participating on a research team, and serving as a consultant). We viewed the four items loading on this factor as reflective of more professional interest ($a = .89$). The two factors collectively accounted for 61% of the variance in the interest data.

**Strategy use measure.** As in prior research (e.g., Alexander, Murphy, Woods, Duhon, & Parker, 1997), our strategy measure focused on the processing and recall of demanding exposition. Participants read a two-page, five-paragraph, 751-word segment of the chapter “Effectiveness of Special Education” (Kavale & Forness, 1999) from the *Handbook of School Psychology* (Reynolds & Gutkin, 1999). This particular segment, entitled “Research in Special Education,” dealt with an evaluation of special-education research and the adverse effect of its overreliance on the scientific method. We selected this particular expository text for several reasons. First, although the text was prepared for an academic audience and contained facts and issues related to the field of special education, it was written for non-special-education readers. Thus, we felt that the text would be comprehensible to our participants, including the general-education undergraduates.

Second, the authors of the text approached the research methodology in special education as a controversial, provocative topic. According to the literature, this controversial tone should have contributed to the interest- ingness of the text (Jetton & Alexander, 2001; Murphy, 1998; Schraw, Flowerday, & Lehman, 2001) and should also have proven personally interesting to those participants who were the consumers or producers of special-education research. Third, we expected the length and demanding- ness of the text to induce some manner of strategic processing on the part of readers attempting to understand and recall the content, including undergraduates, graduate students, and faculty.

In the directions, we were careful to inform participants that they would be asked to recall information from the text. We also gave participants as much time as they needed to complete the processing of the text. Immediately after reading the text, respondents completed a strategy inventory. Modified from the one in the Alexander et al. (1997) study, the strategy inventory listed 21 text-processing strategies that might be used during the reading of the passage. As with prior studies, we did not expect participants to use all or even most of the listed strategies. However, the list was constructed to cover a range of strategies that might be used by readers with varied reading abilities and content exposure, and we felt that this comprehensiveness was useful given the diverse groups in this study. We asked participants to check (*) all the strategies they used when reading and to asterisk (*) the strategies they found most useful. We coded each strategy on a scale of 0 to 2 (i.e., $0 = \text{strategy was not used}, 1 = \text{strategy was used}, 2 = \text{strategy was marked most useful}$).

To determine the underlying structure of the strategy inventory, we submitted the data from the 21 strategy items to a principal components analysis. Using all 21 items, eight components emerged with eigenvalues greater than 1. An inspection of these components, however, revealed that many of them were not meaningful. We felt this was a reflection of the underuse of certain strategies. Thus, we eliminated strategies that were infrequently used. Specifically, if less than 30% of the participants in each educational community reported using a particular strategy, it was eliminated from additional analysis. Using this criterion, we removed 8 listed strategies from subsequent analysis (e.g., skipped difficult parts of the passage and rehearsed the main idea).

We submitted data from the remaining 13 strategy items to a principal components analysis with varimax rotation. Four components were identified as having eigenvalues greater than 1. However, examination of the scree plot supported the extraction of two components. Additionally, we found the two-component solution to be more theoretically meaningful. That is, using a loading of .4 or greater as the criterion, 5 strategies loaded on the first component (i.e., questioned the information, critiqued the information based on prior knowledge, reflected on the reading, assessed the credibility of the cited authors, and related the information to what I already knew). We felt these strategies reflected deep processing of the text.

In contrast, the 4 strategies that loaded on the second component (i.e., reread parts of the passage, mentally summarized the passage, used context to determine meaning, and rephrased main ideas in my own words) dealt more with general comprehension of the textual message. These two components, consisting of 9 of the original 21 strategies, explained 30% of the variance in the strategy data. The Cronbach’s alphas were .71 for the deep-processing strategy component ($n = 5$), .61 for the text-based strategy component ($n = 4$), and .71 for the overall measure after the principal components analysis ($n = 9$).

