Chapter 15

g, Jobs and Life

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1. Horizontal and Vertical Aspects of *g*

Arthur Jensen has reinvigorated and redirected the study of human intelligence in major ways. Perhaps the most important has been to turn the field's attention back to Spearman's *g*, the general intelligence factor. The discovery that the same *g* factor emerges from diverse batteries of mental tests in diverse populations, together with the consequent option to derive scores for individuals on this common factor, has allowed intelligence researchers to make some crucial advances.

- To clearly distinguish "intelligence" (*g*) from the vehicles of its measurement (e.g. test format or content);
- To employ a common working definition of intelligence — *g* — despite using different tests of mental ability;
- To narrow the range of theoretical possibilities for what intelligence is, and to focus specifically on conceptions that emphasize a highly general (i.e. content- and context-free) set of mental capabilities or properties of the brain; and thereby
- To transcend some long-standing debates over the "real" meaning of intelligence and IQ: Which of the many verbal definitions of "intelligence" is correct for guiding research? (With *g* as the common yardstick, the question becomes moot.) Don't IQ scores represent just the arbitrary cultural knowledge that IQ tests happen to require? (No, they tap something much more general.)

The construct of *g* has arguably become our most valuable conceptual tool for probing the nature and origins of differences in "intelligence", as many chapters in this volume attest.

Another advantage of the *g* construct is that, in providing a common scale for measuring the differences in intelligence among people, the *g* factor also provides a common yardstick for comparing the mental *demands* of different *tasks*. Just as individuals can be distinguished in their levels of *g* (their "mental horsepower"), so too can tasks be distinguished in their *g loadedness* (the degree to which they call forth *g*). The classification of tasks and tests by *g* loading (their correlation with the *g* factor) has

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been essential in explaining why test results can differ substantially across different mental tests. In particular, we now know that some IQ tests and subtests are more *g* loaded than others (call forth *g* more effectively) and therefore should yield different patterns of results (for example, to better distinguish retarded from normal or gifted individuals). This variation in results stems not from flaws in intelligence tests or in the concept of intelligence itself, as was once alleged, but from the variability among tasks being used to evoke *g*.

The notion that tasks differ in their demands for *g* has importance far beyond psychometric testing, however. The notion is key to unraveling the consequences of intelligence in social life, what Jensen (1998) calls the horizontal aspect of *g*. Jensen himself has focused mostly on the vertical aspect of *g* (its biological roots), but he has provided the conceptual tools for others to advance its horizontal study. For instance, Jensen's insights on the properties of mental tasks have prompted sociologist Robert Gordon (1997) to analyze the psychometric properties of daily life as an intelligence test. He shows how the degree to which daily life mimics rather than departs from the properties of a reliable, valid test of intelligence helps to explain the pattern of both *g*'s impact across life as well as people's likelihood of perceiving that impact. Jensen's insights on mental tasks have also led to research (Gottfredson 1997; in press) on how differences in task attributes systematically shift *g*'s gradients of effect in employment, health and other domains of life. This chapter develops these themes further in order to show that, by turning attention to the psychometric properties of the tasks people perform, Jensen has opened up new ways of understanding how individual and group differences in *g* shape our individual and collective fates.

2. Life as a Mental Test Battery

"What role does intelligence play in our personal and collective lives?" To date, the answer to this question has been sought primarily in correlating individuals' scores on mental tests (such as IQ tests) with various personal outcomes (such as educational and occupational achievement). Considerable such research has been amassed, and I will summarize major portions of it. What the research has confirmed, besides the pervasive utility of *g*, is that the practical advantages of possessing higher levels of *g* depend on the nature of the tasks performed. In this sense, life is like a mental test battery containing subtests with a wide range of *g* loadings. Viewing life as a mental test (Gordon 1997) raises the following sorts of questions, which in turn prompt new ways of interpreting old evidence and gathering new data on *g*'s gradients of effect.

2.1. What is the Distribution, by g Loading, of the Many "Subtests" we Take in Life's Extensive Mental Test Battery?

Life is like a mental test battery in that the advantages of higher *g* are not uniform; rather, they depend on the complexity (and hence *g* loading) of the tasks we confront. Therefore, what is the distribution of tasks, by *g* loading, within different realms of life (work, family, health, etc.)? Do the distributions differ much from one realm to another, and why?

2.2. To What Extent Do We Take Common Versus Different Sets of "Subtests" in Life?

Life differs from a mental test battery in that we tend to take somewhat different batteries, that is, we are subjected to somewhat different sets of demands for *g*. For instance, we can become experts in some arenas (occupations, avocations, etc.) that other people do not. This non-comparability in undertakings allows us to create niches more compatible with our talents and interests, but it also makes it more difficult to compare the actual impact of *g* in our lives (Gordon 1997). To what extent, then, do we all take the same "subtests" in life?

2.3. To What Extent Do Our Differences in g Determine Which Set of Subtests we Take in Life?

Unlike IQ testers, life offers us some choice in the tests we take (e.g. raising children or not; trying to succeed as a teacher or plumber rather than a bank teller or truck driver). We have some freedom to pursue tasks within our competence and to avoid those that are either too easy or too hard. Our social worlds also parcel out opportunities and obligations to some extent according to our ability to handle them. Indeed, people often choose or are assigned different tasks precisely to avoid invidious distinctions in competence (Gordon 1997). As just suggested, differences in intelligence and their impact on everyday competence become difficult to perceive when people undertake non-comparable activities. (Is person A smarter as an electrician than person B is as a doctor?) However, we often pursue different activities precisely because we do differ in general intelligence. Accordingly, the very act of pursuing different activities often signals intelligence (Person B is likely to be smarter because doctors are brighter than electricians, on average). When we take different "tests", then, to what extent is that owing to ourselves — or others — selecting or refashioning the "tests" we take *based on our g level*?

2.4. To What Extent Are Life's Tests Standardized?

Mental testers work hard to standardize the conditions under which we take tests, precisely to rule out other influences on our performance. Not so life. Most parents want to give their children "a leg up". Such external advantages can either soften or accentuate the impact of *g*, depending on whether the least bright or the brightest individuals receive the most help or make the best use of it. Therefore, even when we do take common tests (e.g. mastering the elementary school curriculum, earning a livelihood, and so on), to what extent do we take them under standard conditions? Do people differ greatly, for instance, in the help or advance preparation they get — or extract — from their social environments? And to what extent is that help correlated — positively or negatively — with *g*? Positive correlations can magnify the practical value of having higher *g*, whereas negative correlations between *g* and help can compensate somewhat for (though never neutralize) lower levels of *g*.

2.5. Do Many Weakly g-Loaded Activities Cumulate to Produce Highly g-Loaded Life Outcomes?

Like the individual items on an IQ test, no single life task is likely to be very highly *g* loaded. *g*'s impact in life may therefore stem largely from the consistency of its influence in long streams of behavior — that is, from virtually all life activities being *g* loaded to at least some small degree. Other factors are often more important than *g* in correctly answering any one particular IQ test item, but none has such a consistent influence throughout the test as does *g*. That is the secret of why IQ tests measure *g* so well — the "specificities" in the items cancel each other out when enough items are administered, but the effects of *g* accumulate. Perhaps so in life too. Might the many weakly *g*-loaded actions in life cumulate in the same manner to account for *g*'s often strong and always robust correlations with the various overall outcomes in life, good and bad (good education, jobs, and income vs. unemployment, out-of-wedlock births, and incarceration)?

2.6. To What Extent, and How, Do a Society's Members (its "Test Takers") Create and Reshape the Mental Test Battery that the Society "Administers" to Current and New Generations?

As noted, people are not passive beings to which some independent, larger social order administers a preordained set of life tests. Rather, individuals shape their own lives in substantial measure by the many big and small choices they make over a lifetime. If their behavior is shaped to a significant degree by their differences in mental ability, as seems to be the case, so too will be the enduring patterns of behavior they collectively create across an entire society and which become institutionalized as elements of social structure. Therefore, just as our different capabilities may head us toward different rungs on the social ladder, might not our disparate choices for ourselves and others create or modify the ladder itself over time — for example, by gradually clustering economic tasks into stable sets (occupations) that differ widely in their information processing demands? Specifically, might the occupational hierarchy itself have evolved in response to enduring human variability in mental competence? And in what other ways might a society's attempts to accommodate this mental diversity be mirrored in the ways it structures itself over time?

In short, understanding the impact of *g* in social life requires knowing more about the mental demands of everyday life and how people try to adjust to or modify them. It requires examining the interaction between, on the one hand, a population whose members differ widely in *g* levels with, on the other hand, a social world whose tasks differ widely over age, place and time in their *g* loadings.

3. Jobs as Life Tests

What evidence is there that life is like a mental test battery, in particular, a highly *g*-loaded one? Some have claimed, for instance, that the general mental ability factor, *g*, is only "a tiny and not very important part" of the mental spectrum (Sternberg 1997: 11) and that it "applies largely, although not exclusively, to academic kinds of tasks" (Sternberg *et al.* 2000: xii). If that were so, then pursuing the foregoing questions would yield useless answers. The considerable evidence about occupations, employment and career development shows, however, that differences in *g* play a powerful role in the world of work.

Next to educational achievement, job performance has probably been the most exhaustively studied correlate of general intelligence. Personnel selection psychologists and job analysts have performed many thousands of studies to determine which aptitudes and abilities different jobs require for good performance. The large status attainment literature in sociology has correlated academic ability (it eschews the term intelligence) with life outcomes such as occupational level and income at different ages. These psychological and sociological literatures are not only vast but also provide a valuable contrast: namely, whereas on-the-job performance is a proximal, short-term correlate of *g*, occupation and income level are more distal, cumulative outcomes because they represent the culmination of a long process of developing and exercising job-related skills as well as negotiating an elaborate social system. This distinction between proximal and distal, discrete and cumulative outcomes becomes very important, as we will see, in understanding *g*'s role in other domains of life, from daily health self-care to ending up with illegitimate children or a prison record.

In what follows, I apply the perspective of occupations as mental tests to the sociological and psychological evidence, reviewed below, on occupational differentiation, job performance and occupational status attainment. Such application reveals that *g* exerts its effects in ways that are not unique to the workplace.

3.1. Hierarchy of Occupations' Recruitment Ranges for IQ

Jobs are similar to psychometric tests in the sense that they are constellations of tasks (items) that individuals are asked to perform, and where performance is judged against some standard of correct or incorrect, better or worse. These task constellations, or "tests", also tend to be reasonably stable and reliably different, that is, they can generally be classified into different "occupations" (classes of test). Just as there are many types of verbal ability tests, intelligence tests and the like, there are different varieties of teacher, electrician and physician.

An early hint that occupations might constitute reliably different mental tests came from several converging lines of research. The most systematic such evidence was the sociological work on the occupational hierarchy, which showed not only that all social groups rank occupations in the same order of prestige (Hodge *et al.* 1966), but also that the average IQ of an occupation's incumbents is correlated 0.8 to 0.9 with that occupation's prestige level (e.g. Canter 1956). Psychological research in both the military and civilian sectors revealed the same high correlation between occupational level and incumbents' IQs (e.g. Stewart 1947; U.S. Department of Labor 1970).

Figure 15.1 illustrates this phenomenon with more recent data from the Wonderlic Personnel Test (Wonderlic 1992). The occupations are ordered hierarchically according to their IQ recruitment ranges, but it is apparent that this ordering mirrors the prestige hierarchy of work. They range from the simplest, lowest-level jobs, such as a packer in a factory, to the most complex and prestigious jobs, such as an attorney. As shown in the figure, the range of IQs from which jobs recruit even the middle 50% of their applicants is wide (typically 15–20 IQ points, or 1.0–1.3 SD), but the recruitment range shifts steadily upward on the IQ continuum for increasingly higher-level jobs. (IQ ranges for actual hires are narrower — Gottfredson 1997 — and so probably differ more from one job to another for incumbents than they do for applicants.) Median IQ for applicants rises from about IQ 87 for packer to IQ 120 for attorney, an increase of over 2.0 SD.

In short, more demanding and more socially desirable occupations recruit their workers from higher reaches of the IQ distribution. This suggests that occupations are, indeed, life tests that differ markedly not only in manifest content but also in their demands for *g* — just as do the tests in any broad battery of mental tests. Figure 15.1 also gives a concrete sense of the wide range of jobs — life's occupational tests — that populate any economy.

3.2. Analyses of Jobs' Task Demands

That smarter workers get better jobs does not mean that better jobs actually require more brains, however. As many sociologists have rightly pointed out, employers may simply prefer, but not really need, smarter workers and may select them, among other reasons, simply for the greater status an elite workforce confers on the employer. Do higher level jobs actually require more brain power to get the work done? One answer comes from job analysis research. I review it in some detail because of its special importance for understanding jobs as mental tests. By illuminating the detailed task content of jobs, the research illustrates that jobs, like mental tests, are purposeful collections of individual tasks that call for skilled performance. And just as people's scores on mental test batteries have been factor analyzed to reveal more basic ability factors (e.g. Carroll 1993), so too have jobs' task demands been factor analyzed to uncover their more fundamental dimensionality.

