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Assessing Individual Differences in Knowledge: Knowledge, Intelligence, and Related Traits

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Twenty academic knowledge tests were developed to locate domain knowledge within a nomological network of traits. Spatial, numerical, and verbal aptitude measures and personality and interest measures were administered to 141 undergraduates. Domain knowledge factored along curricular lines; a general knowledge factor accounted for about half of knowledge variance. Domain knowledge exhibited positive relations with general intelligence (*g*), verbal abilities after *g* was removed, Openness, Typical Intellectual engagement, and specific vocational interests. Spatial and numerical abilities were unrelated to knowledge beyond *g*. Extraversion related negatively to all knowledge domains. Results provide broad support for R. B. Cattell's (1971/1987) crystallized intelligence as something more than verbal abilities and specific support for P. L. Ackerman's (1996) intelligence-as-process, personality, interests, and intelligence-as-knowledge theory of adult intelligence.

It has become clear that domain-specific knowledge plays an important role in intellectual performance. Experts' advantages over novices when performing in specific domains have been attributed mainly to higher levels of knowledge and more integrated knowledge (e.g., Chi, Glaser, & Rees, 1982; Ericsson, 1996; McKeithan, Reitman, Rueter, & Hirtle, 1981). Individual differences in knowledge predict the acquisition of new knowledge in text comprehension tasks (e.g., Alexander, Kulikowich, & Schulze, 1994; Schneider & Bjorklund, 1992; Schneider, Körkel, & Weinert, 1989). Developers of expert systems have achieved success mostly by endowing their systems with domain-specific knowledge (e.g., Fox, 1996; Hexmoor & Shapiro, 1997). Knowledge, once acquired, appears to be relatively enduring, as demonstrated by research on long-term retention (e.g., Bahrick, 1979; Bahrick & Hall, 1991; Semb & Ellis, 1994; Semb, Ellis, & Araujo, 1993) and the observed stability of crystallized intelligence across adulthood (Schaie, 1996).

In the past, researchers concerned with knowledge almost exclusively limited their investigations to a single domain (e.g., Charness, 1979, 1991; Chi et al., 1982; Ericsson, 1996; Ericsson, Krampe, & Tesch-Römer, 1993). The current project was an attempt to measure individual differences in knowledge across multiple domains. A second aim of this work was to locate domain knowledge within a broader nomological network of traits, specifically aptitudes, interests, and personality. It is important to place domain knowledge firmly within a broader framework to understand and predict cumulative influences on the acquisition and retention of knowledge. A third aim of this project was to test part of a recent theory of adult intelligence proposed by Ackerman (1996).

Intelligence and Knowledge

Ackerman (1996) proposed a theory of adult intelligence that introduces domain-specific knowledge as an integral part of intelligence for adults. Ackerman's theory extends Cattell's (1971/1987) distinction between fluid intelligence (Gf) and crystallized intelligence (Gc) by explicitly defining two constructs: intelligence-as-process and intelligence-as-knowledge. Process is exemplified by abstract reasoning and working-memory tasks (e.g., decontextualized reasoning). Knowledge is exemplified by the recall or recognition of declarative facts and by the demonstration of procedural skills. Ackerman's intelligence-as-process, personality, interests, intelligence-as-knowledge (PPIK) theory broadly states that intelligence-as-knowledge is accumulated by the application of intelligence-as-process to learning experiences (see Cattell's [1971/1987] investment hypothesis). Thus, intelligence-as-process represents the building blocks for initial learning. When Gf-type abilities are applied over time to learning experiences, they result in knowledge and skills (see also Ferguson, 1954, 1956). PPIK theory also specifies interactions of Gc-type abilities with particular personality traits (e.g., Openness, Costa & McCrae, 1992; and Typical

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Intellectual Engagement [TIE], Goff & Ackerman, 1992) and interest traits (i.e., Realistic, Investigative, and Artistic; Holland, 1973). The predictions of specific trait–knowledge correlates in the PPIK approach are based on a meta-analysis of personality–intelligence relations, a review of interest–intelligence relations (Ackerman & Heggestad, 1997), and a study of self-report knowledge–trait relations (Rolfhus & Ackerman, 1996).

Self-Reported Knowledge and Traits

In a previous investigation (Rolfhus & Ackerman, 1996), we sought to explore individual differences in knowledge by measuring self-reported knowledge within specific domains. We examined these self-reports within a nomological network of aptitudes, interests, and personality. We included an aptitude battery that sampled a range of abilities representative of Gf and Gc to determine commonalities among domain-specific knowledge and standard ability measures. We also included personality and vocational interests measures from the industrial–organizational and vocational psychology literatures, respectively. Following Holland (1959, 1973), we conjectured that nonability constructs would influence the choices people make regarding what domain of knowledge is to receive intellectual investment and what degree of intellectual investment is made. Therefore, in a sample of college students, we expected to see significant correlations among particular personality traits, interest traits, and compatible knowledge areas.

We asked participants to rate their knowledge of specific topics within 32 academic domains. We found that self-reported knowledge clustered along curricular lines. For example, chemistry, physics, engineering, and biology clustered together as a physical-sciences cluster. Domain-specific knowledge was moderately related to objective tests of verbal abilities but not to spatial or numerical abilities.

The observed pattern of personality–interest–knowledge relations suggested possible roles for a subset of these variables in knowledge acquisition. For example, interests in science were related to self-reported science knowledge but not to self-reported humanities knowledge. Personality traits assessing intellectual orientations toward the world (i.e., Openness, TIE) were broadly related to self-reported knowledge, especially in humanities domains. Thus, personality and interest traits may reflect or influence choices to engage ("invest") in particular domains.

Other work has identified moderate relations among achievement, personality, and interests variables. Schiefele, Krapp, and Winteler (1992), in a meta-analysis of interest–achievement relations, reported a correlation of $\hat{\rho} = .31$ between domain-specific interest and achievement in that domain. In a meta-analysis of personality–intelligence relations, Ackerman and Heggestad (1997) identified two personality traits (TIE and Openness) that correlated $\hat{\rho} = .23$ and $\hat{\rho} = .28$ with measures of knowledge and achievement.

The Present Empirical Investigation—Measuring Knowledge Objectively

Rolfhus and Ackerman's (1996) investigation of individual differences in knowledge was limited in that it relied upon self-reports of knowledge. Although self-reports of knowledge are interesting in their own right, particularly as relevant to feeling-of-knowing issues (e.g., Baeckman & Karlsson, 1985; Butterfield, Nelson, & Peck, 1989; Lundeberg, Fox, & Puncochar, 1994) or the nature and structure of self-concept (e.g., Marsh & Yeung, 1997, 1998), the current investigation focused on measuring what people actually know. However, there is the possibility that the knowledge–trait relations identified by Rolfhus and Ackerman were an artifact of the self-report knowledge measures used and were not due to knowledge itself.

The present study represented a refinement and extension of the study of self-report knowledge (Rolfhus & Ackerman, 1996). The study also served as a partial test of Ackerman's (1996) PPIK theory that specifies a set of intelligence–personality–interest relations. Computerized tests of knowledge for 20 domains were constructed for this study. Trait measures of interests and personality from Rolfhus and Ackerman (1996) were also included.