**Recall Measure**

We designed a 13-item recall measure that used a fill-in-the-blank response format. This measure was similar to one used in a prior investigation of the MDL (Alexander, Kulikowich, & Schulze, 1994). Our primary motive for including the recall measure was to give participants a purpose for being strategic as they read the domain-specific text. The data from the recall measure could also be used as additional validation for the strategy measure by comparing strategy use with recall performance. If the strategy inventory did, in fact, represent text-processing efforts, then there should have been a significant relation between participants’ reported strategy use, especially deep-processing strategies, and the accuracy of their recalls.

The content of this measure was taken directly from the expository text read by participants. That content included information about the authors and the roots of the scientific method, as well as measurement and statistical issues raised by the authors. A draft version of the measure was reviewed by several faculty members in special education and in measure- ment. We made minor changes based on those faculty’s recommendations. This modified measure was then piloted on a small group of special-education graduate students. A sample question from this measure is as follows:

> In research, special education has closely adhered to the scientific method, which has its roots in ______. (logical positivism)

Each item was scored on a 0 (incorrect) or 1 (correct) scale (maximum score = 13). The Cronbach’s alpha for this measure was .81. Despite its informative nature, we decided not to use the recall measure as a clustering variable in analysis for several reasons. For instance, the MDL does not specifically address text recall. Moreover, recall and knowledge would have been highly correlated variables for our participants.

**Criterion Measure: Analogical Reasoning Task**

The particular cluster-analytic procedure applied in this investigation required the use of a criterion measure to demonstrate the statistical distinction between resulting clusters. As the external criterion in this measure, we chose a domain-specific analogy task. This 5-item measure assessed individuals’ domain knowledge of special education through problems of the form A:B::C: _. These items, as with questions in the knowledge measure, were built from content in special-education textbooks and the research literature. Sample items from this domain-specific analogy measure are as follows:

- one limb:monoplegia::side of body: _ (hemiplegia)
- letters:dysexia::numbers: _ (dyscalculia or dyscalculia)

The use of this measure as the external criterion was based on earlier studies following similar procedures (e.g., Alexander & Murphy, 1998). There is also ample documentation that successful performance on verbal analogy problems (e.g., Goswami, 1992), including those that contain domain-specific information (e.g., Kulikowich & Alexander, 1990), re-
Descriptive Data

MDL. To substantiate the emergence of unique clusters, several edge, interest, and strategic processing, as hypothesized by the indicators. For our purposes, cluster analysis can produce profiles that distinguished groups or clusters of individuals based on multiple means of correlational analysis. The resulting correlational matrix

Table 1
Response Categories Used in Scoring the Analogical Reasoning Task

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Nonresponse</td>
<td>one limb:monoplegia::side of body:?</td>
</tr>
<tr>
<td>2</td>
<td>Repetitive</td>
<td>one limb:monoplegia::side of body:monoplegia</td>
</tr>
<tr>
<td>3</td>
<td>Nondomain Response</td>
<td>one limb:monoplegia::side of body:halfbody</td>
</tr>
<tr>
<td>4</td>
<td>Structural Response</td>
<td>one limb:monoplegia::side of body:biplegia</td>
</tr>
<tr>
<td>5</td>
<td>Domain Response</td>
<td>one limb:monoplegia::side of body:paralysis</td>
</tr>
<tr>
<td>6</td>
<td>Target Variant</td>
<td>one limb:monoplegia::side of body:hemiplegia</td>
</tr>
<tr>
<td>7</td>
<td>Correct Response</td>
<td>one limb:monoplegia::side of body:hemiplegia</td>
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Procedure

Three doctoral students were taught the scoring rubric for this task. After training, the three coders scored data from 20 (approximately 10%) randomly selected participants. The interrater reliability for that scoring was .93, with all disagreements resolved in discussion. The remaining data were independently scored.