Personnel researchers have collected extensive data on the aptitude and task demands of different jobs in order to improve hiring and training procedures, rationalize pay scales, and the like. Sociologists have collected parallel data on the socioeconomic requirements and rewards of occupations in order to better understand the nature and origins of social inequality. When factor analyzed, both sets of data reveal a task complexity factor among job demands that coincides with the occupational prestige

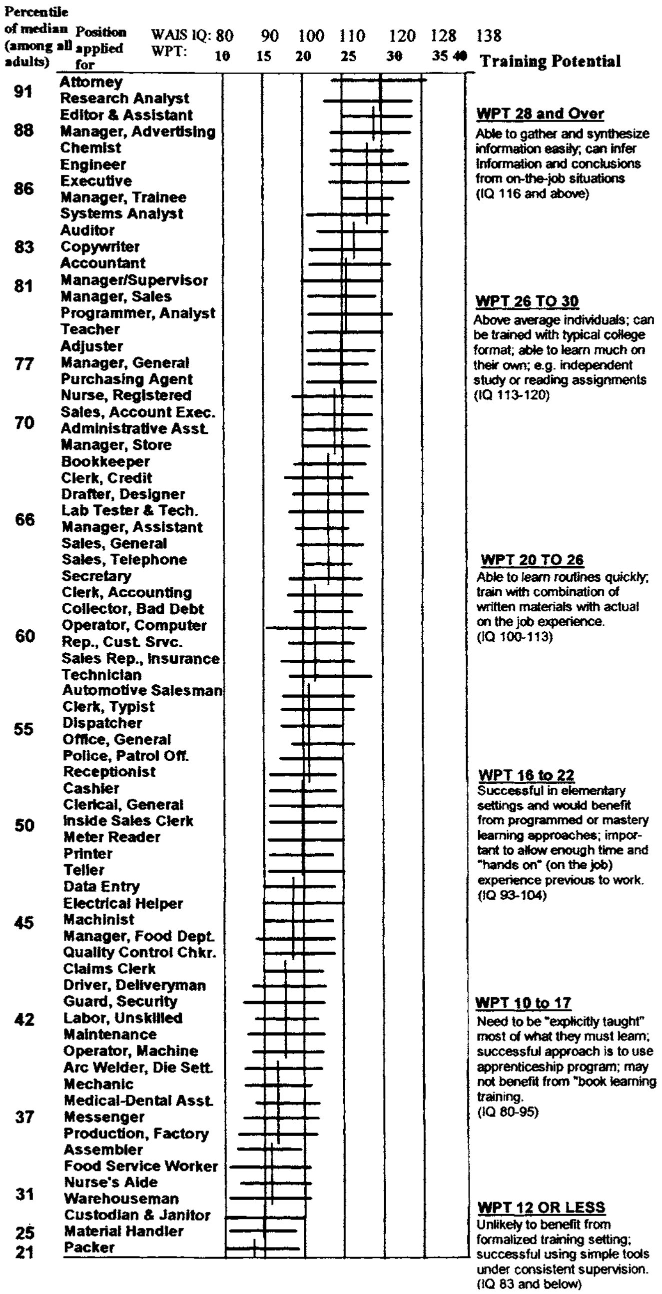

Figure 15.1: Wonderlic Personnel Test (WPT) scores by position applied for (1992). The bold horizontal line shows the range between the 25th and 75th percentiles. The bold crossmark shows the 50th percentile (median) of applicants to that job. Source: Wonderlic (1992: 20, 26, 27). Reprinted by permission of the publisher.

hierarchy. What Figure 15.1 only suggested, the job analysis data prove: there is a *g*-demands factor dominating the occupational structure that parallels the *g*-skills factor dominating the structure of human mental abilities.

Tables 15.1 and 15.2 summarize an analysis of several sets of job analysis data for most occupational titles in the United States economy around 1970. (See Gottfredson 1984, 1997, for a complete description of the data used to create the tables.) Table 15.1 shows the results of a principal components analysis that included the 32 broad "dimension" scores of the Position Analysis Questionnaire (PAQ), a well-known job analysis instrument, together with the rated demands for each of the aptitudes measured by the U.S. Employment Service's General Aptitude Test Battery (GATB).

The principal components analysis yielded 10 factors, the dominant one being the "overall complexity" of the job. The job attributes loading highly on this first factor include the PAQ dimensions of using many sources of information, processing information, making decisions and communicating those judgments, as well as the strictly cognitive GATB aptitudes (verbal, numerical, clerical and not physical strength). The complexity factor that dominates these job analysis data replicates earlier sociological work, which also described the primary distinction among occupations as a "complexity" dimension (Miller *et al.* 1980; Spaeth 1979). The other nine factors remind us that jobs differ along other dimensions as well — for instance, special aptitudes (e.g. spatial ability) and interests required (e.g. people vs. things). Nonetheless, occupations seem to be distinguished primarily by the complexity of their demands for information processing — that is, their demands for *g*.

Table 15.2 provides more evidence of this by correlating each of the 10 factors in Table 15.1 with more specific job attributes that were not included in the principal components analysis. Attributes are listed according to whether they correlate most highly with the complexity factor rather than with one of the nine other factors. The job characteristics are further subdivided according to whether they represent information-processing demands, different kinds of practical problem solving, level of responsibility and respect, degree of structure and supervision, interests required and so on.

With only two consistent exceptions, all information-processing demands (the top panel in Table 15.2) correlate most highly with the job complexity factor. The exceptions involve sight and vigilance with physical materials, and are associated, respectively, with the "work with complex things" and "vigilance with machines" factors. The information-processing demands that are correlated most highly with the task complexity factor involve compiling, combining and analyzing information and, hence, reasoning. They connote *g* itself. The information-processing demands differ in the degree to which they correlate with the job complexity factor, but this variation accords with the complexity of the processes that the demands represent: the more complex information processes (e.g. compiling, combining and analyzing information) correlate more strongly with overall job complexity than do the simpler ones (e.g. transcribing information and holding it in short-term memory).

Intelligence is often described in terms of problem solving, and many of the job requirements associated with the task complexity factor in the second panel of Table 15.2 are, in fact, general forms of problem solving. For example, requirements for advising, planning, decision-making, persuading and instructing correlate highly with

Table 15.1: Factor loadings from a principal components analysis (Varimax rotation) of 32 PAQ divisional factors and 9 DOT aptitude ratings.

PAQ and DOT ratings	Factors									
	1 Overall Complexity	**2 Work With Complex Things**	**3 Vigilance With Machines**	**4 Operating Machines**	**5 Controlled Manual**	**6 Catering to People**	**7 Coordination Without Sight**	**8 Selling**	**9 Using Senses**	**10 Specified Apparel**
2 — Using various info sources	*0.92*									
17 — Communicating judgments	*0.91*									
30 — Job-demanding circumstances	*0.90*									
DOT Verbal aptitude[a]	*0.87*			–0.26						
26 — Businesslike situations	*0.82*				–0.27					
23 — Personally-demanding situations	*0.81*					0.27				
7 — Making decisions	*0.80*				0.34		–0.26			
DOT Numerical aptitude[a]	*0.80*									
DOT Clerical perception[a]	*0.76*						0.29			
DOT Strength	*–0.72*				0.37					
8 — Processing Information	0.71						0.38			
12 — Skilled/technical activities	*0.62*	0.47								
10 — General body movement	*–0.49*				0.28	*0.55*				
24 — Hazardous job situations	–0.38		0.36						0.27	
DOT Form perception[a]		*0.86*								
DOT Finger dexterity[a]		*0.81*					0.32			
DOT Spatial ability[a]		*0.76*	0.26				–0.27			
DOT Motor coordination[a]	–0.30	*0.72*					0.40			
DOT Manual dexterity[a]	*–0.52*	0.70								
3 — Watching devices/materials		*0.59*	–0.38		0.25		–0.34			
5 — Aware of environment			*0.77*	–0.33						
11 — Controlling machines/processes			*0.73*							
32 — Alert to changing conditions			*0.68*	0.34	0.31	0.29				

Table 15.1: Continued.

PAQ and DOT ratings	Factors									
	1 Overall Complexity	2 Work With Complex Things	3 Vigilance With Machines	4 Operating Machines	5 Controlled Manual	6 Catering to People	7 Coordination Without Sight	8 Selling	9 Using Senses	10 Specified Apparel
14 — Misc. equipment/devices			*0.60*							
9 — Using machines/tools	*–0.40*			0.70						
1 — Interpreting what sensed	–0.28		0.30	*0.63*						
31 — Structured work	*–0.48*			0.59			0.29			
25 — Typical day schedule			*–0.46*	–0.46		–0.32				
13 — Controlled manual activities	–0.27	0.38			*0.63*					
20 — Exchanging job information			0.31	0.25	*0.59*		0.38			
22 — Unpleasant environment	*–0.48*		0.27		*0.56*					
19 — Supervisory/coordination			0.26		*0.56*		–0.32			
18 — General personal contacts						*0.86*				
29 — Regular schedule						*–0.49*				
16 — General physical coordination	0.25						*0.82*			
21 — Public/related contacts								*0.80*		
28 — Variable pay vs. salary								*0.73*		0.29
6 — Using various senses									*0.87*	
4 — Evaluating what is sensed									*0.81*	
27 — Optional vs. specified apparel										*–0.82*
15 — Handling/related manual			–0.34	0.37		0.35				*–0.41*
Eigenvalues	10.5	4.6	4.3	2.5	1.9	1.7	1.6	1.4	1.3	1.0
Variance (%)	25.7	11.3	10.6	6.2	4.6	4.2	3.8	3.4	3.1	2.5

[a] DOT aptitude scales are reversed for ease of interpretation.

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Table 15.2: Job attributes that correlate most with the job complexity factor.

Correlate most with "complexity" factor	*r*	Correlate most with another factor	*r*	The other factor
I. Processing information (perceiving, retrieving, manipulating, transmitting it)				
compiling information, importance of	0.90	seeing (DOT)	0.66	work with complex things
combining information, importance of	0.88	information from events, extent of use	0.58	vigilance with machines
language, level of (DOT)	0.88	vigilance: changing events, importance of	0.57	vigilance with machines
reasoning, level of (DOT)	0.86	pictorial materials, extent of use	0.44	work with complex things
writing, importance of	0.86	apply measurable, verifiable criteria (DOT)	0.43	work with complex things
intelligence (DOT)	0.84	vigilance: infrequent events, importance of	0.41	vigilance with machines
written information, extent of use	0.84	patterns, extent of use	0.41	work with complex things
analyzing information, importance of	0.83	interpret others' feelings, ideas, facts (DOT)	0.22	catering to people
math, level of (DOT)	0.79			
math, level of	0.70			
quantitative information, extent of use	0.68			
coding/decoding, importance of	0.68			
oral information, extent of use	0.68			
talking (DOT)	0.68			
behavioral information, extent of use	0.59			
apply sensory/judgmental criteria (DOT)	0.55			
attention to detail, importance of	0.54			
transcribing, importance of	0.51			
short-term memory, importance of	0.40			
recognize/identify, importance of	0.36			

Table 15.2: Continued.

Correlate most with "complexity" factor	*r*	Correlate most with another factor	*r*	The other factor
II. Practical problem solving				
advising, importance of	0.86	supervising non-employees, importance of	0.64	catering to people
planning/scheduling, amount of	0.83	catering/serving, importance of	0.61	catering to people
decision making, level of	0.82	entertaining, importance of	0.59	catering to people
negotiating, importance of	0.79	non-job-required social contact, opportunity	0.25	catering to people
persuading, importance of	0.79			
staff functions, importance of	0.79			
coordinate without line authority, import of	0.74			
public speaking, importance of	0.68			
instructing, importance of	0.67			
direction/control/planning (DOT)	0.59			
dealing with people (DOT)	0.59			
dealing with people (DOT)	0.42			
III. Level of responsibility and respect				
prestige (Temme)	0.82	responsibility for materials, degree of	0.48	vigilance with machines
general responsibility, degree of	0.76	responsibility for safety, degree of	0.47	vigilance with machines
criticality of position, degree of	0.71			

Table 15.2: Continued.

Correlate most with "complexity" factor	r	Correlate most with another factor	r	The other factor
IV. Job structure				
self-direction (Temme)	0.88	complexity of dealing with things (DOT)	0.77	work with complex things
complexity of dealings with data (DOT)	0.83	follow set procedures, importance of	0.54	operating machines
work under distractions, importance of	0.78	meet set limits, tolerances, standards (DOT)	0.53	work with complex things
frustrating situations, importance of	0.77	specified work place, importance of	0.44	operating machines
interpersonal conflict, importance of	0.76	cycled activities, importance of	0.42	operating machines
strained contacts, importance of	0.69	perform under stress/risk (DOT)	0.27	vigilance with machines
complexity of dealing with people (DOT)	0.68			
personal contact required, extent of	0.66			
personal sacrifice, importance of	0.65			
civic obligations, importance of	0.64			
time pressure, importance of	0.55			
precision, importance of	0.53			
variety and change (DOT)	0.41			
repetitive activities, importance of	–0.49			
supervision, level of	–0.73			
repetitive or continuous (DOT)	–0.74			
structure, amount of	–0.79			

Table 15.2: Continued.

Correlate most with "complexity" factor	r	Correlate most with another factor	r	The other factor
V. Education and experience required				
education, level of curriculum	0.88			
general education development level (DOT)	0.86			
update job knowledge, importance of	0.85			
specific vocational preparation (DOT)	0.76			
experience, months/years	0.62			
training, months/years	0.51			
VI Focus of work/interests required				
interest in data vs. things (DOT)	0.73	"conventional" field of work (Holland)	0.51	coordination without sight
interest in creative vs. routine work (DOT)	0.63	"social" field of work (Holland)	0.45	catering to people
interest in social welfare vs. machines (DOT)	0.55	interest in science vs. business (DOT)	0.42	work with complex things
interest in producing vs. esteem (DOT)	–0.48	"investigative" field of work (Holland)	0.37	work with complex things
"realistic" field of work (Holland)	–0.74	"enterprising" field of work (Holland)	0.33	selling
		"artistic" field of work (Hollland)	0.20	work with complex things
VII. Physical requirements				
wet, humid (DOT)	–0.37	outside vs. inside location (DOT)	0.48	vigilance with machines
hazardous conditions (DOT)	–0.39	climbing (DOT)	0.42	controlled manual work
fumes, odors, dust, gases (DOT)	–0.45			
stooping (DOT)	–0.48			
noise, vibration (DOT)	–0.53			
physical exertion, level of	–0.56			
reaching (DOT)	–0.66			

Table 15.2: Continued.

Correlate most with "complexity" factor	*r*	Correlate most with another factor	*r*	The other factor
VIII. Other correlates				
salary, yes/no	0.70	commission, yes/no	0.53	selling
% government workers, males (census)	0.45	tips, yes/no	0.50	selling
% government workers, females (census)	0.45	licensing/certification	0.42	catering to people
% black, females (census)	–0.48	median age, males (census)	0.31	vigilance with machines
% black, males (census)	–0.53	mean hours, males (census)	0.31	controlled manual
wage, yes/no	–0.66	median age, females (census)	–0.28	coordination without sight
		mean hours, females (census)	–0.34	catering to people
		% female (census)	–0.37	controlled manual

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the task complexity factor. Correlations are somewhat lower for more people-oriented than data-oriented problem solving (e.g. instructing vs. planning), but people-related problem solving is still much more typical at higher than lower levels of the job hierarchy (cf., Gottfredson 1986). Only the mostly non-intellectual people-related activities (e.g. catering to and entertaining people, supervising non-employees) correlate most highly with some other task factor ("catering to people").