Predictions of the Present Investigation

On the basis of the self-report knowledge results (Rolfhus & Ackerman, 1996), the meta-analysis of personality–intelligence relations (Ackerman & Heggestad, 1997), and the original specification of PPIK theory (Ackerman, 1996), we made the following predictions:

> *Hypothesis 1:* Domain-specific knowledge will be more closely related to verbal abilities (i.e., Gc) than to numerical or spatial abilities (i.e., Gf).

Verbal abilities were characterized by Carroll (1993) as factors in which

> (a) all or a majority of their variables involved printed tests requiring reading, and (b) the variables covered a wide range of test types measuring general language development including (typically) various types of vocabulary and reading comprehension tests.... [In] nearly every case the [verbal] factor is dominated by a general factor ... interpreted as "crystallized intelligence." This fact can be interpreted as signifying that while the [verbal] factor is generally substantially or even highly correlated with ... crystallized intelligence, it is factorially distinct from these higher-order factors, in that there is variance in it even after higher-order variance is controlled or partialled out. (p. 157)

Although Gc is typically operationalized by researchers with tests of vocabulary knowledge (i.e., verbal abilities), Cattell (1971/1987) defined Gc rather differently. Cattell wrote that crystallized intelligence

> must become different for different people. If [individuals' learning experiences] are sufficiently varied and lack any common core, the very concept of general intelligence begins to disappear. An effort to measure Gc in practice might amount to producing as many tests as there are occupations. (p. 144)

Tests of domain-specific knowledge, therefore, represent an assessment of Gc that is closer to Cattell's specification. By measuring knowledge at the domain level, we examined Gc at a more representative level than can be accomplished with general vocabulary or cultural knowledge tests. We therefore predicted domain knowledge to be related to traditional Gc measures, such as verbal ability, but less so to Gf.

Hypothesis 2: Personality and interests, as they represent measures of typical behavior (Cronbach, 1949; see also Ackerman, 1994), may play an important cumulative role in knowledge acquisition and retention. We predicted a set of convergent and discriminant nonability trait–knowledge relations. Specifically:

Hypothesis 2a: Personality.

Convergent: Openness and TIE will exhibit positive and significant correlations with knowledge and stronger relations to humanities-type knowledge than to the sciences. As these personality traits measure an orientation to reading, learning, study, engaging new ideas, and intellectual activities, we expected them to be related to domain knowledge.

Discriminant: Neuroticism, Extraversion, Agreeableness and Conscientiousness will show no consistent pattern of correlations with knowledge, as none was observed with self-report knowledge.

Hypothesis 2b: Interests.

Convergent: Realistic interests, defined as "activities requiring physical strength, aggressive, motor coordination and skill" (Holland, 1959, p. 36), will show positive and significant relations with the physical sciences and mechanical and technological knowledge domains. Investigative interests will show positive and significant relations with physical and social sciences domains. Holland (1959) defined *investigative individuals* as "task-oriented people who generally prefer to 'think through' rather than 'act out', problems. They have marked needs to organize and understand the world" (p. 36). Artistic interests will show positive and significant relations with art and other humanities domains. Holland defined *artistic individuals* as those who "prefer indirect relations with others. They prefer dealing with environmental problems through self-expression in artistic media. . . . They resemble persons with an intellectual orientation in their intraceptiveness" (p. 37).

Discriminant: Social, Enterprising, and Conventional interests will show no consistent pattern of correlations with knowledge. These variables were related to some self-report knowledge domains in Rolfhus and Ackerman (1996). However, on the basis of a literature review of interest–ability relations, Ackerman and Heggestad (1997) described four trait complexes where aptitude, personality, and interest traits overlap. Social, Enterprising, and Conventional interests did not belong to the trait complex that includes Gc-type abilities.

Method

Development of Knowledge Tests

To provide empirical evaluation of knowledge relations to abilities and other traits, we found it critical to create objective knowledge measures across many different areas. A major problem was to decide what knowledge to measure. In Rolfhus and Ackerman's (1996) study, self-report knowledge was assessed across 32 academic domains. Because one potential application was prediction and classification in academic situations, we decided to limit our initial investigations to sampling from several traditional academic domains, along with a few domains representing knowledge outside the traditional classroom. The College Board aided our test development by providing many of their College Level Examination Program (CLEP) tests and Advanced Placement (AP) examinations, including items, keys, and item statistics.

Pragmatic concerns (for both time and examinee motivation) required that we keep administration time reasonably short. To accomplish both the time and motivation goals, the tests were designed to be power tests. If an individual did not know much about chemistry, this fact needed to be identified quickly and the individual moved on to another test. We accomplished this by ordering items within each domain by difficulty level. Examinees began with the easiest items, and the test terminated when three consecutive items were answered incorrectly. The examinee was assigned a score depending on the number of correct responses to that point and then started the next test. This is partly analogous to the psychophysical method of limits and is the method used in most one-on-one testing of intelligence (e.g., Stanford–Binet, Wechsler). This approach requires a far smaller item pool than most adaptive tests, at the cost of increased testing time and decreased precision of measurement when compared with an item-response theory design.

The power test design has two important requirements: (a) Item-difficulty information must be available for each item so that items can be ordered by difficulty, and (b) items must cover the desired range of difficulty within each domain. Item difficulty is estimated by administering all domain items to a sample of individuals. After obtaining item-difficulty statistics, it is possible to present the items in difficulty order (as a power test) in later studies. Thus, in the first step of the development process, we constructed a large number of multiple-choice items for each domain. Throughout item development, we sought to adequately sample both the depth and breadth of the domains (i.e., maximize content validity). For example, a general test of American history not only should contain Civil War and World War II items but also should address the American Revolution, Great Depression, settlement of the West, and so on.

When we constructed the tests, CLEP and AP examination items were used as the domain core if they were available. CLEP and AP items were initially selected on the basis of item statistics from the College Board. These items tended to be more difficult than those needed for the entire knowledge continuum, as they were designed for a population with more knowledge than the college sample we used for item validation (CLEP and AP tests are used for evaluating knowledge in introductory college-level courses). More items were written to fill gaps not covered by the CLEP and AP tests, usually at the low end of the difficulty continuum. Several knowledge scales were developed entirely locally, as no CLEP and AP tests were available. Study guides, practice tests, textbooks, and subject-matter experts were used to generate and proof items. Both undergraduates and graduate students provided extensive assistance in this process.

More items were generated than were required for the operational test. The best performing items were selected from each validation round. Although the precise "spacing" of items varied by domain, the target was to have an item at every 2% difficulty interval, anchored at both the zero and 100% levels. Each domain item pool was administered to at least 100 introductory psychology students. This particular course (Psychology 1001) fulfills a requirement for most degree programs at the University of Minnesota. Therefore, the samples were fairly representative of the college student body. Data from a similarly drawn sample (Rolfhus & Ackerman, 1996, p. 177) showed that the distribution of intended majors was well represented across six categories: engineering/math/physical sciences (16%), business (21%), social sciences

(15%), health/premed/biological sciences (26%), humanities (14%), and art (8%).

After a knowledge scale was administered, the distribution of item difficulties was examined. We sought to equalize the frequency of items at each difficulty level (i.e., a rectangular or uniform distribution). New items were written to fill gaps within the distribution. When new items were written or old items edited, that knowledge scale was readministered to a new sample. Some knowledge scales underwent three rounds of administration and revision. To complete the knowledge tests, five validation studies were run over a period of 18 months. Across the five studies, 700 participants completed at least 2 hr of testing each, with each participant completing roughly six tests. Extensive details of these development studies can be found in Rolfhus (1999).