Results and Discussion

Descriptive Data

Our purpose in this investigation was to examine the profiles that emerged from individuals’ knowledge and interest in the field of special education, as well as their strategic processing of domain-specific expositions. Cluster analysis is a technique that distinguishes groups or clusters of individuals based on multiple indicators. For our purposes, cluster analysis can produce profiles of expertise based on the interactions among participants’ knowledge, interest, and strategic processing, as hypothesized by the MDL. To substantiate the emergence of unique clusters, several strategies that emerged from individuals’ knowledge and strategic capabilities. Hence, the decision to use the analogical reasoning task provided us a criterion measure that related to two central dimensions of the MDL, domain knowledge and strategic processing.

The scoring of these analogy items followed an empirically validated scheme (Alexander, 1990; Alexander, Murphy, & Kulikowich, 1998) that hierarchically ordered responses on the basis of the knowledge and strategic capability each was assumed to convey (see Table 1). For example, Category 3 (Nondomain) errors were responses that fell outside the target domain, special education (e.g., one limb:monoplegia::side of body:half-body). By comparison, Category 5 (Domain) errors reflected participants’ ability to produce an incorrect response that represented some knowledge of special education (e.g., one limb:monoplegia::side of body:paralysis). The Cronbach’s alpha was .71 for the 5-item analogical reasoning task.

With respect to strategy use, it is notable that the means for both forms of strategy use were low in comparison with the maximum scores across all groups. We believe this may be attributable to various factors. First, the participants were able to select from only a specific number of strategies (i.e., 21), and several of these strategies were dropped from the analyses to create statistically reliable components. Thus, the number of strategies for which individuals could receive credit was limited. Second, the scale used for the strategy measure was also limited. That is, each strategy was scored as not used (0), used (1), or used and considered most useful (2). Consequently, the scale does not capture fully the extent to which participants used each strategy. It is possible that participants relied on a relatively small number of strategies that they used extensively as they read the passage. However, despite these limitations, we hold that the strategy measure is still a useful indicator of participants’ reported strategy use, particularly with respect to the relative strategy use across groups.

Strategy Use and Recall Performance

We examined the relation between strategy use and recall by means of correlational analysis. The resulting correlational matrix

Table 1 Response Categories Used in Scoring the Analogical Reasoning Task

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<td>4</td>
<td>Structural Response</td>
<td>one limb:monoplegia::side of body:biplegia</td>
</tr>
<tr>
<td>5</td>
<td>Domain Response</td>
<td>one limb:monoplegia::side of body:paralysis</td>
</tr>
<tr>
<td>6</td>
<td>Target Variant</td>
<td>one limb:monoplegia::side of body:hemiplegia</td>
</tr>
<tr>
<td>7</td>
<td>Correct Response</td>
<td>one limb:monoplegia::side of body:hemiplegia</td>
</tr>
</tbody>
</table>
for total strategy use, text-based strategies, and deep-processing strategies is presented in Table 3. Several interesting findings resulted from this analysis.

First, the correlation between total strategy use and recall was nonsignificant. Such a finding seems in conflict with the literature on strategy use, which would seem to predict better recall for higher strategy use (Weinstein & Mayer, 1986). However, as predicted by the MDL (Alexander, Jetton, & Kulikowich, 1995), the relation between strategy use and recall becomes clearer when both the quantity and quality of strategies are considered. Specifically, the correlation between text-based strategies and recall was negative and nonsignificant, suggesting that those recalling less may have struggled to make sense of the demanding exposition. However, the positive correlation between deep-processing strategies and recall was significant. This suggests that those who were able to reflect and question the content were better equipped to respond to the text-specific questions in the recall measure. These data also suggest that the strategies reported by our participants were appropriate representatives of their comprehension efforts.

Cluster Analysis

To investigate the expertise profiles of the participants from four educational communities, we performed cluster analysis. Specifically, we chose Ward’s minimum-variance hierarchical clustering technique (Everitt, 1993) to cluster individuals on the basis of their domain knowledge, general interest, professional interest, and text-based and deep-processing strategies. Ward’s hierarchical procedure, an effective means for identifying the underlying structure of data, is an agglomerative technique that groups individuals on the basis of their proximity to one another in multivariate space. That is, at the start of the analysis, each individual represents a single group. Groups are then successively combined on the basis of the estimated between-groups distance until a single group remains.