Turning to the third and fourth panels in Table 15.2, jobs high on the work complexity factor are more prestigious, critical to the organization, and entail greater general responsibility. This finding is consistent with sociological research, cited earlier, on the common prestige hierarchy that characterizes occupations in all industrialized economies. As the structural attributes of jobs suggest, jobs that require considerable discretion and self-direction and which, accordingly, are not highly supervised and routinized, tend to be the most complex overall. The duties of such jobs also appear to entail psychological stress rather than physical stress.

Intelligence is also often described as the ability to learn quickly and efficiently. And, in fact, the fifth panel in Table 15.2 shows that more complex jobs tend to have more intense and more continuous training demands, whether that be formal education, specific vocational training, learning through extensive experience, or continually updating one's job knowledge. These training demands alone would make a job more *g* loaded overall.

Job analysis research by Arvey (1986) with different job attributes and different jobs reveals the same job complexity factor. In a set of 140 jobs from the petrochemical industry, his factor analyses revealed that a "judgment and reasoning factor" best distinguished among them. The chief elements of this factor, shown in Table 15.3, read like a description of intelligence as commonly understood by lay people and experts alike: for example, reason and make judgments, learn new procedures quickly and deal with unexpected situations.

Table 15.3: Job analysis items and factor loadings associated with judgment and reasoning factor developed from 140 petrochemical jobs.

Items	**Factor Loading**
Deal with unexpected situations	0.75
Able to learn and recall job-related information	0.71
Able to reason and make judgments	0.69
Able to identify problem situations quickly	0.69
React swiftly when unexpected problems occur	0.67
Able to apply common sense to solve problems	0.66
Able to learn new procedures quickly	0.66
Alert and quick to understand things	0.55
Able to compare information from two or more sources to reach a conclusion	0.49

Source: Arvey (1986: 148). Reprinted with permission from Academic Press, copyright 1986.

In summary, the job analysis data suggest not only that jobs differ greatly in their *g* loading, but also that this is the most fundamental distinction among them. That is, they differ primarily in the extent to which they call forth or "measure" *g*. If they were all to be populated by representative samples of the population, we might therefore expect the highest-level, more *g*-demanding occupations to function much like IQ tests (that is, workers' differences in job performance would simultaneously measure their differences in IQ), while lower-level, less *g*-loaded occupations would call forth or "measure" *g* less well. As we see next, this is just what yet another body of research reveals — jobs operate like differentially *g*-loaded mental tests.

3.3. Prediction of Job Performance

Personnel selection psychologists have only recently explicitly characterized their cognitive tests as measures of intelligence or *g*, but most now refer to them as measures of the general mental factor, *g* (see Visweswaran & Ones, in press). All mental tests measure mostly *g*, so I will refer to them all simply as measures of *g*, recognizing that they can vary in quality as measures of that construct. Very little research on the relation of mental abilities to job performance has actually extracted *g* scores, which means that the research typically understates the predictive value of *g* to some extent.

Table 15.4 summarizes the pattern of findings from the job performance literature. It is based on a review of several large military studies as well as the major meta-analyses for civilian jobs (Gottfredson, in press). Its first general point, on the "utility of *g*", is that *g* (i.e. possessing a higher level of *g*) has value across all kinds of work and levels of job-specific experience, but that its value rises with: (a) the complexity of work; (b) the more "core" the performance criterion being considered (good performance of technical duties rather than "citizenship"); and (c) the more objectively performance is measured (e.g. job samples rather than supervisor ratings). Predictive validities, when corrected for various statistical artifacts, range from about 0.2 to 0.8 in civilian jobs, with an average near 0.5 (Schmidt & Hunter 1998). In mid-level military jobs, uncorrected validities tend to range between 0.3 and 0.6 (Wigdor & Green 1991). These are substantial. To illustrate, tests with these levels of predictive validity would provide 30% to 60% of the gain in aggregate levels of worker performance that would be realized from using tests with perfect validity (there is no such thing) rather than hiring randomly.

The next point of Table 15.4, on *g*'s utility relative to other "can do" components of performance, is that *g* carries the freight of prediction in any mental test battery. Specific aptitudes, such as spatial or mechanical aptitude, seldom add much to the prediction of job performance, and they provide such increments only in narrow domains of jobs. General psychomotor ability can rival *g* in predictive validity, but its value rises as job complexity falls, which pattern is opposite that for *g*.

Turning to *g*'s utility relative to the "will do" components of performance (e.g. motivation), the latter add virtually nothing to the prediction of core technical performance beyond that provided by *g* alone. These "non-cognitive" (less cognitive) traits, however, substantially out-perform *g* in predicting the non-core, citizenship

Table 15.4: Major findings on *g*'s impact on job performance[a].

Utility of g

(1) Higher levels of *g* lead to higher levels of performance in all jobs and along all dimensions of performance. The average correlation of mental tests with overall rated job performance is around 0.5 (corrected for statistical artifacts).
(2) There is no ability threshold above which more *g* does not enhance performance. The effects of *g* are linear: successive increments in *g* lead to successive increments in job performance.
(3) (a) The value of higher levels of *g* does not fade with longer experience on the job. Criterion validities remain high even among highly experienced workers. (b) That they sometimes even appear to rise with experience may be due to the confounding effect of the least experienced groups tending to be more variable in relative level of experience, which obscures the advantages of higher *g*.
(4) *g* predicts job performance better in more complex jobs. Its (corrected) criterion validities range from about 0.2 in the simplest jobs to 0.8 in the most complex.
(5) *g* predicts the core technical dimensions of performance better than it does the non-core "citizenship" dimension of performance.
(6) Perhaps as a consequence, *g* predicts objectively measured performance (either job knowledge or job sample performance) better than it does subjectively measured performance (such as supervisor ratings).

Utility of g relative to other "can do" components of performance

(7) Specific mental abilities (such as spatial, mechanical or verbal ability) add very little, beyond *g*, to the prediction of job performance. *g* generally accounts for at least 85–95% of a full mental test battery's (cross-validated) ability to predict performance in training or on the job.
(8) Specific mental abilities (such as clerical ability) sometimes add usefully to prediction, net of *g*, but only in certain classes of jobs. They do not have general utility.
(9) General psychomotor ability is often useful, but primarily in less complex work. Their predictive validities fall with complexity while those for *g* rise.

Utility of g relative to the "will do" component of job performance

(10) *g* predicts core performance much better than do "non-cognitive" (less *g*-loaded) traits, such as vocational interests and different personality traits. The latter add virtually nothing to the prediction of core performance, net of *g*.
(11) *g* predicts most dimensions of non-core performance (such as personal discipline and soldier bearing) much less well than do "non-cognitive" traits of personality and temperament. When a performance dimension reflects both core and non-core performance (effort and leadership), *g* predicts to about the same modest degree as do non-cognitive (less *g*-loaded) traits.
(12) Different non-cognitive traits appear to usefully supplement *g* in different jobs, just as specific abilities sometimes add to the prediction of performance in certain classes of jobs. Only one such non-cognitive trait appears to be as generalizable as *g*: the personality trait of conscientiousness/integrity. Its effect sizes for core performance are substantially smaller than *g*'s, however.

Table 15.4: Continued.

Utility of g relative to the job knowledge
(13) *g* affects job performance primarily *indirectly* through its effect on job-specific knowledge.
(14) *g*'s direct effects on job performance increase when jobs are less routinized, training is less complete, and workers retain more discretion.
(15) Job-specific knowledge generally predicts job performance as well as does *g* among experienced workers. However, job knowledge is not generalizable (net of its *g* component), even among experienced workers. The value of job knowledge is highly job specific; *g*'s value is unrestricted.
Utility of g relative to the "have done" (experience) component of job performance
(16) Like job knowledge, the effect sizes of job-specific experience are sometimes high but they are not generalizable.
(17) In fact, experience predicts performance less well as all workers become more experienced. In contrast, higher levels of *g* remain an asset regardless of length of experience.
(18) Experience predicts job performance less well as job complexity rises, which is opposite the trend for *g*. Like general psychomotor ability, experience matters least where *g* matters most to individuals and their organizations.

[a] See Gottfredson (in press) for fuller discussion and citation. Table reprinted from Gottfredson (in press) with permission from Lawrence Erlbaum Associates.

dimensions of performance, although each typically in limited domains of work. Only the conscientiousness-integrity factor of personality inventories seems to have general utility across all kinds of work, but it is still notably less useful than *g* in predicting core performance. In short, no other single personal trait has as large and as pervasive an effect on performance across the full range of jobs as does *g*.

The last two general points of Table 15.4 are that job knowledge and job-related experience sometimes rival *g* in predictive validity, but that their value is always highly job-specific. The same *g* can be useful in all jobs, but knowledge and experience must be targeted to a particular kind of work (carpentry, accounting, etc.). The information-processing capability represented by *g* is highly generalizable; job knowledge and experience are not. Moreover, differences in knowledge among a job's incumbents result primarily from their differences in *g*, and complex jobs continue to require learning and problem solving (the exercise of *g*) for which previous knowledge and experience cannot substitute. That is, higher *g* remains useful, regardless of knowledge and experience, especially in higher level jobs. The advantages of higher *g* (say, another 10 IQ points) hold steady at increasingly higher levels of experience in a job, but the advantages of more experience (say, two years more than one's coworker) fade among workers with higher average levels of experience. Moreover, the predictive validity of experience falls at successively higher levels of job complexity — again, a pattern opposite that for *g*.

In short, possessing higher levels of *g* provides individuals a competitive edge for performing jobs well, especially a job's core technical duties. That edge tends to be small in low-level jobs, both in absolute terms and relative to other personal traits that might affect performance (such as reliability and physical strength). That edge is large in both regards, however, in higher-level, more complex jobs. Superior knowledge and experience may sometimes hide the functional disadvantages of lower *g*, but they never nullify them. Military research shows that less bright workers may out-perform brighter but relatively inexperienced workers, but that the brighter workers will out-distance their less able peers after getting a bit more experience (Wigdor & Green 1991: 163–164). Presumably, their superior information-processing skills allow brighter workers to apply past knowledge more effectively, deal faster with unexpected problems, extract more knowledge from their experience, and the like.

The job performance research also hints at another major difference between life tasks — the extent to which they are instrumental rather than socioemotional in character. As we saw, *g* is more important than personality traits in predicting performance of core technical duties (decontaminating equipment, repairing an engine, determining grid coordinates on a map, and so on), but it is less predictive in activities of a more interpersonal or characterological nature (being a reliable worker or helpful team-mate, showing leadership, impressing superiors and the like). For purposes of understanding the social consequences of *g*, we might therefore distinguish tasks not only along a complexity dimension, but also along a continuum from instrumental to socioemotional, as shown in Figure 15.2. We might expect the *g* loadings of tasks to be

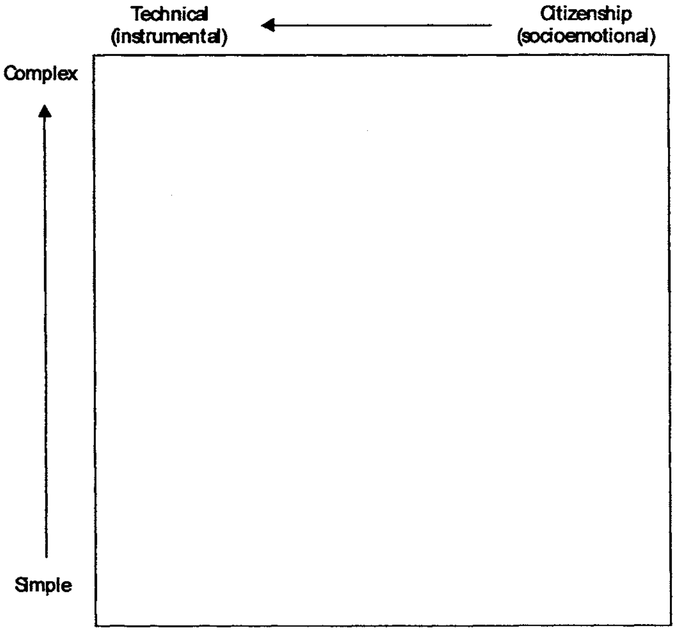

Figure 15.2: Matrix of life tasks.

highest in the upper left corner (complex instrumental tasks), and to drop steadily for tasks located nearer the lower right corner of Figure 15.2 (simple and socioemotional).

How do these results illustrate jobs as mental tests? First, they show that jobs, like mental tests, do indeed differ in their *g* loadings. And they differ just as the job analysis research had indicated they would: differences in *g* produce bigger, more consistent and more consequential differences in job performance (higher predictive validities) in more complex jobs (see Hunter & Schmidt 1996; Schmidt & Hunter 2000, for additional evidence). Conversely, some jobs are quite poor "tests" of *g*; that is, being bright does not boost performance on them very much. Thus, although the data show that higher levels of *g* are always useful to some extent, their value varies from great to slight depending on the activities involved. It is precisely such patterns of effect size that the study of task attributes such as complexity promises to illuminate.

Second, the foregoing results remind us that jobs also differ from psychometric tests in ways that may camouflage *g*'s real effects unless those differences are taken into account. Because jobs are actually more like achievement tests than aptitude tests, their performance generally depends on specialized knowledge, which makes them sensitive to differences in exposure to relevant knowledge. That is why greater relative experience can temporarily level the playing field for lower IQ workers, camouflaging the longer-term disadvantages of lower *g*. Whereas IQ testers try to eliminate all such non-*g* advantages, real life is replete with them. These non-*g* influences do not neutralize the advantages of higher *g*, but they can make it more difficult to identify *g*'s gradients of effect. As the fourth question earlier reminds us ("to what extent are life's tests standardized?"), we cannot trace *g*'s impact in "real life" without understanding how life's "tests" depart from the ideal conditions for mental testing.

3.4. Prediction of Career Level

We turn now from job performance, which is a highly proximal effect of *g* in the workplace, to less proximal but more cumulative outcomes in employment such as income and occupation level. Being less proximal, we might expect them to be less dependent on *g* and more on institutional factors and social forces not under a worker's control. On the other hand, they represent a long series of behaviors and events of which the worker may be the only common component. This raises the possibility that less proximal outcomes may not necessarily be much less *g* loaded than more proximal ones, despite their being affected by a greater variety of external factors.