The final result of this extensive validation process (which also included data from thousands of examinees from the College Board for the CLEP and AP items) was a battery of 20 knowledge tests in a power format. Each test was composed of between 35 and 100 items, ordered in difficulty. Between 2 and 3 hr were required to complete the knowledge battery. The tests are described in Table 1.

Participants

Participants were recruited from an introductory psychology course at the University of Minnesota. For participation, they were offered a combination of cash and course credit. One hundred forty-three individuals completed the study: 49 male students and 94 female students. Ages in this sample ranged from 18 to 27 years (M = 19.1, SD = 1.2). Students in this study represented a broad spectrum of college undergraduates. For the 74 students who reported a major, the breakdown was: physical sciences, 7%; social sciences, 22%; health sciences, 23%; business/economics, 35%; art/humanities, 14%.

Apparatus

Self-report scales and questionnaires were administered using IBM-compatible Pentium computers with standard keyboards and monitors. Up to 15 students were tested at a time. Each student sat in an individual carrel during all computer interaction. Paper-and-pencil tests were administered at classroom-like tables. Instructions

Table 1
Knowledge Tests

Test	Content
American Government	The structure of American government, function of various government units, and the American political system.
American History	American history from pre-Revolutionary times to the present.
American Literature	A broad range of American writers, playwrights, and poets from Revolutionary times to the present.
Art	Identification of works with major artists and artistic styles and movements.
Astronomy	Broad areas of astronomy, observational tools and techniques, structure of the solar system, structure of the universe, and physical principles that govern astronomical observations.
Biology	Broad range of biology, at the cellular, organismal, and ecological levels.
Business/Management	Business management principles and their application.
Chemistry	The content of a 1st-year college course in chemistry, from the structure of the atom to standard laboratory procedures.
Economics	Both micro- and macroeconomics.
Electronics	Basic principles of electricity and their applications in electrical equipment and circuitry. This test was adapted from the U.S. Armed Forces Vocational Aptitude Battery (ASVAB).
Geography	World geography, including the location of mountains, rivers, oceans, cities, nations, and biomes. Approximately half the items are maps.
Law	Basic principles of law and more advanced criminal, civil, and business law. Items require an understanding of basic Constitutional rights, as well as of more complex contract and commercial law.
Music	Basic music terminology and styles, instruments, and composers. About one third of the test involves identification of classical music pieces played over headphones.
Physics	Basic physical principles and their applications. Items address both classical and quantum physics, thermodynamics, and atomic structure.
Psychology	The content of an introductory college course in psychology.
Statistics	The content of a one-semester college course in basic inferential and descriptive statistics.
Technology	Understanding of a wide range of modern technologies.
Tools/Shop	Both tool identification and use. This test was adapted from a discontinued version of the ASVAB.
Western Civilization	Major political, philosophical, and economic events in Europe from Ancient Greece to the Cold War.
World Literature	Non-American literature and poetry, primarily classic Western literature.

and start–stop timings were administered with prerecorded minidiscs over a public address system.

Knowledge testing was accomplished using a program written specifically for the presentation of bitmapped graphic files. The program was also used for playing audio files as part of item administration and for different response types (e.g., true–false, fill-in-the-blank, numerical response). Most important, the program scored participant responses on-line. It recorded verbatim participant input, response time, and whether the response was correct or incorrect. It also tracked the number of consecutive incorrect answers. When this count equaled three, the program terminated questions in that knowledge test and moved on to the next test.

Procedure

The current study included many of the trait measures originally used in the investigation of self-report knowledge (Rolfhus & Ackerman, 1996), although it also included the objective knowledge measures described above and a biographical questionnaire (which was part of a different study). The study consisted of two 3-hr sessions, with an additional take-home questionnaire, for a total of about 7 hr. In the first session, participants completed a consent form and then an aptitude battery assessing spatial, numerical, and verbal abilities, as listed in the Appendix. The battery contained 10 tests.[1] Total testing time was about 2 hr, including a 5-min break approximately halfway through testing. Research assistants monitored all phases of testing to ensure that participants understood directions and were able to follow testing procedures.

Subsequent to ability testing, participants completed a self-paced computerized questionnaire that contained the self-report personality and interest-trait measures shown in the Appendix. The questionnaire included a measure of the Big Five personality factors (NEO-FFI; Costa & McCrae, 1992), the TIE questionnaire (Goff & Ackerman, 1992), a vocational interest measure, the Unisex Edition of the American College Testing Interest Inventory (UNIACT; Lamb & Prediger, 1981), and a series of additional measures that were part of another study. The questionnaire items required approximately 60 min to complete.

Participants returned for the second session within 1 week of completing the first session. The second session was composed entirely of the computerized knowledge tests. Knowledge testing of the 20 domains required between 2 and 3 hr of testing time, including two 5-min breaks. The knowledge tests were given in one of two orders, forward or reverse, assigned at random to each participant. The test presentation order was arranged so that closely related domains were spread out (e.g., the physical sciences domains were not all administered sequentially). Each test started with items at the lowest level of difficulty and was terminated when the participant answered three questions in a row incorrectly.

Results

Because of the large number of variables and their interrelations to be investigated, the results are separated into four sections. First, the knowledge test results are described. Item statistics from the development studies and the main study are reviewed, along with a factor analytic representation of the knowledge scale intercorrelations. Next, the standard ability tests are presented, along with respective factor analytic results. Third, cross-comparisons between individual differences in knowledge and individual differences in abilities are presented. Finally, cross-comparisons between nonability traits and individual differences in knowledge are reviewed.

Knowledge Scales

Table 2 provides descriptive statistics for the individual knowledge tests. The first column lists the total number of items in each test. This is the number of items that would be attempted if a participant did not respond incorrectly to three consecutive items.

Means and standard deviations are given for each test. Only correct responses were used to compute test scores. For example, a participant might easily have attempted 40 American Literature items but answered only 20 items correctly. With a perfectly unidimensional test and no measurement error, there would be only three consecutive incorrect attempts at the end. In practice, a participant might answer 1 or 2 consecutive items incorrectly then answer 1 correctly, thus resetting the counter. For the multiple-choice items, there was a probability of answering correctly because of chance alone (.20 for five-choice or .25 for four-choice items). The final set of columns in Table 2 provides an estimate of the internal consistency or homogeneity (Cronbach's α) for each test. For each test, the information is from the last development study that included the test in question. In the development studies, participants completed all items in the knowledge scale. Therefore, alpha is reported for all items.

Because "α is an upper-bound to the concentration in the test of the first factor among the items" (Cronbach, 1951, p. 332) and is a lower bound to "the proportion of test variance attributable to common factors among the items" (Cronbach, 1951, p. 331), the reported alpha coefficients provide a means for assessing how well each of our tests captured a common domain. Although many of the alpha indexes were relatively high (as would be expected in an achievement test), several tests had alpha indexes below .80. Most notably, the Law Knowledge subscale had the lowest alpha (.56), followed by alphas in the .70–.79 range for American History, American Literature, Electronics, Statistics, Astronomy, and Chemistry. Such levels suggest that there may be more unique knowledge questions in these tests, compared with the others. Of course, low alpha levels might also be indicative, in concert with other measures, of ceiling or floor effects (e.g., the floor effect apparent from the mean and standard deviation results in the Statistics test).