We used dendrograms, a type of visual aid, to help in determining the appropriate number of meaningful clusters represented in the data. Additionally, we used two analyses to ensure the validity of our emergent clusters. First, we examined how the clusters differed for the external criterion, domain-specific analogical reasoning, with the expectation that members of the emergent clusters would differ with respect to their performance on the domain-specific analogy measure. Second, we used discriminant function analysis to verify the multidimensional nature of the identified clusters.

As hypothesized, the analysis of the criterion measure revealed three major gaps in the dendrogram, suggesting four viable clusters. An analysis of variance examining the analogical reasoning scores for the four clusters was statistically significant, $F(3, 80) = 12.38, p < .001$, $MSE = 38.58, \eta^2 = .33$, indicating that the clusters differed on this external criterion (see Table 4). Post hoc analyses of the between-groups differences using Fisher’s least significant difference (LSD) elaborated the differences among the groups. Specifically, members of Cluster 1 had significantly lower scores than did all other clusters ($d > .97$). Further, those in Cluster 2 scored significantly below those in Cluster 4 ($d = .87$). Finally, there were no significant differences and the effect sizes were moderate to small for comparison of Clusters 2 and 3 ($d = .60$) and Clusters 3 and 4 ($d = .27$) on the analogical reasoning measure.

Because we assumed that there is a multidimensional character to developing expertise, we expected the interaction of the knowledge, interest, and strategy variables to predict cluster membership better than one variable alone. This assumption was particularly
critical to distinguishing the MDL from prior expert/novice models that focus almost exclusively on knowledge-based factors because it is conceivable that knowledge alone could explain cluster formation. Discriminant function analysis allowed us to test those assumptions (Der & Everitt, 2001). Unlike cluster analysis, in which groups are allowed to form from the data, discriminant function analysis tests the fit of each member of preformed groups for all designated predictor variables. We could test whether each member of a particular cluster had the right configuration of domain knowledge, general and professional interest, and text-based and deep-processing strategies expected of that cluster.

Using individuals’ domain knowledge and general and professional interest, as well as their use of deep-processing and text-based strategies, we predicted correct cluster membership for 96% of the cases. Predicted membership in Cluster 1 and Cluster 2 was 100% accurate, followed by a 95.5% accuracy rate for Cluster 4 and a 92.9% accuracy rate for Cluster 3. Calculation of Cohen’s kappa revealed that the accuracy of the predicted classification was a 94% improvement over what would be expected by chance. These findings offer evidence that the four emergent clusters are unique and multidimensional.

**Descriptions of the Clusters**

The means and standard deviations for the clustering variables and the analogical reasoning external criteria are displayed in Table 4. As stated, four clusters were identified in the analysis. To understand more fully the nature of the clusters, we conducted a multivariate analysis of variance (MANOVA). Domain knowledge, general interest, professional interest, text-based strategies, and deep-processing strategies were the dependent variables, and cluster group was the independent variable. The results indicated a significant multivariate effect, $F(15, 202) = 42.39, p < .001$. $\eta^2 = .73$. Additionally, the univariate effects for the five variables were statistically significant—that is, $F$s$(3, 80) \geqslant 3.40, ps < .05$, $MSEs \leqslant 10,636.10$—and the effect sizes for the univariate effects approached or surpassed Cohen’s guidelines for large effects (i.e., .14; Cohen, 1977) for each of the five variables (i.e., domain knowledge: $\eta^2 = .45$; general interest: $\eta^2 = .87$; professional interest: $\eta^2 = .89$; text-based strategies: $\eta^2 = .12$; deep-processing strategies: $\eta^2 = .12$). Post hoc multiple comparisons were then conducted using Fisher’s LSD, a procedure found to be effective in identifying differences in three or more groups. The effect sizes for all significant post hoc multiple comparisons were moderate to large (i.e., 0.58 to 7.08), indicating that the clusters differed by at least a half a standard deviation. On the basis of the cluster differences identified by the MANOVA and the composition of the clusters, we refer to them as Acclimation, Early Competence, Mid-Competence, and Proficiency. These labels suggest the developmental position of the clusters within the MDL.