Correlations of IQ with socioeconomic success vary in size depending on the outcome in question, but they are consistent and substantial (see especially the re-analysis of 10 large samples by Jencks *et al.* 1979, ch. 4): years of education (generally 0.5–0.6), occupational status level (0.4–0.5), and earnings, where the correlations rise with age (0.2–0.4). The predictions are the same whether IQ is measured in Grades 3–6, high school, or adulthood (Jencks *et al.* 1979: 96–99). Moreover, they are underestimates, because they come from single tests of uncertain *g* loading (Jencks *et al.* 1979: 91). Various specific aptitude and achievement tests (both academic and non-academic) also predict education, occupation and earnings, but essentially only to the extent that they also measure *g* (Jencks *et al.* 1979: 87–96). This finding is consistent with that for the prediction of job performance: tests of specific abilities add little beyond *g* when predicting core performance. In short, *g* is what drives a test's predictions of socioeconomic success, and the predictions are substantial even from childhood when *g* is reasonably well measured.

Differences in *g* are clearly a major predictor of differences in career success, but why? The answer is not as obvious as it is for proximal outcomes such as on-the-job performance. Sociologists and economists have put much effort into modeling the interrelated processes of how people "get ahead" on the educational, occupational and income hierarchies (e.g. Behrman *et al.* 1980; Jencks *et al.* 1972, 1979; Sewell & Hauser 1975; Taubman 1977). Their statistical modeling suggests that "academic ability" (whether measured as IQ or standardized academic achievement) has both direct and indirect effects on each successive outcome in the education-occupation-income chain of development. Cognitive ability is by far the strongest predictor of education level relative to others studied (0.5–0.6 for IQ vs. 0.3–0.4 for parents' socioeconomic status (see Duncan *et al.* 1972, p. 38 for latter), and therefore seems to have large direct effects on how far people go in school. Educational level is, in turn, the major predictor of occupational levels attained. After controlling for educational attainment, mental ability's direct effect is much smaller on *occupational* than educational level, but still larger than the influence of family background. Jencks *et al.* (1979: 220) summarize mental ability as having a "modest influence" through age 25 in boosting young adults up the occupational ladder. Much the same pattern is found for *earnings*, after controlling for both education and occupation — the impact of IQ is mostly indirect. However, the direct effects of cognitive ability on earnings grow with age, leading Jencks *et al.* (1979: 119) to comment that IQ's direct effects are "substantively important" for raising earnings through at least middle age.

In summary, *g* is hardly the only predictor of career success, but it is a surprisingly strong one, both in absolute and relative terms. As complexly and externally influenced as it is, career development seems to be moderately tied to *g* level.

3.5. g's Causal Impact on Careers

IQ and SES background are not independent forces, of course. Sociologists tend to assume that IQ differences are largely created by differences in family resources, such as better educated parents, more books in the home, and the like. In other words, IQ scores really reflect mostly socioeconomic advantage. In contrast, many intelligence researchers assume that the accomplishments of parents and children have overlapping genetic roots. Namely, if parents have favorable genes for IQ, this genetic advantage will yield them greater socioeconomic success as well as brighter than average children who, consequently, will have their own favorable odds for socioeconomic success. If this assumption is true, then controlling for family background before assessing the causal impact of *g* actually controls away part of *g* itself and results in underestimating its impact.

Thus, although there is no argument among social scientists that IQ correlates moderately strongly with socioeconomic success, there is heated debate about whether higher intelligence might be a *result* rather than a *cause* of social advantage. The causal question has not been an issue in the job performance literature, partly because it strains credulity to attribute differences in job performance — for example, post-training success at assembling a rifle, reading maps, making good managerial decisions, and so on — to distal social forces rather than to proximal personal ones. The job performance research leaves no doubt, either, that earlier cognitive ability predicts *later* performance in training and on the job. It also shows that the most relevant distal characteristics, such as years of education, have scant value in predicting who performs best in a particular job (Hunter & Hunter 1984).

The causal question is still a major one, however, when the job outcomes at issue are broader, more personally consequential ones such as occupational prestige and income level attained. Although many social scientists still assume that intelligence is a result rather than a cause of social class differences, research continues to show the opposite. Sibling studies, for instance, provide evidence that *g* does, in fact, have a big causal influence and that social class has a comparatively weak one on children's adult socioeconomic outcomes. Biological siblings differ two-thirds as much in IQ, on the average, as do random strangers (12 vs. 17 IQ points). Despite growing up in the very same households, their differences in IQ portend differences in life outcomes that are almost as large as those observed in the general population (Jencks *et al.* 1979, ch. 4; Murray 1997a, 1997b; Olneck 1977: 137–138). Even in intact, non-poor families, siblings of below average intelligence are much less likely to have a college degree, work in a professional job, and have high earnings than are their average-IQ siblings, who in turn do much less well than their high-IQ siblings (Murray 1997b).

Behavioral genetic research also indicates that *g* is much more a cause than consequence of social advantage. First, research on the heritability of IQ indicates that differences in family advantage have a modest effect on IQ scores — about equal to that of genes — in early childhood, but that these family effects — called *shared* environmental effects — wash out by adolescence (Bouchard 1998; Plomin *et al.* 2000). Perhaps counterintuitively, the socioeconomic advantages and disadvantages that siblings share turn out to have no lasting effect on IQ. By late adulthood, the heritability of IQ is about 0.8, which means that phenotypic intelligence is correlating about 0.9 with genotypic intelligence (0.9 being the square root of 0.8). Environmental differences account for up to 20% of IQ differences in adulthood, but they represent *non-shared* effects that we experience one person at a time (such as illness), not family by family (such as parents' income and education). In short, differences in adult IQ are not due at all to differences in socioeconomic advantage.

Second, multivariate behavioral genetic analyses reveal not only that education, occupation and income level are themselves partly heritable (that is, our differences in education, occupation and income can be traced partly to our genetic differences), but that they also share some of the same genetic roots as does IQ. The heritabilities of educational level, occupational level and income are, respectively, about 0.6–0.7, 0.5, and 0.4–0.5 (e.g. Lichtenstein & Pedersen 1997; Rowe *et al.* 1998). More importantly, half to two-thirds of the heritability for each outcome overlaps the genetic roots of IQ.

Specifically, about 40%, 25% and 20% of the total (phenotypic) variation in education, occupation and income, respectively, can be traced to genetic influences that each *shares* with *g* (e.g. Lichtenstein & Pedersen 1997; Rowe *et al.* 1998). These overlapping heritabilities provide additional evidence that much variation in socioeconomic outcomes can be traced back to variation in *g*, in this case, to its strictly genetic component. In fact, behavioral genetic research has shown that most social environments and events are themselves somewhat genetic in origin (Plomin & Bergeman 1991).

To summarize, not only do differences in social environments and events not create differences in adult *g*, but career outcomes are themselves moderately genetic in origin, probably owing in part to genetic differences in *g*. "Getting ahead" is not only like taking a mental test battery, but one that taps genetically-conditioned mental abilities. Because getting ahead socioeconomically is a moderately rather than highly *g*-loaded life test, high *g* provides a big but not decisive advantage. As with other mental test batteries, the size of the advantage that higher levels of *g* confer differs from one subtest to another. It is largest in education, smallest in income, and intermediate for both occupational level attained and performance in the typical job.

3.6. Possible Mode of g's Cumulative Effects on Careers

The *g* factor has moderately large, causal effects on many long-term outcomes, as these and other data indicate, but its manner of effect is ill-understood. The sociological explanations are rudimentary and tend either to ignore or misconstrue the nature of intelligence, while psychological research on intelligence tends to ignore long-term career development. As noted before, the role of *g* in everyday life may largely mimic the role of *g* in IQ tests, where small effects can become big ones when other influences are less consistent — sort of a tortoise and hare effect. The following re-analysis of data from a longitudinal study of military careers illustrates this process. It also shows how the long-term impact of *g* can be underestimated by focusing too narrowly on the individual events that cumulate into a "career".

In 1966, during the era of President Johnson's Great Society programs, U.S. Secretary of Defense Robert McNamara inaugurated Project 100,000. Until its demise several years later, the project required each of the four military services to induct a certain percentage of men whose low level of mental ability would normally have disqualified them from service (percentiles 10–15 on the Armed Services Qualifying Test, AFQT, which corresponds to about IQ 80–85). The project was a social experiment intended to enhance the life opportunities of men who normally would have difficulty succeeding in civilian life. Part of the initiative therefore involved comparing the progress of the New Standards Men (NSM), as they were called, with a control group from each of the services. (See Laurence & Ramsberger 1991; Sticht *et al.* 1987, for details on Project 100,000, including the mixed nature of the four control groups.) Not all the New Standards Men actually were of low-normal ability (the threshold for mild mental retardation is IQ 70–75), because recruiters sometimes coached brighter applicants how to score poorly on the AFQT so that such men could enlist when the quota for bright men had already been met. Such instances, although probably proportionately small, would lead to underestimating somewhat the differences in career progress between New Standards and control men.

Table 15.5 provides the percentages of New Standards Men and control men who passed each of six basic hurdles in a military career: completing basic training, completing entry-level skill training and not being discharged for any reason during each of four successive periods during the first two years of service. The specialty (job) for which one is trained also affects the likelihood of performing well (e.g. low-ability men would be expected to perform better in lower-level jobs), so level of job specialty (technical vs. not) is listed too. Also listed are four criteria of success near the conclusion of the two years: pay grade, performance rating, non-judicial punishment and court martial conviction. The entries in Table 15.5 for each career stage refer to the percentage of men who, having entered that particular stage and became eligible to move to the next stage. Each successive stage therefore applies to successively fewer men — the dwindling pool of survivors, so to speak.

Analysts have often interpreted the data in Table 15.5 as showing that the New Standards Men did almost as well as the control men, and therefore that the military should welcome rather than avoid inducting low ability men (e.g. Sticht *et al.*'s 1987 book, *Cast-Off Youth*). Such positive interpretations might indeed seem warranted at first glance. The vast majority of New Standards Men succeeded at each level, and at a not much lower rate than did the control men. For instance, of men entering service in 1966–1969, 94.6% of the New Standards Men completed basic training compared to 97.5% of the control men. By 1969–1970 the need for military manpower had eased, and the services became more selective in who they would retain. Basic training retention rates for New Standards Men dropped considerably, especially in the three normally more selective services, from 94.6% overall in the earlier years to 87.6% in 1969–1970. The retention rate is nonetheless still high. Except in the Marine Corps, retention rates beyond basic training for New Standards Men seldom dropped much below 80% at any stage in the two-year careers. This would seem to paint a portrait of surprisingly consistent success for men of moderately low ability. Skeptics of Project 100,000 have pointed out that great pressure was put on the services to make the experiment succeed, and extra help and special leniency were no doubt offered the New Standards Men. Some were recycled through basic training several times. But however they were attained, the success rates do seem impressive.

This positive interpretation ignores two phenomena, however: rates of success relative to the control men, and *cumulative* rates of success over time. Table 15.6 shows the odds ratios calculated from each of the forms of success in Table 15.5. Odds ratios are one form of *risk ratio* used in epidemiology to quantify degree of risk *relative* to some comparison group, in this case the control men. To portray levels of risk, the ratios in Table 15.6 refer to the odds of *failure*, not success. They are calculated as (a) the odds of failure in the at-risk group (its members' odds of failure *rather than* success) divided by (b) the odds of failure in the comparison group. The odds ratio thus gives a sense of the *relative balance* of failure to success when moving from one group to another. To illustrate, the odds of *not* completing basic training were 5.4% to 94.6% (or 0.057) for New Standards Men and 2.5% to 97.5% (or 0.026) for control men, yielding an odds

Table 15.5: Success rates at different milestones in the first two years of military service: New Standards Men (NSM) and Control (C) Men (Percentages).

Stage in military career (for those who get that far)	Total		Army		Navy		Marine Corps		Air Force	
	NS	C	NS	C	NS	C	NS	C	NS	C
Completed basic training[a]										
entered 1966–1969	94.6	97.5	96.3	98.0	91.4	97.2	88.9	95.6	90.8	97.0
entered 1969–1970	87.6	95.6	94.5	97.5	83.0	94.1	62.2	85.9	85.6	96.2
Assigned to technical specialty[b] (e.g. *not* infantry, cook, driver, or clerk)	7.6	19.5	9.6	n.a.	4.7	n.a.	1.1	n.a.	4.2	n.a.
Completed entry-level skill training[c]	(91.9)[d]	(95.7)	92.8	96.3	86.8	91.3	92.8	96.8	89.1	96.0
Not discharged by:[e]										
13–15 months	81.1	92.8	88.4	91.9	86.8	96.1	56.4	91.5	80.8	94.4
16–18 months	82.9	92.0	88.6	90.9	88.4	95.4	64.8	89.0	78.3	95.8
19–21 months	82.7	91.0	88.4	89.7	86.3	94.7	67.2	89.3	76.0	94.6
22–24 months	86.1	90.7	88.9	90.0	89.8	94.0	69.0	88.2	76.9	92.5
Late-term performance										
promoted to paygrade E4 or E5 by 19–24 months[f]	66.7	81.6	85.7	94.1	13.0	70.1	75.1	87.4	16.5	30.1
rated "good or "highly effective" worker at 22–24 months	(95.1)	(97.9)	97.5	98.9	89.6	96.9	85.7	96.1	91.2	92.9
no non-judicial punishment[h]	(83.4)	(90.6)	81.9	89.7	93.1	96.5	72.2	81.8	95.9	98.6
no court martial convictions[h]	96.8	98.4	96.8	98.4	99.0	99.7	94.7	95.3	99.8	~ 100.0

Table 15.5: Continued.

n.a. = not available.
[a] Laurence & Ramsberger (1991: 44).
[b] Laurence & Ramsberger (1991: 40). Electronic equipment repair, communications & intelligence, medical & dental, other technical.
[c] Sticht *et al.* (1987: 48)..
[d] Percentages in parentheses have been estimated by weighing the percentages in each of the services by the quotas for new standards men that each service was to meet in 1968 (respectively, 72%, 10%, 9% and 9% of all New Standards Men for the Army, Navy, Marine Corps, and Air Force, Laurence & Ramsberger, 1991: 29)..
[e] Laurence & Ramsberger (1991: 50).
[f] Laurence & Ramsberger (1991: 47). The disparities in rates can probably be traced to two key factors: (a) Navy and Air Force require tests for promotion; and (b) the jobs held by New Standards men in the Army and Marine were less technical (pp. 46, 49–50).
[g] Sticht *et al.* (1987: 54)..
[h] Laurence & Ramsberger (1991: 49) "Total" figures for court martial convictions are from Sticht *et al.* (1987: 52).