The correlations among the knowledge tests are provided in Table 3. Particularly interesting is the fact that nearly all the knowledge tests exhibited at least low to moderate positive correlations with each other. This broad positive manifold is similar to that normally found among aptitude tests and suggests a general factor underlying the knowledge scales. The highest pairwise correlations were found be-

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[1] A mechanical reasoning test (Mechanical Knowledge from the Cognitive Ability Battery) was included but is not presented in the main analyses here, because it falls between the ability and knowledge domains. As a single-ability test, it could not be used to sufficiently identify a factor.

Table 2
Total Number of Items, Means, SDs, and Internal Consistency Reliability Indexes for Knowledge Scales

Test	Total number of items	Current study *M*	Current study *SD*	Bootstrapped from validation studies: α
		Humanities		
American Literature	84	33.8	14.6	.73
Art	35	12.1	6.0	.84
Geography	59	20.8	12.2	.92
Music	64	19.9	10.2	.87
World Literature	91	30.8	14.2	.84
		Science		
Biology	74	16.2	10.9	.87
Business/Management	71	13.2	7.6	.91
Chemistry	58	15.9	8.9	.77
Economics	84	18.0	13.4	.82
Physics	48	12.8	6.5	.85
Psychology	50	13.9	7.6	.94
Statistics	42	7.4	4.6	.76
Technology	66	18.8	11.1	.84
		Civics		
American Government	82	24.1	13.6	.80
American History	123	38.9	20.3	.71
Law	76	17.8	10.4	.56
Western Civilization	100	22.8	12.6	.88
		Mechanical		
Astronomy	71	16.3	10.1	.76
Electronics	42	10.5	5.9	.73
Tools/Shop	48	16.1	6.3	.88

tween the American History and American Government and the American History and Western Civilization subscales ($rs = .72$) and between the Literature subscales ($r = .65$). These correlations may appear lower than might be expected considering the similarity of content, but one must also take into account the internal consistency values in Table 2. The lowest correlations were observed between Art and both Economics ($r = .00$) and Tools/Shop ($r = .01$).

Factor analysis techniques were used to investigate the structure of the 20 knowledge domains. They were conducted using programs developed by Carroll (1990) for review and reanalysis of factor analytic studies (e.g., see Carroll, 1993). The 20 knowledge scales were first factored using principal-axis factor analysis with squared-multiple correlations as initial communality estimates. The Humphreys–Montanelli (H-M) parallel analysis procedure (Humphreys & Montanelli, 1975; Montanelli & Humphreys, 1976) provides a strategy for determining the number of factors that underlie a correlation matrix. The H-M procedure generates a set of random roots (which are based on sample size and the number of variables) that are compared to real roots identified from the correlation matrix. The H-M method suggested that four factors underlay the current matrix of correlations. After initial factoring, the factor matrix was rotated to an oblique factor solution, using the Direct Artificial Personal Probability Factor Rotation (DAPPFR) technique (Tucker & Finkbeiner, 1981).

The first-order, four-factor solution was generally interpretable and parsimonious; the factors corresponded to major divisions of study at the undergraduate level. These knowledge factors were identified as Humanities, Science, Civics, and Mechanical. Because the correlations among factors were positive, a hierarchical factor analysis was performed (first, by factor analyzing the factor intercorrelation matrix). The hierarchical factor solution was orthogonalized using the Schmid–Leiman (Schmid & Leiman, 1957) procedure. This technique allowed the second-order factor (General Knowledge) to account for the common variance among the first-order factors. Variance that remained attributable to the first-order factors was therefore uncorrelated with the other factors in the final hierarchical ability solution. The solution, one second-order General Knowledge factor and four first-order Knowledge factors (along with communality estimates), is shown in Table 4. Salient loadings, defined as loadings greater than .300, are shown in bold.

Most noteworthy is the fact that nearly all the knowledge tests loaded saliently on the General Knowledge factor (the exception being Statistics, which had an extremely low communality and failed to load saliently on any common factor). The highest loadings were produced by the American History and American Government subscales, which is not surprising given that these tests had the highest respective intercorrelations. However, even Physics and Music had substantial loadings on the factor, suggesting that it may be a

Table 3
Correlations Among the 20 Knowledge Scales

Test	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Humanities																				
1. American Literature	—																			
2. Art	.498	—																		
3. Geography	.507	.359	—																	
4. Music	.565	.479	.443	—																
5. World Literature	.647	.532	.473	.630	—															
Science																				
6. Biology	.478	.425	.410	.424	.538	—														
7. Business/Management	.395	.281	.382	.411	.441	.441	—													
8. Chemistry	.274	.153	.335	.234	.312	.468	.329	—												
9. Economics	.248	−.001	.311	.167	.348	.279	.451	.392	—											
10. Physics	.421	.143	.396	.245	.389	.483	.427	.466	.443	—										
11. Psychology	.384	.275	.292	.264	.417	.523	.540	.379	.394	.515	—									
12. Statistics	.186	.195	.229	.226	.217	.325	.261	.219	.358	.265	.226	—								
13. Technology	.366	.159	.351	.387	.479	.349	.430	.474	.526	.536	.481	.189	—							
Civics																				
14. American Government	.541	.262	.539	.445	.521	.459	.523	.310	.496	.417	.495	.260	.404	—						
15. American History	.549	.326	.595	.512	.601	.455	.545	.367	.487	.511	.374	.257	.493	.716	—					
16. Law	.391	.207	.351	.359	.450	.347	.528	.201	.415	.475	.365	.210	.370	.591	.520	—				
17. Western Civilization	.502	.369	.545	.442	.541	.367	.456	.366	.411	.360	.392	.032	.515	.603	.716	.412	—			
Mechanical																				
18. Astronomy	.448	.266	.519	.353	.421	.453	.319	.277	.352	.484	.487	.199	.517	.423	.416	.340	.366	—		
19. Electronics	.218	.117	.354	.209	.240	.356	.343	.326	.368	.465	.270	.169	.416	.350	.277	.365	.305	.377	—	
20. Tools/Shop	.199	.012	.304	.144	.108	.174	.143	.186	.227	.329	.186	.115	.346	.255	.347	.251	.242	.375	.456	—

Note. *N*s vary slightly, with maximum $N = 143$. Generally, correlations over .21 are significant at $p < .01$, and correlations .16 or higher are significant at $p < .05$.