**Acclimation cluster.** Individuals in the Acclimation cluster demonstrated the least knowledge of the field of special education, with regard to domain knowledge test ($ds \geqslant 1.13$) and on the criterion measure, the analogical reasoning task ($ds \geqslant 0.87$). As hypothesized, this cluster consisted almost exclusively of non-special-education majors ($n = 16$), along with 2 special-education majors. In comparison with the other clusters, this cluster was also characterized as having the lowest reported individual interest in special education at both a general level ($ds \geqslant 5.02$) and a professional level ($ds \geqslant 1.43$).

With regard to strategic processing, the mean for the Acclimation cluster’s text-based strategy use was descriptively higher than the mean for their deep-processing strategy use (see Table 4). Individuals in this cluster were among the highest users of the text-based strategies but used deep-processing strategies less than any other cluster. The Acclimation cluster was statistically significantly lower than Cluster 4 on both strategy variables (i.e., text-based strategies: $d = 1.01$; deep-processing strategies: $d = 0.64$). Primarily because of the low levels of domain knowledge and individual interest, we felt this group reflected characteristics of individuals who are becoming acclimated to the domain (Alexander, 1997).

**Early competence cluster.** Individuals in the Early Competence cluster demonstrated significantly higher levels of both knowledge ($d = 1.13$) and interest (general: $d = 5.02$; professional: $d = 1.43$) than did those in the Acclimation cluster. That is, individuals in this cluster performed better on the domain knowledge test and the analogy task, and they reported greater individual interest in special education, general and professional, than the Acclimation cluster.
Although individuals in the Early Competence cluster were more knowledgeable than those in the Acclimation cluster, their knowledge and interest were still relatively moderate. Their means on these various measures did not approach the maximum score values. Additionally, there were no significant differences between the strategic processing of individuals in Acclimation and Early Competence clusters (see Figure 1). Like those in the Acclimation cluster, Early Competence individuals tended to use more text-based than deep-processing strategies. Consequently, although these individuals had acquired more knowledge and had increased interest in special education, they were still focused on building text-based understanding.

There were 16 special-education majors, 7 graduate students, 4 non-special-education majors, and one faculty member in this cluster. With the exception of the one faculty member, this composition was not wholly unexpected. That is, we would regard special-education majors as having more knowledge and interest in special education than the general college population. However, it is unlikely that at this point in their education, they would process information any differently than their peers. At the same time, it is probable that some non-special-education majors may have more knowledge and interest in the field than their peers because of other personal or professional circumstances not assessed in this study (e.g., a relative with special needs or pursuit of a field related to special education such as occupational or speech therapy). Further, as we assessed both master’s and doctoral-level graduate students at various points within their programs, it is possible that those just beginning their graduate work may not have been as advanced with regard to their knowledge or strategic processing. Thus, they would have been more similar to undergraduates than those who were more advanced in their study of the field.

We did not expect to have any faculty members associated with this group. However, possible explanations can be forwarded. For instance, some faculty may have considerable specialized knowledge of one area of special education (i.e., autism) but not have a breadth of domain knowledge. Our knowledge measure contained information pertinent to a broad variety of domain content, and experts were not asked specifically about their area of expertise. Of course, we must accept the possibility that this individual did not elect to invest the time or energy required of the experimental task.

Mid-competence cluster. The Mid-Competence cluster was distinguished as being one of the top performers on the domain knowledge test and the analogy task. This cluster also reported the highest level of general individual interest. The members of this cluster consisted of 10 graduate students, 2 special-education majors, and one faculty member. Specifically, there were significant differences between the Mid-Competence cluster and the Acclimation and Early Competence clusters on the domain knowledge test ($d_s = 1.25$ and 0.79, respectively) and between the Mid-Competence cluster and the Acclimation cluster on the analogical reasoning task ($d = 1.57$). Individuals in the Mid-Competence cluster also reported a higher level of professional interest than individuals in the Acclimation ($d = 6.91$) and Early Competence ($d = 1.88$) clusters.