Table 15.6: Odds ratios for *not* succeeding during the first two years of military service: New Standards Men (NSM) telative to Control (C) Men[a].

Stage in Military Career	Total	Army	Navy	Marine Corps	Air Force
Did not complete basic training					
entered 1966–1969	2.2	1.6	3.2	2.7	3.3
entered 1969–1970	3.1	2.3	2.5	3.7	4.3
Not assigned to technical specialty	2.9	2.3	5.0	20.0	5.6
Did not complete entry-level skill training	(2.0)	2.0	1.6	2.3	2.9
Discharged by:					
13–15 months	3.4	1.5	3.7	8.3	4.0
16–18 months	2.4	1.3	2.2	4.4	6.2
19–21 months	2.1	1.1	2.9	4.0	5.6
22–24 months	1.6	1.1	1.8	3.3	3.7
Late-term performance					
not promoted to paygrade E4 or E5 by 19–24 months	2.1	2.6	16.7	2.3	2.2
not rated "good or "highly effective" worker at 22–24 months	(2.4)	2.3	3.6	4.2	1.2
non-judicial punishment	(1.9)	1.9	2.0	1.4	3.0
court martial convictions	2.0	2.0	3.3	1.1	5.0

[a] Calculated from data in Table 15.5.

ratio of 2.2 (0.057/0.026). That is, the odds of failing rather than succeeding were more than twice as high for the New Standards Men as for the control men. Conversely, the New Standards Men's relative "risk" of success was less than half that of the control men (0.45, or the inverse of 2.2). In epidemiology, risk ratios of 2.0 to 4.0 represent a "moderate to strong" level of association, and above 4.0 a "very strong" association (Gerstman 1998: 128).

Risk ratios fall below 2.0 for New Standards Men only in the Army and in several of the more winnowed (e.g. longer-surviving) groups in the other services. The risk ratios thus paint a less positive picture of success: however high the success rates may be for New Standards Men in absolute terms, they tend to be markedly lower in relative terms in all the aspects of career development.

Figure 15.3 shows the cumulative consequences of one group having consistently lower rates of success at each stage in a cumulative or developmental process. It reflects the cumulative probability of men passing hurdles at each successive stage of a two-year career, from completing basic training to being recognized as a good worker after two years on the job. As shown in the figure, entering cohorts of New Standards Men experienced a higher probability of failure (discharge) than success (retention) by 18 months of military service. Of the New Standards Men entering basic training, fewer than half remained after 18 months, compared to almost three quarters (72.8%) of the control men. By that point, failure (discharge) had become the norm for New Standards Men whereas success was still the norm for control men. Their *rates* of failure had not increased at more advanced career stages (if anything, they fell), but because subsequent successes were contingent on earlier ones, their risks compounded faster with time than did those for the control men. As gamblers and investors know, even much smaller differences in odds or rates of return can compound over time to produce enormous differences in profit or loss.

In summary, careers are like mental tests in that what matters most is one's total score, not the odds of passing any particular item. The factor with the biggest impact on the total score is generally the one with the most pervasive influence, relative to all others, over the long haul. The advantage it provides may be small in any one task, but each new task adds its own sliver of advantage to the growing pile. Thus, the more long-term or multi-faceted an outcome, the more we ought to consider the consistency, not just the size, of any variable's impact.

3.7. g-Based Origins of the Occupational Hierarchy

This chapter, like most research on *g*, has focused on individual-level correlates of *g*. The most important impact of biologically-rooted variability in mental competence may occur at more aggregate levels, however, as Gordon (1997) described. At the level of the interpersonal context, for instance, our differences in *g* affect how and with whom we interact (cooperate, compete, marry, and so on) as well as the kinds of subcultures we produce. At the broader societal level, information, risk and disease can be seen to diffuse at different rates across different segments of the IQ distribution. Gordon also describes how social norms and political institutions evolve partly in response to the

	Completed Basic Training +	Completed Skills Training +	Not discharged within: 13-15 months +	16-18 months +	19-21 months +	22-24 months +		Success at two years
NSM:	94.6	86.9	70.5	58.4	48.3	41.6	→	27.7 Good paygrade 39.6 Good performance rating 34.7 No non-judicial punishment 40.3 No non-judicial punishment
C:	97.5	93.3	86.6	80.0	72.8	68.8	→	56.1 Good paygrade 67.4 Good performance rating 62.3 No non-judicial punishment 67.7 No court martial conviction

Figure 15.3: Cumulative probability of remaining in the military for two years and then succeeding against four criteria: New Standards Men (NSM) and Control (C) Men[a].

social processes that are set in motion by noticeable and functionally important individual and group differences in mental competence. I therefore conclude the review of evidence on occupations by speculating about one such higher-order effect, specifically, how individual differences in mental competence may account for the emergence of the occupational prestige-complexity hierarchy.

People tend to take the occupational hierarchy for granted, but we can imagine other ways that a society's myriad worker activities might be chunked. Some sociologists have suggested that we either level these distinctions in occupational level or else rotate people through both good and bad jobs (e.g. Collins 1979), apparently on the assumption that virtually everyone can learn virtually any job. Their view is that the occupational hierarchy is merely an arbitrary social construction for maintaining the privileges of some groups over others (e.g. see the classic statement by Bowles & Gintis 1972/1973). Research on job performance and the heritability of *g* disproves their assumptions about human capability, however. Moreover, it hardly seems accidental that the key dimension along which occupations have crystallized over the ages (complexity of information processing) mirrors the key distinction in human competence in all societies (the ability to process information). Rather, the *g*-segregated nature of occupations is probably at least partly a social accommodation to a biological reality, namely, the wide dispersion of *g* in all human populations (Gottfredson 1985).

How might that accommodation occur? As described earlier, occupations are constellations of tasks that differ, not just in their socioeconomic rewards, but also in the human capabilities required to actually perform them and perform them well. It seems likely that both the systematic differences among task constellations (job differentiation) and the highly *g*-based process by which people are sorted and self-sorted to these constellations have evolved in tandem in recent human history. Both of these enduring regularities in human organization are examples of *social structure*. They would have evolved in tandem owing to the pressures and opportunities that a wide dispersion in human intelligence creates for segregating tasks somewhat by *g* loading.

Specifically, individuals who are better able to process information, anticipate and solve problems, and learn quickly are more likely to take on or be delegated the more complex tasks in a group, whatever the tasks' manifest content. For the same reason, persons with weak intellectual skills are likely to gravitate to or be assigned intellectually simpler tasks (see Wilk *et al.* 1995, on evidence for the gravitational hypothesis). Over time, this sorting and assignment process can promote a recurring *g*-based segregation of tasks because it provides a steady and substantial supply of workers whose levels of mental competence match those usually required by the work. Only when such *g*-differentiated supplies of *workers* are regularly maintained, can any *g*-related segregation of *tasks* emerge and become institutionalized over time as distinct occupations (e.g. into accountant vs. clerk, teacher vs. teacher aide, electrical engineer vs. electrician, nurse vs. hospital orderly).

If *g*-based distinctions among occupations can be sustained only when the workers populating those jobs differ reliably in their typical levels of *g*, then we might expect the *g*-based differences among jobs to grow or shrink depending on changes in the efficiency with which people are sorted to jobs by *g* level (Gottfredson 1985). More efficient sorting, if sustained, could lead eventually to greater distinctions among occupations, perhaps creating altogether new ones. Lower efficiency in sorting would narrow or collapse *g*-based distinctions among jobs, because the jobs in question would now have to accommodate workers with a wider dispersion in *g* levels. That is, a *g*-based occupational hierarchy could be expanded or contracted, like an accordion, depending on how much the means and variances in incumbents' *g* levels change along different stretches of the occupational hierarchy. Constellations of job duties (an *occupation*) therefore would be stable only to the extent that the occupation's usual stream of incumbents becomes neither so consistently able that it regularly takes on or is delegated more *g*-loaded tasks, thereby changing the usual mix of job duties, nor so wanting in necessary capacities that more complex tasks are shed from the occupation's usual mix of duties. Figure 15.1 suggests that the efficiency of *g*-based sorting of people to jobs is only modest, indicating that only modest levels of efficiency are needed to create a high degree of occupational differentiation.

We are less likely to notice work duties than workers being sorted to jobs, the former on the basis of their demands for *g* and the latter for their possession of it. However, both *g*-related sorting processes are always at work. The military provides a large-scale example of the task resorting process. Some decades ago, the Air Force outlined ways to redistribute job duties within job ladders so that it might better accommodate an unfavorable change in the flow of inductees, specifically, an anticipated drop in the proportion of cognitively able recruits when the draft (compulsory service) was ended in the 1970s. One proposal was to "shred" the easier tasks from various specialties and then pool those tasks to create easier jobs that less able men could perform satisfactorily (Christal 1974).

Purposeful reconfiguration of task sets to better fit the talents or deficits of particular workers can be seen on a small scale every day in workplaces everywhere, because many workers either exceed or fall short of their occupation's usual intellectual demands. Recall that all occupations recruit workers from a broad range of IQ, so some proportion of workers is always likely to be underutilized or overtaxed unless their duties are modified. However, it is only when the proportion of such misfit workers in a job rises over time that the modification of a job's *g* loading becomes the rule for all and not the exception for a few, and hence establishes a new norm for the now-reconfigured occupation.

The evolution of economies from agrarian, to industrial, to post industrial has provided much opportunity for occupational differentiation to proceed, because many new economic tasks have emerged over time. The internet information industry represents only the latest wave. With a greater variety of jobs and more freedom for individuals to pursue them, there is also increasing incentive for both individuals and employers to compete for the most favorable worker-job matches (respectively, individuals seeking better jobs and employers seeking more competent workers). Such competitive pressures will sustain occupational differentiation as long as individuals are free to buy and sell talent in the workplace.

These pressures can also be expected to *increase* occupational differentiation as economies become more complex and put ever-higher premium on information processing skills. Indeed, ours is often referred to as the Information Age. The prospect of greater occupational differentiation, and the greater social inequality it portends, have attracted much attention among social policy makers. Former U.S. Secretary of Labor Robert Reich, although rejecting the notion that people differ in intelligence, has nonetheless described the growing demand for what he calls "symbolic analysts" in clearly *g*-related terms: "The capacity for abstraction — for discovering patterns and meanings — is, of course, the very essence of symbolic analysis" (Reich 1992: 229). Like many others, Reich is concerned that increased occupational differentiation of this sort is leading to increased social bifurcation.

What we see here is the evolution of social structure in *g*-relevant ways, which is the issue raised by the sixth question earlier ("to what extent do a society's members create and reshape the mental test battery that it administers to new generations?"). That is, not only are jobs mental tests, but ones that societies actively construct and reconstruct over time. Reich's concern over the consequences of this ongoing process also illustrates how the relative risks for people along one segment of the IQ distribution can be greatly altered by the social and economic restructuring wrought by persons elsewhere on the IQ distribution. The evolution of work provides an example of high-IQ people changing social life in ways that harm low-IQ persons, but other domains of life provide examples where the effects flow in the opposite direction (Gordon 1997).

3.8. Jobs as a Template for Understanding the Role of g *Elsewhere in Daily Life*

Jobs collectively represent a vast array of tasks, both in content and complexity. While not reflecting the full range of tasks we face in daily life, many of them are substantially the same, from driving to financial planning. There is no reason to believe that *g* and other personal traits play a markedly different role in performing these same tasks in non-job settings, because *g* is a content- and context-free capability. To take just one example, the likelihood of dying in a motor vehicle accident doubles and then triples from IQ 115 to IQ 80 (O'Toole 1990).

To the extent that there is overlap between the task domains of work and daily life, the research on jobs and job performance forecasts what to expect from research on daily life. Namely, we will find that the many "subtests" of life range widely in their *g* loadings; that people "take" somewhat different sets of subtests in their lives; that their own *g* levels affect which sets they take, voluntarily or not; that life tests are even less standardized than jobs, which further camouflages *g*'s impact when taking any single life test; that life's full test battery is large and long, giving *g* more room to express itself in more cumulative life outcomes; and that social life (marriage, neighborhoods, etc.) will frequently be structured substantially along *g* lines.

More specifically, the research on job duties and job performance describes the topography of *g*'s impact that we can expect to find in social life: higher *g* has greater utility in more complex tasks and in instrumental rather than socioemotional ones; *g*'s utility can sometimes swamp the value of all other traits, but many other traits can also enhance performance and compensate somewhat for low *g*; and the practical advantages of higher *g* over a lifetime probably rest as much on the steady tail wind it provides in all life's venues as on its big gusts in a few.

4. Everyday Life as an IQ Test Battery

IQ scores predict a wider range of important social outcomes and they correlate with more personal attributes than perhaps any other psychological trait (Brand 1987; Herrnstein & Murray 1994). The ubiquity and often-considerable size of *g*'s correlations across life's various domains suggest that *g* truly is important in negotiating the corridors of daily life. If this is so, then the common "tests" that we all take in life, outside of school and work, should provide clear evidence of *g*'s role in our everyday lives. Two bodies of evidence are particularly informative in this regard — functional literacy and IQ-specific rates of social pathology. The former addresses the minutiae of daily competence; the latter addresses the cumulative consequences of daily competence or incompetence.

4.1. Functional Literacy: A Literate Society's Minimum Competency Test

If *g* has a pervasive and important influence in daily life, then we should be able to create an IQ test, *de novo*, from the "items" of everyday life. Indeed, it should be difficult to avoid measuring *g* with tests developed specifically to measure everyday competence. As we shall see, at least two sets of researchers, both of whom eschew the notion of intelligence, have nonetheless inadvertently created good tests of *g* from the daily demands of modern life.

The first test is the National Adult Literacy Survey (NALS), which was developed for the U.S. Department of Education by the Educational Testing Service (ETS; Kirsch *et al.* 1993). The second is the Test of Health Functional Literacy of Adults (TOHFLA), developed by health scientists working in large urban hospitals with many indigent patients (Williams *et al.* 1995). Functional literacy refers to competence at using written materials to carry out routine activities in modern life. Both the NALS and TOHFLA were developed in the wake of mounting concern that large segments of the American public are unable to cope with the basic demands of a literate society, for instance, filling out applications for jobs or social services, calculating the cost of a purchase, and understanding instructions for taking medication (see Gottfredson, in press, for additional information about the two tests).