Table 4
Orthogonalized Hierarchical Factor Structure of Knowledge Tests, Using the Schmid–Leiman (1957) Procedure

Test	Factor: General	Humanities	Science	Civics	Mechanical	h^2
		Humanities				
American Literature	**.612**	**.445**	.037	.137	.065	.596
Art	**.367**	**.624**	−.005	.026	−.054	.528
Geography	**.603**	.265	.000	.154	.260	.525
Music	**.551**	**.443**	−.017	.145	.004	.521
World Literature	**.665**	**.404**	.117	.164	−.078	.652
		Science				
Biology	**.524**	**.359**	**.408**	−.039	.057	.574
Business/Management	**.628**	−.040	**.330**	.178	−.152	.560
Chemistry	**.426**	.018	**.375**	.003	.112	.335
Economics	**.573**	**−.363**	**.387**	.183	−.021	.644
Physics	**.556**	−.011	**.440**	.014	.250	.565
Psychology	**.526**	.061	**.480**	.017	−.016	.511
Statistics	.284	.032	.283	.004	−.031	.163
Technology	**.586**	−.021	**.318**	.086	.228	.505
		Civics				
American Government	**.756**	−.024	.124	.299	−.041	.679
American History	**.813**	.030	.013	**.344**	.035	.781
Law	**.601**	−.063	.181	.207	−.004	.441
Western Civilization	**.705**	.090	−.023	.293	.053	.595
		Mechanical				
Astronomy	**.508**	.242	.229	−.005	**.383**	.516
Electronics	**.410**	−.010	.249	−.004	**.425**	.410
Tools/Shop	**.314**	.001	.010	.014	**.625**	.490

Note. General = second-order factor; h^2 = communality. Salient factor loadings with an absolute value greater than .300 are shown in bold.

very broad representation of Gc. Nonetheless, substantial independent variance remained in the first-order factors even after General Knowledge was partialed out, especially in Humanities, Science, and Mechanical Knowledge.

The Humanities factor is clearly defined by Art, Music, and both literature domains, along with secondary loadings from Biology and a negative loading from Economics. The loading from Biology might be explained by the fact that, on further examination, a large proportion of the CLEP Biology items concerned word definitions, which might share variance with the verbal emphasis of the literature scales. Geography appeared to be a complex variable, loading on both the Humanities and Mechanical factors. It may represent general cultural–current events knowledge not restricted to the academic domains in this study. The moderate negative loading on this factor from Economics does not fit well. It could represent a differentiation between humanities and business majors, in that they may tend not to complete each other's coursework.

The Science factor in this solution was very broad, including both physical (Biology, Chemistry, Physics) and social sciences (Economics, Management, Psychology). In addition, Statistics loaded moderately on this factor, reflecting in part the mathematical knowledge associated with a science education. The loading by Technology was somewhat incongruent, except to the degree that the test content was more highly associated with the principles of how technology works (e.g., how a microwave oven works) than it was with Mechanical Knowledge (as in the Tools/Shop test, which focused more on procedural uses of tools). The factor analysis suggests that the Technology Knowledge subscale may in fact be better labeled *Engineering* Knowledge.

The Civics factor (in the oblique solution) was defined by the two history tests (American History and Western Civilization) but also by Law and American Government. Secondary loadings are contributed by Economics and Management. This factor appears to represent an understanding of Western culture from a historical basis and how it is currently operationalized in politico-legal systems. In the hierarchical solution, much of the variance in this factor was taken by the General Knowledge factor, suggesting that participants who were knowledgeable about Civics were also more likely to be knowledgeable about the other domains as well. Whether transfer of knowledge is implied from such results, though, can only be established by a longitudinal evaluation.

The final factor, Mechanical Knowledge, is represented by Tools/Shop, Electronics, and Astronomy. The first two tests clearly define this factor, but the reason for the loading from Astronomy is not obvious. Further examination of the Astronomy item set, however, does provide a partial post hoc explanation. Many of these items ask applied questions about astronomical devices and measurement, as well as about space exploration. Thus, there is content overlap with both Electronics and Tools/Shop. It is useful to note also that the variables defining the Mechanical knowledge factor had the lowest loadings on the General Knowledge factor, a point that is concordant with the fact that the content of some of these tests falls outside a traditional liberal arts and sciences curriculum.

Overall, the structure of the knowledge domains appears to have fallen along curricular lines—in other words, along the lines of common educational "treatments." The structure of knowledge identified was similar to the structure identified through self-report (Rolfhus & Ackerman, 1996). The factor solution in self-report data seems to make clearer distinctions between knowledge domains than do objective knowledge data, which suggests that students tend to polarize their self-concept (see discussions by Ackerman, Kanfer, & Goff, 1995; Rolfhus & Ackerman, 1996).

Ability Tests

Means, standard durations, intercorrelations, and underlying factors for the ability tests are shown in Table 5. The same procedure used in identifying knowledge factors was followed with the aptitude tests. Three factors were extracted and rotated with the DAPPFR procedure. As expected, the factors were clearly identified as Verbal, Spatial, and Numerical Ability factors. These three factors were themselves factor analyzed to identify a higher order General Ability factor, using the Schmid–Leiman (Schmid & Leiman, 1957) technique, and then transformed to the hierarchical solution shown in the lower part of Table 5.

Knowledge–Ability Relations

In one of Cattell's (1957) original specifications of Gc, he stated that "an effort to measure Gc in practice might amount to producing as many tests as there are occupations" (p. 144). He suggested that appropriate assessment of Gc might involve testing rather specific knowledge. However, in most studies of crystallized ability, Gc has usually been operationalized with tests of general knowledge, vocabulary, and verbal fluency. If Cattell's conception of Gc were correct, we should find that domain-specific knowledge correlates substantially with the Verbal Ability factor used in this study. However, we should also find that Verbal Ability does not completely account for the reliable variance in the knowledge scales. Also, domain-specific knowledge should not correlate as strongly with the Spatial and Numerical Ability factors, of which constituent tests (all except math knowledge) are often used as markers for Gf.

To evaluate the relations between knowledge scales and the ability factors, we used the Dwyer (1937) extension procedure. The Dwyer procedure (and the generalization by Mosier, 1938; see Gorsuch, 1983, for a more recent description) is a general linear model approach that allows one to

Table 5
Ability Test Means, SDs, Intercorrelations, and Orthogonalized Hierarchical Factor Solution

												Orthogonalized Hierarchical Factor Solution				
Ability test	*M*	*SD*	1	2	3	4	5	6	7	8	9	*g*	Verbal	Spatial	Numerical	h^2
1. Verbal Analogies	26.71	5.75	**.540**[a]									**.629**	**.544**	.030	.015	.692
2. Vocabulary	15.19	6.72	.588	**.401**[a]								**.476**	**.538**	−.033	−.058	.520
3. Controlled Associations	23.24	7.67	.556	.437	**.356**[a]							**.493**	**.411**	.010	.036	.414
4. Math Knowledge	17.35	6.36	.266	.183	.204	**.178**[a]						**.408**	.000	−.042	**.370**	.305
5. Problem Solving	4.30	2.29	.483	.442	.418	.320	**.370**[a]					**.569**	.294	−.011	.218	.458
6. Number Series	10.22	2.84	.329	.168	.260	.304	.351	**.240**[a]				**.472**	.008	.061	**.338**	.341
7. Paper Folding	12.39	5.09	.409	.310	.318	.324	.375	.376	**.459**[a]			**.632**	.012	**.453**	.167	.632
8. Verbal Test of Spatial Ability	11.49	4.34	.535	.394	.375	.230	.435	.350	.583	**.488**[a]		**.627**	.209	**.391**	.036	.591
9. Spatial Orientation	7.19	3.91	.264	.160	.228	.134	.230	.201	.478	.439	**.273**[a]	**.408**	−.004	**.485**	−.028	.403

Note. Salient factor loadings over .300 are shown in bold; correlations larger than .16 are significant at $p = .05$; correlations greater than .21 are significant at $p = .01$; g = general intelligence; h^2 = communality.
[a]Diagonal entries in correlation matrix (in bold) are squared multiple correlations.

correlate factors derived from one set of variables with new variables, without using factor scores. The hierarchical ability structure was thus extended to the individual knowledge scales, and the resulting correlations are shown in Table 6.