In contrast to the Acclimation and Early Competence individuals, Mid-Competence members reported descriptively more use of deep-processing strategies than text-based strategies (see Table 3). Individuals in the Mid-Competence cluster also used significantly fewer text-based strategies than individuals in the Early Competence cluster ($d = 0.78$). The Mid-Competence cluster was not significantly different from the Acclimation and Early Competence clusters with respect to deep-processing strategy use. Consequently, although individuals in this cluster demonstrated a more well-defined body of declarative and pedagogical knowledge and greater interest in the field, they were only beginning to show a shift in their use of strategies. That is, their strategies focused less
on surface-level processing of information and, descriptively, more on reflective, critical text analysis (see Figure 1).

Proficiency cluster. Individuals in the Proficiency cluster were markedly different in professional interest and strategic processing from those in other clusters. As expected, the Proficiency group consisted largely of faculty members ($n = 18$) and 4 doctoral students. These individuals scored the highest on both the domain knowledge test and the analogy task. Further, they were significantly more knowledgeable than individuals in the Acclimation ($d = 2.39$) and Early Competence groups ($d = 1.25$), but not those in the Mid-Competence cluster. With respect to interest, Proficiency individuals reported significantly less general interest than Mid-Competence individuals ($d = 0.79$) but significantly more general interest than the Acclimation cluster ($d = 6.13$) and the Early Competence cluster ($d = 1.10$). Further, Proficiency individuals had significantly more professional interest in the field than the Acclimation ($d = 7.08$), Early Competence ($d = 5.65$), and Mid-Competence clusters ($d = 3.58$). Thus, as reflected in their professional activities, these individuals were distinct in their long-term and deep-seated commitment to special education, although other mechanisms for manifesting personal interest for those professionals working within the public school system rather than the academy cannot be dismissed. In addition, on the basis of their involvement, they appeared to be contributing to the advancement and development of the field of special education, in keeping with the tenets of the MDL.

There were also notable differences between this cluster and the other clusters with regard to strategic processing (see Figure 1). Specifically, Proficiency individuals used text-based strategies significantly less often than Acclimation ($d = 0.63$) and Early Competence individuals ($d = 0.73$). However, they used deep-processing strategies significantly more than those same clusters ($d_s = 1.01$ and 0.57, for Acclimation and Early Competence, respectively). Proficiency individuals were not statistically significantly different from individuals in the Mid-Competence cluster with respect to strategy use.

To summarize, the Proficiency cluster was significantly different from the Acclimation and Early Competence clusters on all of the variables that we assessed. In examining the compositions of the groups, these differences would be predicted by the MDL. However, on the basis of the analyses conducted, interest was the only variable that statistically distinguished between the Mid-Competence and Proficiency clusters. That is, individuals in the Proficiency cluster had more professional interest and less general interest than individuals in the Mid-Competence cluster. The clusters were not significantly different on the other variables.

Although we expected more significant differences between these groups, we viewed these findings as indicative of certain limitations of this study. For instance, our knowledge and strategy measures may not have been sensitive enough to discover statistically significantly different levels of knowledge and strategy use between those who are proficient and those who are quite competent and actively pursuing domain expertise. Perhaps with a knowledge measure that assessed both the depth and breadth of individuals’ knowledge and a strategy measure that reflected the degree to which specific strategies are used, significant differences may have emerged.

Even so, our findings suggest that there are some differences between individuals in the Mid-Competence and Proficiency stages. In particular, general and professional interest appears to be a key construct that separates those seeking proficiency from those who have already reached that stage of their academic development. As predicted by the MDL, those at the proficiency stage should be actively engaging in contributing to the field. Thus, we would expect them to be more involved in activities reflective of professional interest (e.g., publishing and consulting) than those in the competency stage. In contrast, individuals in the competency stage may have a deep-seated general interest in the field and want to be of service to those with special needs. However, they have not become involved in professional activities that contribute to the field’s knowledge base or are pursuing an alternative path to personal interest.