The developers of both tests began with the same assumption, namely, that low literacy consists of deficits in highly specific and largely independent skills in decoding and using the written word. Guided by this hypothesis, the NALS researchers attempted to measure three distinct kinds of literacy by writing test items for three kinds of written material — prose (P), document (D) and quantitative (Q). Both sets of researchers, however, aimed for "high fidelity" tests, that is, they created items that measure real-world tasks in a realistic manner. So, for example, NALS respondents might extract information from news articles, locate information in a bus schedule, and use a calculator to calculate the cost of carpet to cover a room; TOHFLA respondents would read the label on a vial of prescription medicine to say how many times a day the medicine should be taken and how many times the prescription can be refilled. Sample items for the NALS are listed in Figure 15.4 and for the TOHFLA in Table 15.7. The

Proficiency Level	Sample Items[a]	Information-Processing Demands[b]
0	69 Sign your name (D) 191 Total a bank deposit entry (Q) 224 Underline sentence explaining action stated in short article (P)	*Level 1* (NALS ≤225) tasks require identifying or matching single pieces of information or performing a single, simple, specified arithmetic operation (like addition) in contexts where there is little or no distracting information. (Includes about 14% of white and 38% of black adults aged 16 and over.[c])
225	232 Locate intersection on a street map (D) 250 Locate two features of information in sports article (P) 270 Calculate total costs of purchase from an order form (Q)	*Level 2* (NALS 226-275) tasks introduce distractors, more varied information, and the need for low-level inferences or to integrate two or more pieces of information. Information tends to be easily identifiable, despite the presence of distractors, and numeric operations are easily determined from the format of the material provided (say, an order form). (Includes about 25% of white and 37% of black adults.)
275	280 Write a brief letter explaining error made on a credit card bill (P) 308 Using calculator, determine the discount from an oil bill if paid within 10 days (Q) 323 Enter information given into an automobile maintenance record form (D)	*Level 3* (NALS 276-325) tasks require integrating multiple pieces of information from one or more documents, which themselves may be complex and contain much irrelevant information. However, the matches to be made between information and text tend to be literal or synonymous, and correct information is not located near incorrect information. (Includes about 36% of white and 21% of black adults.)
325	328 State in writing an argument made in lengthy newspaper article (P) 348 Use bus schedule to determine appropriate bus for given set of conditions (D) 368 Using eligibility pamphlet, calculate the yearly amount a couple would receive for basic supplemental security income (Q)	*Level 4* (NALS 326-375) tasks require more inferences, multiple-feature matches, integration and synthesis of information from complex passages or documents, and use of multiple sequential operations. (Includes about 21% of white and 4% of black adults.)
375 500	387 Using table comparing credit cards, identify the two categories used and write two differences between them (D) 410 Summarize from text two ways lawyers may challenge prospective jurors (P) 421 Using calculator, determine the total cost of carpet to cover a room (Q)	*Level 5* (NALS 376-500) tasks require the application of specialized background knowledge, disembedding the features of a problem from text, and drawing high-level inferences from highly complex text with multiple distractors. (Includes about 4% of white and less than 0.5% of black adults.)

Figure 15.4: Sample items and information-processing demands at five levels of NALS literacy.

Sources:
[a] Brown *et al.* (1996: 10). P = prose scale, D = documents scale, Q = quantitative scale.
[b] Brown *et al.* (1996: 11).
[c] Kirsch *et al.* (1993, Table 1.1A). Percentages are for Prose Scale.

Table 15.7: Percentage and relative risk (odds ratios) of patients incorrectly answering test items on the TOFHLA, by level of health literacy.

Test item		Literacy level		
		Inadequate	Marginal	Adequate
Numeracy items				
How to take medication on an empty stomach	%	65.3	52.1	23.9
	OR	**6.0**	3.2	1.0
How to take medication four times a day	%	23.6	9.4	4.5
	OR	**6.6**	2.2	1.0
How many times a prescription can be refilled	%	42.0	24.7	9.6
	OR	**6.8**	3.1	1.0
How to determine financial eligibility	%	74.3	49.0	31.5
	OR	**9.0**	3.0	1.0
When next appointment is scheduled	%	39.6	12.7	4.7
	OR	**13.5**	3.0	1.0
How many pills of a prescription should be taken	%	69.9	33.7	13.0
	OR	**15.6**	3.4	1.0
Prose Cloze passages				
Instructions for preparing for upper gastrointestinal tract radiographic procedure	%	57.2	11.9	3.6
	OR	**36.2**	3.7	1.0
Rights and Responsibilities section of Medicaid application	%	81.1	31.0	7.3
	OR	**54.3**	5.7	1.0
Standard informed consent document	%	95.1	72.1	21.8
	OR	**70.5**	9.4	1.0

Source of percentages: Williams *et al.* (1995, Table 3). Reprinted with permission from the American Medical Association.

tests are thus meant to sample common, practical tasks that are not tied to any particular knowledge base or special expertise.

Both tests have been individually administered to large samples in the United States, the NALS to a nationally representative sample of 26,091 adults aged 16 and older, and the 20-minute TOHFLA first being administered to 2,659 patients in two large urban hospitals. (Because the NALS was meant to provide a snapshot of the entire adult population, and not to calculate scores for individuals, no respondent took the entire, very long survey).

Although most NALS and TOHFLA tasks might seem relatively simple, large proportions of the American population have difficulty performing them correctly. As shown in Figure 15.4, fully 40% of whites and almost twice that proportion of blacks routinely function at only Levels 1 or 2, which NALS researchers have described as inadequate for "competing successfully in a global economy and exercising fully the rights and responsibilities of citizenship" (Baldwin *et al.* 1995: 16). The TOHFLA survey of urban hospital patients (Williams *et al.* 1995) classified 43% of patients as having either "inadequate" or "marginal" health literacy. Among the 26% of patients having inadequate literacy, Table 15.7 shows that two-thirds did not understand instructions on how to take prescription medication on an empty stomach or how many pills to take. Error rates for the two items were much lower for patients judged to have "adequate" literacy, respectively, 24% and 13%.

In a separate study of patients with chronic illnesses such as diabetes and hypertension, generally only about half of those with inadequate literacy knew even the most basic facts about their disease or how to cope with it, despite presumably having received instruction (Williams *et al.* 1998). Table 15.8 shows, for instance, that among diabetic patients with inadequate literacy, 62% did not know that they need to eat some form of sugar if they suddenly get sweaty, nervous or shaky (a signal that their blood sugar has dropped too low — also a fact that only about half knew).

Such low levels of functional competence were no surprise to the NALS and TOHFLA researchers. Rather, what greatly surprised both sets of researchers was to discover that low literacy actually represents a global poverty of higher order information-processing capabilities — the ability to learn, understand and solve problems. NALS analysts concluded that adult literacy reflects "problem solving", "complex information processing", and "verbal comprehension and reasoning, or the ability to understand, analyze, interpret, and evaluate written information and apply fundamental principles and concepts" (Venezky *et al.* 1987: 25, 28; Baldwin *et al.* 1995: xv). Health literacy researchers concluded that health literacy is the "ability to acquire new information and complete complex cognitive tasks", and that low literacy reflects "limited problem-solving abilities" (Baker *et al.* 1998: 795–797).

The health scientists also rediscovered what reading researchers had learned decades earlier in "work literacy" research for the Army (Sticht 1975): "literacy" reflects comprehension of both the spoken and written word. People with low literacy understand the spoken word no better than they do the written word. In other words, differences in functional literacy have nothing to do with reading and writing per se. Rather, "literacy" concerns information processing of any sort in either modality. The written word just provides a handy means of gauging this cross-modality competence.

The juxtaposition of the two sets of literacy studies is compelling because the research teams worked in different fields addressing different institutional needs, their tests differed greatly in manifest content and psychometric sophistication, and they were administered to quite different populations and in different contexts, and yet their results led the researchers to the same unexpected conclusion. As noted, they now describe

Table 15.8: Percentage and relative risk (odds ratios) of patients incorrectly answering selected questions about their chronic disease, by level of health literacy.

Patient does not know that		**Literacy level**		
		Inadequate	**Marginal**	**Adequate**
		Diabetes		
If you feel thirsty, tired, and weak, it usually means your blood glucose level is high	%	40.0	30.8	25.5
	OR	**2.0**	**1.3**	**1.0**
When you exercise, your blood glucose level goes down	%	60.0	53.8	35.3
	OR	**2.7**	**2.1**	**1.0**
If you suddenly get sweaty, nervous, and shaky, you should eat some form of sugar	%	62.0	46.1	27.4
	OR	**4.3**	**2.3**	**1.0**
Normal blood glucose level is between 3.8–7.7 mmol/L (70–140 mg/dL)	%	42.0	23.1	11.8
	OR	**5.4**	**2.2**	**1.0**
If you feel shaky, sweaty, and hungry, it usually means your blood glucose level is low	%	50.0	15.4	5.9
	OR	**15.9**	**2.9**	**1.0**
		Hypertension		
Canned vegetables are high in salt	%	36.7	24.0	19.2
	OR	**2.4**	**1.1**	**1.0**
Exercise lowers blood pressure	%	59.7	56.0	32.0
	OR	**3.1**	**2.7**	**1.0**
Blood pressure of 130/80 mm Hg is normal	%	58.2	32.0	28.8
	OR	**3.4**	**1.2**	**1.0**
Losing weight lowers blood pressure	%	33.2	16.0	8.3
	OR	**5.5**	**2.1**	**1.0**
Blood pressure of 160/100 mm Hg is high	%	44.9	30.0	8.3
	OR	**9.0**	**4.7**	**1.0**

Source of percentages: Williams *et al.* (1998, Tables 2 and 3).

literacy in the very language of critical thinking and information processing that researchers use to describe the manifestations of *g*.

We can therefore safely infer that both literacy tests are highly *g* loaded. But how *g* loaded are they? High enough to essentially constitute IQ tests, at least for non-immigrant populations? The answer is not clear for the TOHFLA, although different health literacy tests do behave like different IQ tests in certain ways: specifically, various health literacy scales correlate 0.7–0.9 with each other and with tests of known high *g* loading (Davis *et al.* 1998), such as the Wide Range Achievement Test (WRAT), even in samples that are highly restricted in range on ability.

I am not aware of any correlations of the NALS with IQ scores, but NALS technical reports provide other, more compelling evidence that the NALS is a reasonably good test of *g*: namely: (a) the NALS measures only a single factor; and (b) that factor is the ability to process complex information. The early NALS reports had scores on the three literacy scales correlating about 0.5 with each other, but then errors in calculation were discovered. When recalculated correctly, the three scales intercorrelated over 0.9, before correction for attenuation. Not surprisingly, the three separate scales produce virtually identical results — the same findings "in triplicate, as it were" (Reder 1998: 39, 44) — despite clear differences in item content. In short, the three different NALS scales measure the same general factor and virtually nothing else.

NALS researchers also carried out a lengthy analysis of test results that is rarely performed but which is invaluable for understanding the construct that a test is actually measuring — a detailed task analysis (separately for each of the three scales) to determine which of the items' attributes accounted for their differences in difficulty. The task analyses identified the same sources of item difficulty for all three scales, which the researchers labeled "processing complexity". Figure 15.4 summarizes the differences in processing complexity across the five NALS levels. They clearly represent differences in the complexity of information processing and problem solving, which, again, is the very language of *g*. In other words, NALS difficulty levels represent differences in demands for the information-processing skills that *g* embodies. They do not reflect readability per se (Kirsch *et al.* 1994), which supports the inference that functional literacy, as measured in large (non-immigrant) American samples, is mostly *g*.

We have just seen two examples where life yields a highly *g*-loaded mental test when researchers attempted to measure consequential differences in everyday competence, in this case, with written materials. But which domains of life activity might offer up such IQ tests, and why? Is literacy the exception? Probably not, but everyday literacy may be the prototype for where to find them. First, literacy tests sample highly instrumental tasks rather than socioemotional ones, that is, tasks primarily to the left side of Figure 15.2. The personnel selection research reviewed earlier suggests that instrumental activities depend more on *g* and less on personality traits than do interpersonal activities. Were we to build a life test from daily tasks of a more socioemotional nature, such as getting along with one's neighbors or influencing others, we would probably end up with a test that taps favorable personality traits more and *g* less than do either the NALS or the TOHFLA.

Second, literacy tasks constitute a life test that we are all obliged to take. They are among the common subtests in life, not only because we are all exposed to demands to use written materials, but also because they represent inescapable, ubiquitous self-maintenance tasks in any literate society. Adults who cannot perform the simpler tasks in the NALS scales in effect fail a minimum competency test for modern life. Ethnographic studies of mildly retarded adults poignantly describe how they often attempt to hide their inability to read, fill out job applications, and make change in order to avoid being stigmatized as incompetent and "retarded". But whether they succeed in hiding it or not, their low literacy renders them unable to live independent lives without considerable assistance (Koegel & Edgerton 1984).

Few functional literacy tasks may be discretionary if individuals want to protect their health and welfare over the long-run. It may matter little whether one occasionally fails to adequately describe the problems with an appliance needing repair, select the best values in a supermarket, capitalize on opportunities for cheaper goods and services, identify available social services, understand public issues affecting one's welfare, take medication properly, or recognize the symptoms of one's chronic illness that require immediate action, such as an imminent asthma attack or insulin reaction. Repeated such failure, however, especially across multiple arenas of life, can threaten one's health, disposable income and overall quality of life. Research on health literacy indicates, for example, that low-literacy individuals experience much higher health costs, poorer health and more frequent hospitalization (National Work Group on Literacy and Health 1998).

Moreover, the ability to master moderate- to high-complexity literacy tasks — for instance, to use bus and airline schedules, understand news articles and hospital consent forms, distinguish the merits of different employee benefits packages or credit cards, and recognize when and how to respond to the symptoms of one's chronic illness — enables one to participate more fully in civic and economic life, better exploit one's opportunities, waste less time and money, avoid accidents, better maintain one's health and simply live a less error-plagued daily existence. As functional literacy researchers have summed it up, "literacy is a currency not only in our schools, but in our society as well; and, as with money, it is better to have more literacy than less" (Kirsch & Jungeblut 1990: v–12). As health literacy researchers point out, it can also be a matter of life and death. Referring to the complicated new treatment regimens for heart attack victims, Baker *et al.* (1998: 791) warn that a "patient's ability to learn this regimen and follow it correctly will determine a trajectory toward recovery or a downward path to recurrent myocardial infarction, disability, and death".