The General Ability factor correlated positively with all of the knowledge scales (though Art and Statistics fell just below the .300 cutoff for salient correlations). More important, however, the Verbal factor shared a substantial amount of variance with most knowledge scales after General Ability was partialed out. Such a result is consistent with the representation of verbal ability as part of a crystallized aptitude complex.

The fact that many correlations between Verbal Ability and the various knowledge scales were moderate in magnitude is important as well. If the correlations between Verbal Ability and the knowledge scales were very high, then the constructs might very well be redundant. That is, under such circumstances, we might conclude that Gc is adequately operationalized as verbal ability. Clearly, these correlations do not suggest such an alignment between Verbal Ability and domain-specific knowledge, especially for some of the Science, Civics, and Mechanical domains.

The correlations for Spatial and Numerical Ability factors (Gf surrogates) indicated little shared variance with any of the knowledge scales. In fact, none of the knowledge scales showed salient correlations with Spatial or Numerical factors, other than the variance in the ability tests attributable to general intelligence. Only three correlations even approached the level of .30 with the Numerical factor (namely, Chemistry, Astronomy, and American Government). The first two make sense in terms of content, but the third has no clear explanation. The spatial composite shared little variance with any knowledge domain. Clearly, Spatial and Numerical Abilities, with general intelligence partialed out, shared very little with domain-specific knowledge in this sample of college students and tests.

Such results are generally supportive of Hypothesis 1, that knowledge is more highly associated with Gc-type abilities than with Gf-type abilities.

Table 6
Correlations Between Knowledge Scales and Ability Factors

Test	Factor			
	g	Verbal	Spatial	Numerical
Humanities				
American Literature	**.414**	**.432**	−.076	.018
Art	.298	**.401**	−.069	−.056
Geography	**.497**	.299	.068	.095
Music	**.373**	**.404**	.050	−.088
World Literature	**.426**	**.581**	.032	−.187
Science				
Biology	**.450**	**.526**	−.114	−.007
Business/Management	**.354**	**.418**	−.064	−.028
Chemistry	**.479**	.234	−.121	.282
Economics	**.451**	.232	−.048	.204
Physics	**.476**	**.326**	.048	.067
Psychology	**.441**	**.381**	−.061	.073
Statistics	.292	.149	−.015	.121
Technology	**.494**	**.305**	.144	.029
Civics				
American Government	**.497**	.288	−.130	.255
American History	**.495**	**.317**	.036	.101
Law	**.353**	.291	.118	−.056
Western Civilization	**.400**	**.394**	−.067	.033
Mechanical				
Astronomy	**.513**	.167	.060	.231
Electronics	**.382**	.284	−.025	.084
Tools/Shop	**.325**	.013	.148	.145

Note. Loadings over .300 are shown in bold; *g* = general intelligence.

Knowledge–Nonability Relations

On the basis of previous research (e.g., Ackerman & Heggestad, 1997), we hypothesized that three of the personality variables measured in this study would relate meaningfully to domain knowledge: TIE, Openness, and Extraversion. Table 7 displays the correlations between the personality scales (from the NEO-FFI and the TIE) and the 20 knowledge scales. As hypothesized, Openness and TIE shared similar patterns of significant correlations with knowledge. For 16 of the 20 knowledge scales, TIE correlated more highly (although nonsignificantly) with knowledge than did Openness. This was probably due to the fact that the TIE scale was written specifically to capture intellectual investment behaviors (Goff & Ackerman, 1992) and the fact that the TIE Scale has substantially more items than the NEO-FFI Openness subscale (and thus, higher reliability). Similarly, consistent with the Ackerman and Heggestad (1997) meta-analysis of personality–intelligence relations, Agreeableness and Conscientiousness exhibited no significant correlations with domain knowledge (nor did Neuroticism). Surprisingly, however, Extraversion was negatively correlated with all but one of the knowledge scales. This finding is in conflict with meta-analytic results (Ackerman & Heggestad, 1997, p. 231) that have indicated an estimated true-score correlation, aggregated across 63 studies, of .11 between Gc and Extraversion and a correlation of .05 between Extraversion and knowledge/achievement measures (across 7 studies). Ackerman and Heggestad did conclude, however, that Extraversion belonged to a cluster of traits that excluded specific ability or achievement measures.

With respect to interest–knowledge associations, the literature suggested that both convergent and discriminant relations between knowledge and vocational interests would be found (e.g., Ackerman and Heggestad, 1997; Rolfhus & Ackerman, 1996; and see Holland's 1959, 1973, extensive theoretical and empirical research). In particular, three domains of interest would be related to intellect (and academic knowledge), namely Realistic, Investigative, and Artistic interests, whereas Conventional, Enterprising, and Social interests would not be related to individual differences in academic knowledge. Table 8 provides the correla-

Table 7
Correlations Between Personality Scales and Knowledge Scales

Test	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness	TIE
		Humanities				
American Literature	.013	−.271**	.289**	−.057	−.132	**.328****
Art	.034	−.079	**.333****	.029	−.136	**.342****
Geography	.005	−.180*	.274**	−.021	−.096	.270**
Music	.046	−.210*	.298**	−.093	.010	**.302****
World Literature	.007	−.191*	**.375****	.042	−.116	**.454****
		Science				
Biology	.049	**−.325****	.239**	−.093	.090	**.348****
Business/Management	.027	−.280**	.153	−.098	.025	.258**
Chemistry	.020	−.283**	.218**	.019	.045	.234**
Economics	−.001	−.276**	.168*	−.135	−.010	.138
Physics	−.031	−.283**	.194*	−.095	.007	.272**
Psychology	.006	−.256**	.258**	.019	.018	.274**
Statistics	.145	−.196*	.087	−.130	.023	.138
Technology	−.010	−.178*	.204*	−.010	.007	.253**
		Civics				
American Government	.030	**−.336****	.181*	−.148	−.088	.194*
American History	−.012	−.275**	.234**	−.046	−.096	.296**
Law	−.050	−.265**	.119	−.117	−.000	.114
Western Civilization	−.008	−.218*	.284**	−.025	−.127	**.324****
		Mechanical				
Astronomy	.050	−.282**	.189*	−.085	−.036	.180*
Electronics	−.026	−.170*	.158	.016	.094	.172*
Tools/Shop	−.066	−.167*	.073	−.130	−.161	.118

Note. Correlations with an absolute value greater than .300 are shown in bold; N (max) = 143; TIE = typical intellectual engagement.
$^*p < .05$. $^{**}p < .01$, two-tailed.

tions between each of Holland's six interest themes (from the UNIACT) and the 20 knowledge scales. Consistent with expectations, Conventional, Social, and Enterprising interests exhibited only two small, but significant, correlations.

Realistic interests correlated significantly with Technology and Tools/Shop and also with Physics and Chemistry; Investigative interests correlated with Biology, Chemistry, and, to a lesser degree, Tools/Shop. Significant correlations were found for Artistic interests and knowledge domains, including Art, Music, American and World Literature, American History, Western Civilization, Geography, as well as Business/Management. Although many of the significant correlations were modest in magnitude, the pattern of relations was consistent with expectations.