Conclusions and Implications

Our goals for the current investigation were multileveled. First, through cluster analysis, we wanted to determine how dimensions of domain-specific expertise—knowledge, interest, and strategic processing—change and interact within the field of special education. We held that special education is an important and informative arena for study that has garnered only minimal attention within the expertise literature (Stough & Palmer, 2003). Second, because we built our predictions about developing expertise around the MDL (Alexander, 1997), we sought to test the central premises of that model. Third, beyond testing a particular model of expertise, we wanted to examine distinctions between earlier expert/novice theories and models (e.g., Charness, 1991; Salthouse, 1991) and recent, alternative perspectives (e.g., Ackerman, 1996, 1998), such as the MDL.

The responses of 81 participants from four varied educational communities were the data source in this study. We selected those four communities (i.e., undergraduate non-special-education majors and undergraduates, graduate students, and faculty from special education) precisely because we believed that they would capture developing expertise in the field of special education and would be a strong test of the MDL. In general, we expected participants to exhibit different characteristics not only in terms of their declarative and pedagogical knowledge of the target domain but also with regard to their domain-specific interests (i.e., general and professional) and their strategic performance (i.e., text-based and deep-processing).

On the surface, one might question whether the elaborate analyses conducted in this study were warranted because it would intuitively seem that the varied educational communities in this study would behave differently on the clustering and criterion variables. For instance, one might expect special-education faculty and graduate students to perform better than undergraduate non-majors on domain-specific measures. However, such an intuitive judgment would in fact overlook subtle yet significant differences that might be predicted by the MDL and that could inform one generally about the development of expertise.

For example, although membership in the four clusters was somewhat predictable on the basis of educational community (e.g., undergraduate majors vs. nonmajors), the alignment between community and expertise is not perfect. For instance, there are four graduate students who joined the ranks of faculty within the Proficiency cluster, and there is one faculty member who fell within the Mid-Competence cluster dominated by graduate stu-
dent students. This finding suggests that expertise, although strongly associated with educational background, is not simply a matter of years of experience or community identity. Rather, expertise is directly tied to the knowledge individuals manifest, the involvement they show, and the strategic processing they report.

Moreover, it was not simply that we expected faculty to know more about special education than undergraduate nonmajors—a distinction well documented in the traditional expert/novice research (Chi et al., 1988; Ericsson & Smith, 1991). We expected the experts—whomever they turned out to be—to demonstrate differences in their general and professional interests, their text-based and deep-processing strategies, and their domain-specific analogical reasoning. Similarly, we expected clear differences on those clustering and criterion variables for each of the resulting clusters and not merely for the more extreme groupings (i.e., experts and undergraduate nonmajors). Results of the multivariate cluster analysis and discriminant function analysis supported those expectations. The clusters are distinct from each other on both the clustering and the criterion variables.

Finally, although we perceived a hierarchical nature to the four clusters in that the Acclimation cluster should have manifested less expertise than the Early Competence cluster, which should in turn have shown less expertise than either the Mid-Competence or Proficiency clusters, we predicted that differences would not always be linear or favor the more expert cluster. The shifting reliance on text-based and deep-processing strategies by clusters serves as a case in point for such nonlinear predictions, as do the shifting interests from more general to professional across the clusters. For example, we expected that a rise in expertise would be associated with a concomitant rise in deep-processing strategies but with a decreased reliance on text-based strategies, as was the case. Further, although the overall interest of clusters was expected to differ, it was the significant increase in activities related to the professional interest component that distinguished between Mid-Competence and Proficiency clusters, rather than their general domain-specific interests.

Certainly, this is not the first study to report such interrelations among knowledge, interest, and strategies variables (Alexander & Murphy, 1998) or the first to provide tentative support for the MDL (Alexander et al., 1995, 1997). However, the present study has expanded and clarified the findings of prior research in several important ways. For one, there was less domain diversity among participants in prior studies. Previous studies produced only snapshots of developing expertise instead of the more panoramic view in this study. Given their restrictive range of expertise, those earlier studies could offer only a partial test of the MDL. By including participants from four different educational communities, this study undertook a more comprehensive exploration of both the MDL and developing expertise. Of course, we acknowledge that a truly longitudinal study that tracks development within a domain over decades would be preferable to even this broad cross-sectional investigation.