Health self-care clearly constitutes a common test that none of us can afford to spurn. It is not entirely cognitive, of course (how many of us fail to act on our knowledge of proper diet and exercise?), but health researchers are concerned that the motivational component of patient "compliance" has been overestimated relative to its cognitive demands. Other realms of life also impose equally common tests on us — for instance, being a friend, neighbor, co-worker and law-abiding citizen — but, as suggested earlier, many of these are more socioemotional or characterological than is functional literacy. They can thus be expected to be less *g* loaded. On the other hand, equally instrumental tasks in some arenas of life are more discretionary and therefore do not constitute common life tests — many avocations, for instance. Because they are discretionary, fewer people will choose to undertake them. This means, in turn, that differences in quality of performance will depend more heavily on degree of exposure and length of practice, and thus that the utility of *g* will be somewhat camouflaged by differences in exposure and practice. That is, discretionary activities may or may not be fundamentally less *g* loaded than is functional literacy, but their dependence on *g* will be harder to ascertain because the "test takers" will be unrepresentative and highly self-selected.

4.1. "Making It": A Free Society's Decathlon

The earlier discussion of *g* and jobs suggested that there is a nexus of good life outcomes — socioeconomic outcomes, at least — that is associated with higher *g*. The behavioral genetic studies cited earlier reveal the association to be not only phenotypic, but also genetic to some degree. Figure 15.5 encapsulates that nexus of positive outcomes by arraying the levels of training and job potential that are typical for individuals at each of five broad segments of the IQ distribution, from the "high-risk" zone (IQ 75 and below) to the "yours to lose" zone (above IQ 125). Estimated IQ equivalents for the five NALS levels are indicated in the same figure. There are many factors besides *g* that affect success in education, training and employment, but the probability of success steadily improves at successively higher levels of IQ. These outcomes reflect the decathlon of socioeconomic life in a free society — citizens competing with one another in a long series of events to gain, and keep, a congenial place on the social ladder. The competitions are not entirely fair and open, of course, but they are free and open enough for competence — and hence *g* — to make a considerable difference in who succeeds. "Making it" socioeconomically does not represent a person's moral worth, but it does represent a common, valued pursuit in American life.

But what about the flip side of socioeconomic success — dropping out of high school, going to jail, bearing illegitimate children and other negative outcomes? This troubling nexus of social pathology, one that concerns social policy makers so, is part of the same decathlon of adult life in a free society as are the positive outcomes. One difference between the contests for obtaining good outcomes and avoiding bad ones, however, is that the latter often function as pass-fail tests: you either have or have not gone to prison, borne a child out of wedlock or gone on welfare. Failing these tests can be highly stigmatizing as well as debilitating, so they are tests that many people are loathe to fail or to have family members fail.

People of all IQ levels fail these tests, of course, and the role that *g* plays in the nexus of social pathology is still little understood. It is clear, however, that the probability of failure rises steeply toward lower levels of the IQ continuum. Moreover, IQ often predicts such outcomes at least as well as do the social class variables that social scientists had long assumed to account for why some people succumb and others do not (Herrnstein & Murray 1994; Gordon 1997).

Tables 15.9 and 15.10 illustrate how the relative risk of various unfavorable social outcomes rises steadily and substantially at each of 5 successively lower ranges of IQ, from above IQ 125 (about the 95th percentile) to below IQ 75 (about the 5th percentile). The data in Table 15.9 are based on young white American adults whose IQ scores were estimated from the Armed Forces Qualifying Test (AFQT), which is a reasonably good measure of *g* (Ree *et al.* 1998/1999; Herrnstein & Murray 1994, app. 3); Table 15.10 is based on NALS results for American white adults aged 16 and older, which results have also been translated into the IQ metric. The five score ranges overlap but are not identical across the two tests, with the five NALS levels in Table 15.10 for older adults representing somewhat higher levels of IQ than do the five levels in Table 15.9 for young white adults.

The two tables nonetheless reveal the same two trends. First, looking across the columns of odds ratios, relative risk at least doubles at each successively lower range of

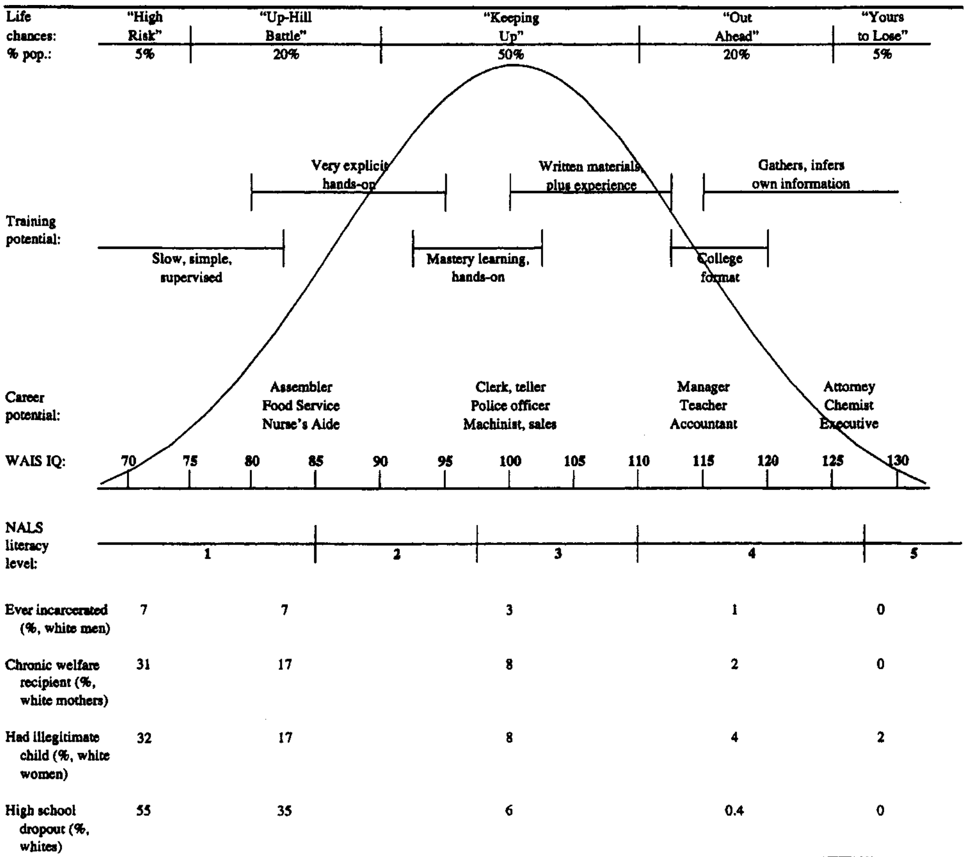

Figure 15.5: Career chances along different segments of the IQ continuum.

Source: Adapted from Figure 3 in Gottfredson, L. S. (1997). Why *g* matters: The complexity of everyday life. *Intelligence*, *24*, 79–132, with permission from Elsevier Science.

[a] WPT = Wonderlic Personnel Test.

[b] NALS = National Adult Literacy Survey. See Gottfredson (1997) for translation of NALS scores into IQ equivalents.

[c] See Gottfredson (1997) for calculation of percentile.

Table 15.9: Relative risk of bad outcomes associated with lower IQ: Prevalence (%) and Odds Ratios (OR) for young white adults.

Outcome		IQ level				
		≥75	76–90	91–110	111–125	≥125
Bell Curve data: General population[a]						
Out of labor force	%	22	19	15	14	10
1 + mo/yr (men)	OR	**1.6**	**1.3**	**1.0**	**0.9**	**0.6**
Unemployed	%	12	10	7	7	2
1 + mo/yr (men)	OR	**1.8**	**1.5**	**1.0**	**1.0**	**0.3**
Ever in carcerated (men)	%	[7][b]	7	3	1	0
	OR	[2.4]	**2.4**	**1.0**	**0.3**	**0.1**[c]
Chronic welfare recipient	%	31	17	8	2	0
(women)	OR	**5.2**	**2.4**	**1.0**	**0.2**	**0.05**[d]
Had illegitimate children	%	32	17	8	4	2
(women)	OR	**5.4**	**2.4**	**1.0**	**0.5**	**0.2**
Lives in poverty as an	%	30	16	6	3	2
adult	OR	**6.7**	**3.0**	**1.0**	**0.5**	**0.3**
Went on welfare after 1st	%	55	21	12	4	1
child (women)	OR	**9.0**	**2.0**	**1.0**	**0.3**	**0.1**
High school drop out	%	55	35	6	0.4	0
	OR	**19.0**	**8.4**	**1.0**	**0.1**	**0**
Bell Curve data: Sibling pairs[e]						
Not working in professional	%	100	99	98	92	77
job	OR	**hi**[f]	**2.0**	**1.0**	**0.2**	**0.1**
Not a college graduate	%	100	97	81	50	18
	OR	**hi**[f]	**7.6**	**1.0**	**0.2**	**0.1**

[a] *Source of percentages:* Herrnstein & Murray (1994, pp. 158, 163, 247 194, 180, 132, 194 & 146 respectively).
[b] See text for explanation.
[c] Assuming that % rounded to zero from 0.4, which yields odds of 0.004 and an odds ratio of 0.13.
[d] Assuming that % rounded to zero from 0.4, which yields odds of 0.004 and an odds ratio of 0.046.
[e] Source of percentages: Murray (1997b).
[f] OR can not be calculated because the odds of 100 : 0 (its numerator) cannot be calculated.
Table from Gottfredson (in press) and reprinted with permission from Lawrence Erlbaum Associates.

Table 15.10: Economic outcomes at different levels of NALS literacy: Whites aged 16 and over (% and odds ratios).

Outcome		**Prose Literacy Level**				
		1 (≤225)	**2** (226–275)	**3** (276–325)	**4** (326–375)	**5** (376–500)
Employed only part-time	%	70	57	46	36	28
	OR	2.7	1.6	1.0	0.7	0.5
Out of labor force	%	52	35	25	17	11
	OR	3.2	1.6	1.0	0.6	0.4
Uses food stamps	%	17	13	6	3	1
	OR	3.2	2.3	1.0	0.5	0.2
Lives in poverty	%	43	23	12	8	4
	OR	5.5	2.2	1.0	0.6	0.3
Employed *not* as professional or manager	%	95	88	77	54	30
	OR	5.6	2.2	1.0	0.4	0.1

Source of percentages: Kirsch *et al.* (1993, Figures 2.5, 2.6, 2.7, 2.9 & 2.10).
Table reprinted from Gottfredson (in press) and reprinted with permission of Lawrence Erlbaum Associates.

IQ for the more cumulative outcomes, that is, for all but the two employment outcomes (not looking for work or being unemployed if looking, respectively). For example, compared to women of average IQ (IQ 91–110), women of somewhat below average IQ (IQ 76–90) are four times as likely to bear an illegitimate child (17% vs. 4%; ORs of 2.4 vs. 0.5, respectively) and eight times as likely to become chronic welfare recipients (17% vs. 2%; ORs of 2.4 vs. 0.2, respectively). The relative risk for women of low IQ (IQ 75 and below) is doubled yet again (ORs over 5.0). On the other hand, the relative risk of either social problem drops to near zero for high-IQ women.

Second, comparing these trends across different outcomes, we see that the risk gradients are steeper (shift more dramatically) for the more cumulative, pass-fail outcomes (chronic welfare use, living below the poverty line, dropping out of high school) than for the more episodic and more easily reversed outcomes (out of the labor force or unemployed for a month during the year). For instance, whereas odds ratios for the latter rise from under 0.6 to 1.6 when down up the IQ distribution, the ratios rise from under 0.3 to over 5.0 for poverty and welfare use. That the latter gradients are steeper is consistent with the hypothesis that *g* exerts its major effects on life outcomes largely by consistently tilting the odds of success and failure in the smaller events that eventuate in the more consequential outcomes. The results in Table 15.10 also support this thesis. Although they are based on a different test of ability (the NALS) in a much broader age segment of the population, they show the same pattern.

The heated debate over *The Bell Curve* (Herrnstein & Murray 1994) revealed, once again, that many if not most policy researchers assume that differences in intelligence do not play much role in who exhibits the behaviors that policy makers seek to reduce. They nonetheless seem willing to attribute causal importance to what are actually good surrogates for *g* — for instance, literacy and "basic skills" — if they attribute them to socioeconomic disadvantage rather than to *g*. To illustrate, a well-received 1988 report for the Ford Foundation (Berlin & Sum 1988) "explores the basic-skills crisis, presenting evidence that inadequate skills are an underlying cause of poverty and economic dependency" (p. 2). What was their measure of "basic skills?" The highly *g*-loaded AFQT. The report's authors concluded from their data that poverty is rooted substantially in skills deficits, but they minimize the implications of this by mistakenly conceiving "basic skills" as a collection of highly specific, discrete, remediable skills rather than a suite of relatively stable, highly general ones. In fact, as the bottom panel of Table 15.9 shows, risk gradients for *siblings growing up in the same household* parallel those in the general population for similar outcomes (Tables 15.9 and 15.10). This provides additional evidence that *g* plays a strong role *independent* of one's family circumstances.

How *g* plays a role in social pathology is unclear, as noted earlier. We might gain more insight, however, by treating each pathology as a long test battery or *career*. Indeed, we routinely talk about criminal careers in the same way we talk about educational careers — as a long stream of behavior that can push one over certain social thresholds, whether good ones (performing sufficiently well over the years to graduate from high school, college or graduate school) or bad ones (committing more numerous and more serious crimes that eventually lead to a first arrest, then a longer arrest record, a conviction and imprisonment one or more times). Disabling sexual careers can be conceptualized in the same manner — as a cumulating series of small mistakes and misjudgments that can precipitate life-altering events (illegitimate births, HIV infection).

This is essentially the same process we saw in Figure 15.3, which compared the careers of New Standards Men to those of a control group. At IQ 80–85, the New Standards Men are below average but still above the threshold for mild retardation. They can thus be compared to the second-to-lowest IQ range in Figure 15.5 (IQ 76–90), labeled "up-hill battle" (also column 2 in Table 15.9). The control men in the military study are probably somewhat above average in IQ (and therefore higher in IQ than the comparison group in Table 15.9), because federal law forbids the military to induct men from the lowest 10% of the ability distribution (below about IQ 80). The risk ratios that led to the majority of New Standards Men to "fail" (be discharged from the military) within 18 months on the job, like those for failing at each prior step along that road, generally hovered between 2.0 and 4.0 (Table 15.6).