Thus, with the exception of the Extraversion–knowledge correlations (which were opposite our original prediction), the personality and interest measures show the convergent and discriminant correlational patterns that were specified in Hypothesis 2.

Discussion

The present study provides support for the two primary hypotheses of the PPIK theory: (a) Domain-specific knowledge is closely related, but not identical, to Gc-type abilities and less related to Gf-type abilities, and (b) the study identified both convergent and discriminant relations among a small set of personality and interest trait variables related to domain knowledge (i.e., Openness; TIE personality constructs; and Realistic, Investigative, and Artistic interests appear to have been positively related to the accumulation of intelligence-as-knowledge). Extraversion was broadly and negatively related to domain knowledge. All predictions of the PPIK theory but one (that Extraversion would not be related to knowledge) were supported. From a post hoc perspective, the Extraversion–knowledge finding might be explainable in terms of investment—the more time that individuals spend socializing, the less time they have available for knowledge acquisition through reading and academic study.

Knowledge and Intelligence

A substantial higher order Knowledge factor was found in this study, accounting for approximately 50% of the variance in domain knowledge. A General Knowledge factor suggests common causes for individual differences in academic knowledge across domains. Gc, as represented by a composite of verbal ability tests (verbal analogies, controlled associates, and vocabulary), correlated .72 with a General Academic Knowledge composite. That is, even at the highest level of aggregation of knowledge tests, Gc as

Table 8
Correlations Between Interest Theme Scores and Knowledge Scales

Test	Realistic	Investigative	Artistic	Social	Enterprising	Conventional
			Humanities			
American Literature	.080	.128	.222**	.030	−.028	−.157
Art	.007	.146	.294**	−.022	−.066	−.177*
Geography	.090	.109	.232**	−.021	−.045	−.064
Music	.105	.122	**.341****	.009	−.113	−.095
World Literature	.075	.167*	**.334****	.037	−.026	−.158
			Science			
Biology	.058	.273**	.222**	.048	−.143	−.071
Business/Management	.106	.105	.196*	−.041	−.025	.005
Chemistry	.173*	**.306****	.090	−.020	−.175*	−.081
Economics	.017	.037	.053	−.111	.132	.056
Physics	.182*	.149	.108	−.060	−.066	.014
Psychology	.035	.138	.124	.065	−.020	−.051
Statistics	.012	.051	.036	−.014	.120	.138
Technology	.253**	.183*	.136	.050	.041	.028
			Civics			
American Government	−.031	−.009	.140	−.071	.109	.023
American History	.048	−.016	.216*	−.032	.103	−.020
Law	.077	−.049	.125	−.150	.049	.087
Western Civilization	.042	.108	.192*	.001	.037	−.095
			Mechanical			
Astronomy	.067	.059	.145	−.106	−.021	−.025
Electronics	.171*	.155	−.003	−.144	−.166	.048
Tools/Shop	.282**	.191*	.005	−.124	−.092	.068

Note. Correlations over .300 are shown in bold; N (max) = 143.
$^*p < .05$. $^{**}p < .01$, two-tailed.

typically assessed is related, but not identical, to Gc as typically operationalized. In addition, the General Knowledge factor, Gk, accounted for only approximately 50% of the variance among the knowledge tests, suggesting that the remainder must be explained by domain-specific influences, such as college course selection, outside reading, hobbies, domain interests, and so on. The proportion of individual knowledge test variance accounted for by Gk may also have been influenced by the common educational treatments that the current participants (freshmen and sophomores) have received during their precollege years and thus may be an overestimate of the influence of Gk in an older and more diverse sample of students.

PPIK Theory and Education

The current study was an attempt to test part of the PPIK theory, which takes a broad view of intelligence, traits, and adult development. Potentially, PPIK has much to offer the field of education. Although work is still at an early stage, we envision three sources of future applications: educational selection, educational classification, and instruction.

For academic selection in colleges and universities, traditional approaches involve multiple regression models with grade point average and standardized ability tests (though the ACT also includes several knowledge-intensive content tests and there are subject GRE tests that are essentially knowledge tests—see Willingham, 1974, for a discussion of the selection usefulness of these measures). Whereas both sources of information have provided valid predictions of college achievement, one main advantage of grade point average predictors is that they capture "typical" performance, rather than maximal performance (i.e., the ability tests are indicators of maximal performance). Grades represent an aggregation of study and learning behaviors over long periods of time. Grades may therefore be better predictors of future knowledge acquisition than are ability tests. Knowledge tests themselves reflect historical typical performance in that additional attention and effort during the test administration yields limited improvements to performance.

Moreover, narrower tests of knowledge may be expected to be more highly differentiated in an underlying factor structure than are traditional ability and broad achievement tests (e.g., see Humphreys, 1973), especially as examinees reach adulthood. There may be clear advantages to predictive equations that are built on an approach that encompasses both maximal and typical performance (and are not subject to teacher- or school-driven incommensurability of grades). Also, there is a secondary advantage to including knowledge tests in the selection process, because knowledge acquisition yields to motivation and effort over extended periods of time. That is, future demonstrations of validity for knowledge scales in predicting academic performance provide a clear path toward educational policy that lies beyond the "teaching to the test" approach that is prevalent in aptitude and ability testing. Students and teachers could work toward establishing the knowledge foundations that various research programs have shown to be especially important in later learning and skill development. Knowledge tests would be less likely to be subjected to the worries about bias and discrimination that ability tests have withstood over the last 4 decades, because knowledge tests can be scaled in a meaningful way (rather than normatively). From this perspective, knowledge assessment may provide significant information (in terms of providing feedback about level of performance).

From a classification perspective, knowledge assessment may prove to be sufficiently differentiated so as to provide useful profile data (e.g., see discussion by Cronbach, 1990) that are not typically available in traditional ability testing (because ability tests are too highly intercorrelated, thus making all but the most extreme intraindividual differences lack statistical significance). Because of the general premise of the literature that knowledge builds on knowledge, students may benefit from educational or vocational counseling that focuses on what the students know. Such classification may make it possible to better place a student into an educational program that is more suitable to building new knowledge onto the student's current repertoire of knowledge and skills. In addition, nontraditional students (e.g., middle-aged adults returning to the educational system) may especially benefit from a classification approach that allows them to maximize transfer of knowledge and skills that are based on an assessment of what knowledge structures they have developed through work or vocational activities.

From an instructional perspective, conventional wisdom suggests that instructional effectiveness is maximized when the content and difficulty of the instruction match the knowledge and skills (and the limitations of intelligence-as-process) of the individual learner. By focusing on what knowledge the student brings to the classroom, it may be possible to restructure instruction so that new knowledge is presented in a fashion that maximizes transfer of the student's preexisting knowledge. It is important to note, though, that the current approach does not value depth of knowledge over breadth of knowledge (or vice versa). There are enough plausible arguments on both sides of this particular controversy to make either position viable. On the one hand, it may be that for some situations (e.g., a liberal arts major), breadth of knowledge may be more important than for other situations (e.g., a physics major). On the other hand, either breadth or depth may be maximally useful for most situations. Future investigations will focus on assessing knowledge profiles for deciding these issues. More generally speaking, though, a movement to reemphasize knowledge implicitly carries with it an implication that instruction on other topics (such as critical thinking) may be overemphasized in current curricula. The current study is but a first step in developing a series of knowledge tests and evaluating a multiple-trait framework that represents knowledge development as a function of the investment of intelligence-as-process, personality, and interests.