Overall, the results of this study shed light on traditional and alternative conceptualizations of expertise. In past decades, those conceptualizations have focused on the sharp contrasts between novices and experts, with limited consideration for any profiles of expertise that might exist between those polar positions. In addition, the distinctions made between novices and experts in the past tended to rest solely on cognitive factors and almost exclusively on knowledge-specific variables. Yet, as we found in this study, knowledge and cognitive variables alone cannot adequately explain the clusters that formed, nor do they sufficiently differentiate those with the highest levels of expertise from other profiles. A measure of interest, a motivational variable, was also required. In fact, although the domain-specific knowledge of those in the Proficiency cluster was descriptively higher than that of all other clusters, including those in the Mid-Competence cluster, those differences were not statistically significant. Together, these differences support the contention of alternative theories and models that expertise is multidimensional, encompassing both cognitive and motivational components. The findings of this study also suggest that expertise is developmental and therefore cannot be well understood simply by contrasting the performance of novices and experts.

Beyond these significant theoretical issues, we believe this study has implications for educational practice. As discussed, theories and models of expertise have been frequently applied in the development of educational interventions intended to move learners toward expertise in academic domains (Clement, 1991; Harris & Graham, 1992; Leinhardt & Young, 1996; VanSledright, 2002; Wineburg, 2001). However, interventions that target only cognitive or knowledge-specific aspects of expertise may prove incomplete or insufficient. The present study demonstrates that as individuals develop expertise, there are shifts in their interest and strategic processing. Therefore, it may be beneficial for educators, particularly those in specialized fields such as special education or teacher education, to provide learning experiences for their students that scaffold these forms of interest and strategic processing as learners progress through the stages of domain learning. For example, providing preservice teachers with opportunities for explicit exploration and participation in more professional activities, such as participating in local and national professional associations, attending national conferences, or participating in research, may help to direct and influence their professional interest in the field. Further, as individuals progress in a domain, there are changes in the level and types of strategic processing used. This suggests that those who guide others on the journey toward expertise may need to give explicit attention to the development of strategies relevant to learning within domains.

The present study, however, only suggests these implications. One of the next steps is to explore the effectiveness of educational interventions based on this approach. That is, researchers must explore the effects of implementing activities that stress domain-specific interest and strategic processing on individuals engaged in learning within that domain. Similarly, given the stage structure of the MDL, it seems important to identify when and how these domain-specific components should be emphasized in the learning process. Additionally, the present study explored the academic domain of special education utilizing the end point of university professor and researcher as the culminating point of expertise. However, it is conceivable that in special education or other complex domains, expertise can take multiple career paths (e.g., special-education coordinator). Therefore, it would seem advisable to investigate whether or not alternative forms of expertise yield different profiles than those documented herein.

Still, according to this investigation, the meaningful pursuit of declarative and pedagogical knowledge, text-based and deep-processing strategies, and individual interest remains central to
developing expertise. Consequently, such ingredients should be hallmarks of educational programs committed to fostering students’ academic expertise. Although we recognize that educators in K–12 settings cannot hope to create learning environments that result in truly expert performance in any complex academic domain, we believe that they can do a great deal to establish the foundation upon which expertise can flourish and from which expertise may indeed emerge.

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**New Editor Appointed for Journal of Occupational Health Psychology**

The American Psychological Association announces the appointment of Lois E. Tetrick, PhD, as editor of *Journal of Occupational Health Psychology* for a 5-year term (2006–2010).

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Manuscript submission patterns make the precise date of completion of the 2005 volume uncertain. The current editor, Julian Barling, PhD, will receive and consider manuscripts through December 31, 2004. Should the 2005 volume be completed before that date, manuscripts will be redirected to the new editor for consideration in the 2006 volume.