These are similar to the risk ratios seen in Table 15.9 for social pathology among young white adults in the "up-hill battle" IQ range: their ratios generally range between approximately 2.0 and 3.0. (That the NSM odds ratios are somewhat larger than for the "up-hill battle" group may be due to the former's control group probably being somewhat brighter than the latter's.) No one would say that these levels of relative risk for social pathology are small in human terms but, as we saw, differences of this magnitude are often hastily dismissed as inconsequential when social scientists examine the role of low *g* in the individual events culminating in employment outcomes. Such haste is unwarranted for any sphere of life.

It is also useful to note that the predominance of failure over success among Project 100,000 men occurred despite the considerable help that they apparently received. Help tends to flow down the IQ continuum in any society, whether from family members or social service agencies, because that is one way that societies soften the consequences of low *g* for their least able members. The levels of help that the New Standards Men received, however, may not be routinely available in many domains in life. Help is prohibited, of course, on tests of aptitude and achievement, and it is probably discouraged whenever individuals and institutions seek "honest" signals of competence before entering long-term commitments (e.g. hiring, marriage). The point here is simply that "help" constitutes one of the common non-standard conditions under which we take life's tests, and that understanding such "non-standard" conditions is key to charting *g*'s gradients of effect in particular times and places. The more help that is routinely given to the least able, the less steep the IQ risk gradients will be, all else equal.

Turning from understanding the impact of low *g* to concerns over ameliorating it, we could predict that help would have to be as ubiquitous as are the risks created by low *g* — an impossible and intrusive enterprise — in order to maintain equally favorable life trajectories for low-IQ individuals. Flattening all risk gradients is not an option, but moderating them might be.

5. Conclusion

Understanding the role of *g* in the lives of individuals and societies requires that we psychometrically analyze the components of everyday life. Just as psychologists have task analyzed paid employment, so might researchers open up the psychometric black box of life's other daily demands. This strategy promises to speed our understanding of *g*'s gradients of effect in many arenas of social life, as well as help identify the personal and external factors that can steepen or flatten those risk gradients.

There are many other areas of life yet to be plumbed with the psychometric tools to which Jensen has pointed us. At the individual level, they include interpersonal relations, parenting and family life, health and safety, good citizenship, civic engagement and aging. As *g*-based gradients of risk play out at the individual level, they yield higher-order effects that are also ripe for study: *g*-based residential and social segregation; patterns of cooperation and competition, envy and respect, compassion and contempt; political tensions between populations that differ noticeably in *g*; evolution of social policy, law and mores in response to *g*-based social inequalities; the special difficulties of stemming preventable epidemics in some populations; and much more.

Most broadly, we might ask "what kind of mental test battery has modern life become?" Are developed societies ordering their activities and their members increasingly according to distinctions in *g*? If so, can — or should — the trend be reversed, accelerated, or ignored? If so, how might citizens in the "high-risk" and "uphill battle" ranges of IQ (below IQ 90) be helped to weather the new challenges?

References

Arvey, R. D. (1986). General ability in employment: A discussion. *Journal of Vocational Behavior, 29* (3), 415–420.

Baker, D. W., Parker, R. M., Williams, M. V., & Clark, W. S. (1998). Health literacy and the risk of hospital admission. *Journal of General Internal Medicine, 13*, 791–798.

Baldwin, J., Kirsch, I. S., Rock, D., & Yamamoto, K. (1995). *The literacy proficiencies of GED examinees: Results from the GED-NALS comparison study.* Washington, D.C.: American Council on Education and Educational Testing.

Behrman, J. R., Hrubec, Z., Taubman, P., & Wales, T. (1980). *Socioeconomic success: A study of the effects of genetic endowments, family environment, and schooling.* New York: North-Holland Publishing Co.

Berlin, G., & Sum, A. (1988). *Toward a more perfect union: Basic skills, poor families, and our economic future.* (Occasional paper 3, Project on Social Welfare and the American Future). New York: Ford Foundation.

Bouchard, T. J. Jr. (1998). Genetic and environmental influences on adult intelligence and special mental abilities. *Human Biology, 70* (2), 257–279.

Bowles, S., & Gintis, H. (1972/1973). IQ in the U.S. class structure. *Social Policy, 3* (4 & 5), 65–96.

Brand, C. (1987). The importance of general intelligence. In: S. Modgil, & C. Modgil (Eds), *Arthur Jensen: Consensus and controversy* (pp. 251–265). New York: Falmer Press.

Brown, H., Prisuta, R., Jacobs, B., & Campbell, A. (1996). *Literacy of older adults in America: Results from the National Adult Literacy Survey.* Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Canter, R. R. (1956). Intelligence and the social status of occupations. *Personnel Guidance Journal, 34*, 258–260.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analysis studies.* New York: Cambridge University Press.

Christal, R. E. (1974). *The United States Air Force Occupational Research Project.* Lackland AFB, TX, Air Force Human Resources laboratory (AFSC). (NTIS No. AD774 574).

Collins, R. (1979). *The credential society: An historical sociology of education and stratification.* New York: Academic Press.

Davis, T. C., Michielutte, R., Askov, E. N., Williams, M. V., & Weiss, B. D. (1998). Practical assessment of adult literacy in health care. *Health Education & Behavior, 25* (5), 613–624.

Duncan, O. D., Featherman, D. L., & Duncan, B. (1972). *Socioeconomic background and achievement.* New York: Seminar Press.

Gerstman, B. B. (1998). *Epidemiology kept simple: An introduction to classic and modern epidemiology.* New York: Wiley.

Gordon, R. A. (1997). Everyday life as an intelligence test: Effects of intelligence and intelligence context. *Intelligence, 24* (1) 203–320.

Gottfredson, L. S. (1984). *The role of intelligence and education in the division of labor.* (Report No. 355). Baltimore: Johns Hopkins University, Center for Social Organization of Schools.

Gottfredson, L. S. (1985). Education as a valid but fallible signal of worker quality: Reorienting an old debate about the functional basis of the occupational hierarchy. In: A. C. Kerckhoff

(Ed.), *Research in sociology of education and socialization* (Vol. 5, pp. 119–165). Greenwich, CT: JAI Press.

Gottfredson, L. S. (1986). Occupational Aptitude Patterns (OAP) Map: Development and implications for a theory of job aptitude requirements (Monograph). *Journal of Vocational Behavior, 29*, 254–291.

Gottfredson, L. S. (1997). Why *g* matters: The complexity of everyday life. *Intelligence, 24* (1), 79–132.

Gottfredson, L. S. (in press). *g*: Highly general and highly practical. In: R. J. Sternberg, & E. L. Grigorenko (Eds), *The general intelligence factor: How general is it?* Mahwah, NJ: Erlbaum.

Herrnstein, R. J., & Murray, C. (1994). *The bell curve: Intelligence and class structure in American life*. New York: Free Press.

Hodge, R. W., Treiman, D. J., & Rossi, P. H. (1966). A comparative study of occupational prestige (pp. 309–334). In: R. Bendix, & S. M. Lipset (Eds), *Class, status, and power: Social stratification in comparative perspective* (2nd ed.). New York: Free Press.

Hunter, J. E., & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin, 96* (1), 72–98.

Hunter, J. E., & Schmidt, F. L. (1996). Intelligence and job performance: Economic and social implications. *Psychology, Public Policy, and Law, 2* (3/4) 447–472.

Jencks, C., Bartlett, S., Corcoran, M., Crouse, J., Eaglesfield, D., Jackson, G., McClelland, K., Mueser, P., Olneck, M., Schwartz, J., Ward, S., & Williams, J. (1979). *Who gets ahead? The determinants of economic success in America*. New York: Basic Books.

Jencks, C., Smith, M., Acland, H., Bane, M. J., Cohen, D., Gintis, H., Heyns, B., & Michelson, S. (1972). *Inequality: A reassessment of the effect of family and schooling in America*. New York: Basic Books.

Jensen, A. R. (1998). *The g factor: The science of mental ability*. Westport, CT: Praeger.

Kirsch, I. S., & Jungeblut, A. (Eds.) (1990). *Literacy: Profiles of America's young adults*. Princeton: Educational Testing Service.

Kirsch, I. S., Jungeblut, A., Jenkins, L., & Kolstad, A. (1993). *Adult literacy in America: A first look at the results of the National Adult Literacy Survey*. Princeton, NJ: Educational Testing Service.

Kirsch, I. S., Jungeblut, A., & Mosenthal, P. B. (1994). *Moving towards the measurement of adult literacy*. Paper presented at the March NCES meeting, Washington, D.C..

Koegel, P., & Edgerton, R. B. (1984). Black six hour retarded children as young adults. In: R. B. Edgerton (Ed.), *Lives in progress: Mildly retarded adults in a large city* (pp. 145–171). Washington, D.C.: American Association on Mental Deficiency.

Laurence, J. H., & Ramsberger, P. F. (1991). *Low-aptitude men in the military: Who profits, who pays?* New York: Praeger.

Lichtenstein, P., & Pedersen, N. L. (1997). Does genetic variance for cognitive abilities account for genetic variance in educational achievement and occupational status? A study of twins reared apart and twins reared together. *Social Biology, 44* (1–2), 77–90.

Miller, A. R., Treiman, D. J., Cain, P. S., & Roos, P. A. (Eds) (1980). *Work, jobs, and occupations: A critical review of the Dictionary of Occupational Titles*. Washington, D.C.: National Academy Press.

Murray, C. (1997a). Brains, rather than family background, determine how well our children will do in later life, says author of The Bell Curve Charles Murray. *Sunday London Times*. (May 25).

Murray, C. (1997b). IQ and economic success. *The Public Interest*, (128), 21–35.

National Work Group on Literacy and Health (1998). Communicating with patients who have limited literacy skills: Report of the National Work Group on Literacy and Health. *The Journal of Family Practice, 46* (2), 168–176.
Olneck, M. R. (1977). On the use of sibling data to estimate the effects of family background, cognitive skills, and schooling. In: P. Taubman (Ed.), *Kinometrics: Determinants of socioeconomic success within and between families* (pp. 125–162). New York: North-Holland.
O'Toole, B. J. (1990). Intelligence and behavior and motor vehicle accident mortality. *Accident analysis and prevention, 22*, 211–221.
Plomin, R., & Bergeman, C. S. (1991). The nature of nurture: Genetic influence on "environmental" measures. *Behavioral and Brain Sciences, 14*, 373–427.
Plomin, R., DeFries, J. C., McClearn, G. E., & McGuffin, P. (2000). *Behavioral genetics* (4th ed.). New York: Worth Publishers.
Reder, S. (1998). Dimensionality and construct validity of the NALS assessment. In: M. C. Smith (Ed.), *Literacy for the twenty-first century* (pp. 37–57). Westport, CT: Praeger.
Ree, M. J., Carretta, T. R., & Doub, T. (1998/1999). A test of three models of the role of *g* and prior job knowledge in the acquisition of subsequent job knowledge. *Training Research Journal, 4*, 1–16.
Reich, R. (1992). *The work of nations*. New York: Vintage Books.
Rowe, D. C., Vesterdal, W. J., & Rodgers, J. L. (1998). Herrnstein's syllogism: Genetic and shared environmental influences on IQ, education, and income. *Intelligence, 26* (4), 405–423.
Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin, 124* (2), 262–274.
Schmidt, F. L., & Hunter, J. E. (2000). Select on intelligence. In: E. A. Locke (Ed.), *The Blackwell handbook of principles of organizational behavior* (pp. 3–14). Malden, MA: Blackwell Publishers.
Sewell, W. H., & Hauser, R. M. (1975). *Education, occupation, and earnings: Achievement in the early career.* New York: Academic Press.
Spaeth, J. L. (1979). Vertical differentiation among occupations. *American Sociological Review, 44*, 746–762.
Sternberg, R. J. (1997). *Successful intelligence: How practical and creative intelligence determine success in life*. New York: Penguin Putnam.
Sternberg, R. J., Forsythe, G. B., Hedlund, J., Horvath, J. A., Wagner, R. K., Williams, W. M., Snook, S. A., & Grigorenko, E. L. (2000). *Practical intelligence in everyday life*. New York: Cambridge University Press.
Stewart, N. (1947). Relationship between military occupational specialty and Army General Classification Test standard score. *Educational and Psychological Measurement, 7*, 677–693.
Sticht, T. (Ed.) (1975). *Reading for working: A functional literacy anthology.* Alexandria, VA: Human Resources Research Organization.
Sticht, T. G., Armstrong, W. B., Hickey, D. T., & Caylor, J. S. (1987). *Cast-off youth: Policy and training methods from the military experience*. New York: Praeger.
Taubman, P. (Ed.) (1977). *Kinometrics: Determinants of socioeconomic success within and between families*. New York: North-Holland Publishing Co.
U.S. Department of Labor (1970). *Manual for the USTES general aptitude test battery.* Washington, D.C.: U. S. Government Printing Office.
Venezky, R. L., Kaestle, C. F., & Sum, A. M. (1987). *The subtle danger: Reflections on the literacy abilities of America's young adults*. Princeton, NJ: Educational Testing Service.
Viswesvaran, D., & Ones, D. S. (Eds.) (in press). Role of general mental ability in industrial, work and organizational (IWO) psychology. *Human Performance*, (Special issue).

Wigdor, A. K., & Green, B. F., Jr. (Eds) (1991). *Performance for the workplace* (Vol. 1). Washington, D.C.: National Academy Press.

Wilk, S. L., Desmarais, L. B., & Sackett, P. R. (1995). Gravitation to jobs commensurate with ability: Longitudinal and cross-sectional tests. *Journal of Applied Psychology, 80* (1), 79–85.

Williams, M. V., Baker, D. W., Parker, R. M., & Nurss, J. R. (1998). Relationship of functional health literacy to patients' knowledge of their chronic disease. *Archives of Internal Medicine, 158*, 166–172.

Williams, M. V., Parker, R. M., Baker, D. W., Parikh, N. S., Pitkin, K., Coates, W. C., & Nurss, J. R. (1995). Inadequate functional health literacy among patients at two public hospitals. *Journal of the American Medical Association, 274* (21), 1677–1682.

Wonderlic Personnel Test, Inc. (1992). *Wonderlic Personnel Test and Scholastic Level Exam: User's manual.* Libertyville, I: Author.