Conclusions and Future Directions

The current investigation was predicated on the belief that something fundamental is missing from the conceptualization and assessment of adult intelligence for educational applications. The upward extension of the Binet–Simon paradigm (Binet & Simon, 1973) emphasized individual differences in processes, such as reasoning and memory, over specific knowledge and skills. That approach is clearly useful for educational purposes early in the school system (when common curricula exist). However, concentrating on common cultural knowledge (or educational knowledge acquired in high school) may be suboptimal for predicting the academic performance of adults in different educational specializations. Such concentration may also be inappropriate for predicting the performance of nontraditional students, especially those who are far removed in time from their high school education. Our first foray into the objective assessment of domain-specific knowledge supported our contention that domain-specific knowledge is related to, but also substantially independent of, a traditionally assessed verbal–Gc ability. In addition, individual differences in knowledge are related to relevant measures of conative and affective traits, supporting the notion that a trait-complex perspective (see Ackerman & Heggestad, 1997) may be useful for understanding and predicting the accumulation of domain-specific knowledge over the educational life of the individual learner—a viewpoint that is concordant with Snow's (1989) vision of aptitude complexes in learning and instruction.

This work offers broad support to Ackerman's (1996) PPIK theory of adult intellectual development. The results are also relevant to other attempts to link knowledge and skill-acquisition research to the educational milieu. With respect to domain-specific learning theories such as the model of domain learning (Alexander, Jetton, & Kulikowich, 1995; Alexander, Murphy, Woods, Duhon, & Parker, 1997), the current approach provides a multitrait, multidomain perspective that may help augment predictions of individual differences in domain-specific learning. That is, the broader theoretical approach provided by PPIK offers a set of cognitive, conative, and affective trait candidates that may be predictive of future learning in particular domains. Moreover, the finding of a General Knowledge factor suggests a possible mediating variable that might be taken account of to delineate the efficacy of broad learning from that of narrow learning. This consideration is a two-way street, though. The model of domain learning may, in turn, provide a rubric for assessing changes to conative and affective traits that result from increments in domain-specific knowledge, something that has only been proposed (e.g., Holland, 1973) and not yet empirically evaluated.

With respect to the expertise literature, the current work is partly supportive of the unique nature of some domain-specific knowledge and of the conative and affective roles in accumulation of expertise (e.g., Ericsson et al., 1993). In contrast, the demonstrated communality between general ability, a traditional measurement of Gc (a General Knowledge factor), and domain-specific knowledge presents a substantial challenge to those researchers who claim no role for aptitudes in knowledge acquisition and performance (e.g., Ericsson et al., 1993; Ericsson & Lehmann, 1996). We believe that the implicit assertions of the deliberate practice community that abilities are irrelevant to be as ill advised as Watson's (1925) claim about his ability to develop "a dozen healthy infants" (p. 10).

This article represents a small but essential step toward supporting a theoretical framework that is multitrait, multidomain, longitudinal, and life span oriented. The PPIK framework is broad enough to incorporate other individual-difference variables that have been discussed elsewhere (e.g., self-concept; Ackerman, 1997) but have not yet been explicitly placed within the model. PPIK is not yet complete: It awaits more data and, particularly, a longitudinal test. There are obvious limitations to this single study, such as the fact that we sampled mainly academic knowledge, that we sampled only a relatively homogeneous college student population, that our measure of personality traits was a short-form inventory instead of a more intensive questionnaire, and so on. These shortcomings limit the generalizability of the study, but they do not detract from the demonstration that we can indeed assess multiple domains of knowledge in an efficient, reliable, and valid fashion. The common variance among knowledge, ability, and nonability traits provides an impetus for conducting future longitudinal studies that evaluate both how knowledge is developed and the role of these various traits in determining the depth and breadth of knowledge. Development of knowledge ultimately is an important aim of postsecondary education and fundamentally may be the dominant correlate of success in the academy and beyond.

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(Appendix follows)

Appendix

Trait Measures

Ability Battery

Verbal Ability

Verbal analogies.[a] This is a standard four-term analogical reasoning test. The test has one part, with a time limit of 15 min. Score = number correct − .25(number wrong).

Controlled associations.[b] This is a test of verbal fluency. Participants are given four words and asked to produce as many words as they can that have similar meanings. This test has two parts; each part has a time limit of 3 min.

Extended range vocabulary test.[b] This is a classic vocabulary test. Individuals are presented with a word and must choose the word that most closely matches it. This test has two parts; each part has a time limit of 7 min.

Numerical–Mathematical Ability

Math knowledge.[a] This is a wide-range test of mathematical knowledge, from simple computation to algebra, geometry, and other advanced topics. The test has one part, with a time limit of 12 min. Score = number correct − .25(number wrong).

Problem solving.[a] This is a test of math word problems. The test has one part, with a time limit of 5 min. Score = number correct − .25(number wrong).

Number series.[c] This is a test of inductive reasoning in which a series of numbers generated by a rule is provided and the next number in the series is to be identified. The test has one part, with a time limit of 4 min. Score = number correct − .20(number wrong).

Spatial Ability

Paper folding.[a] This test is an adaptation of other classic tests of the same name. The test has two parts. Each part has a time limit of 6 min. Score = number correct − .25(number wrong).

Verbal test of spatial abilities.[a] This is a test of image generation and manipulation. Participants are asked to close their eyes and imagine the items described verbally. They are then asked a multiple-choice question about the items in the image. This test has one part and is experimenter paced. The test takes about 12 min. Score = number correct − .25(number wrong).

Spatial orientation.[a] This is a test of three-dimensional visualization. Participants are required to imagine a block figure, as seen from a different perspective. This test has two parts. Each part has a time limit of 2.5 min. Score = number correct − .25(number wrong).

Nonability Measures

Personality

NEO-FFI. The NEO-FFI (FFI = Five-Factor Inventory) assesses broad personality markers. This inventory is a short form of the NEO-Personality Inventory (Costa & McCrae, 1992) and is composed of 60 items measuring five factors: Neuroticism, Extraversion, Openness, Conscientiousness, and Agreeableness. Participants respond to a 5-point scale ranging from *strongly disagree* (1) to *strongly agree* (5).

TIE. The 59-item Goff and Ackerman (1992) typical intellectual engagement (TIE) questionnaire. Sample items are "I prefer my life to be filled with puzzles I must solve" and "I read a great deal." A 6-point response scale is used, ranging from *strongly disagree* (1) to *strongly agree* (6).

Interests

UNIACT. The 90-item Unisex Edition of the American College Testing Interest Inventory (UNIACT; Lamb & Prediger, 1981) provides an assessment of six interest themes identified by Holland (1959, 1973) as Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. The items (15 per scale) assess an individual's preference for specific job tasks like "studying biology" and "compose or arrange music." A 6-point response scale is used, ranging from *strongly dislike* (1) to *strongly like* (6).

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[a] From Ackerman and Kanfer (1993).

[b] From the Educational Testing Service Kit of Factor-Referenced Cognitive Tests (Ekstrom, French, Harman, and Dermen, 1976).

[c] From the Primary Mental Abilities test battery (Thurstone, 1962).

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