THE RELATIONSHIP BETWEEN LEARNING AND INTELLIGENCE

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ABSTRACT: The historical separation of the study of learning and of intelligence is seen as an anomaly in the development of scientific psychology. Although learning and intelligence can be conceptually distinguished in terms of formal definitions and measurements, a review of evidence on the relationship between individual differences in measures of learning and of intelligence suggests that no clear distinction can be made between the cognitive processes that contribute to individual differences in these two definitionally different realms. Problems of measurement and methodology in the study of individual differences in learning have often contributed to misleading results and conclusions. The results of proper analyses are consistent with the conclusion that performance on learning tasks and on conventional tests of intelligence, or IQ, both reflect common factors, principally Spearman's g, or the general factor common to all cognitive abilities. There is no evidence of a general factor of learning ability independent of g. It is argued that the observed correlations between individual differences in learning and in g can best be understood from the viewpoint of information processing theory, in particular, in terms of individual differences in the speed of operation of the various components of the information processing system.

It has been observed that some people acquire knowledge and skills 10 or 20 times faster than others (Payne & Tirre 1984). Certain people can acquire particular knowledge and skills that some others cannot acquire at all with any amount of training. Such conspicuous individual differences in learning are most commonly thought of as differences in intelligence. Indeed, ability to learn is part of many psychologists' definitions of intelligence, and most educators and the laity hardly make any distinction between learning and intelligence.

Therefore it seems paradoxical that the study of learning and the study of intelligence have advanced along quite separate paths throughout the history of psychology. These began and developed as different fields of investigations, each with its own distinctive phenomena, and with different specialized vocabularies, different conceptual and theoretical systems, and different methodologies. It

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Learning and Individual Differences, Volume 1, Number 1, 1989, pages 37-62. Copyright © 1989 by JAI Press, Inc. All rights of reproduction in any form reserved. ISSN: 1041-6080. seems incredible that such closely related behavioral phenomena could have become so sharply divided into separate fields of psychological inquiry.

This strange division of labor in the history of psychological research is a prime example of what Cronbach (1975, 1975) has referred to as the "two disciplines of scientific psychology." The two disciplines are experimental psychology and differential psychology (i.e., the study of individual and group differences, with its closely allied field of psychometrics). The former claimed learning in its domain; the latter claimed human variation in mental abilities, particularly intelligence. The research aim of experimental psychology has been to discover general laws of behavior, without reference to individual variation, in the tradition of the physical sciences. The aim of differential psychology has been to classify and quantify variation in human abilities and traits and discover their essential nature or "structure" in terms of more basic and elemental sources of variance, or factors.

This dichotomy in research and theory, which set the study of learning and intelligence on different paths, has been deplored in many reviews over the past 25 years (Allison 1960; Cronbach 1957, 1975; Estes 1970, 1974, 1981, 1982; Jensen 1979). The many pleas for some kind of theoretical unification have far out-numbered the actual attempts. The achievement of a unified conceptual framework remained impossible until experimental psychologists interested in learning and differential psychologists interested in intelligence were able to find a common ground on which they could pursue their own research interests.

The common ground, as it turned out, was not research on intelligence per se, or on psychometrics, or on learning, or even on individual differences in learning, but research on *information processing*. It was ushered in with developments in experimental cognitive psychology, largely within the last two decades.

Theory and research on information processing concern the testing of hypotheses about how information (i.e., the stimulus inputs that must precede the acquisition of knowledge and skills) is apprehended, encoded, stored, organized, retrieved, and mentally manipulated to enable a person to perform intellectual tasks.

A methodological necessity of this endeavor has been the revival of *mental chronometry*, which, through the influence of Wundt's laboratory, had been the most prominent line of research in the early history of experimental psychology. Mental chronometry in those days was never associated with the study of learning. But about the same time (around 1880) that chronometric studies gained prominence in Wundt's laboratory, Sir Francis Galton (1822–1911) introduced chronometry into differential psychology, with his attempt to assess intelligence by measuring reaction times to visual and auditory signals. Galton believed that individual differences in reaction time, sensory acuity, discrimination thresholds, and the like, all of which he measured with his rather primitive "brass instrument" techniques, reflected individual differences in the inherited aspects of the general mental ability that natural selection in the course of evolution had made the most distinguishing feature of the human species. But the results yielded by Galton's "brass instrument" techniques looked unpromising at the time, and, for a number of additional reasons we need not go into here, mental chronometry

died out almost completely, to remain dormant for three-quarters of a century, until its recent revival as a prominent methodology in experimental cognitive psychology.

Posner (1978) has defined mental chronometry as "the study of the time course of information processing in the human nervous system" (7). The study of individual differences in information processing made chronometry an absolute necessity because the elemental information processes in which investigators wished to measure individual differences could be elicited only by having persons perform tasks, called *elementary cognitive tasks* (ECTs), which are so simple, as compared to conventional intelligence test items or typical laboratory learning tasks, that the only reliable source of individual differences on the ECTs is *speed* of response. In an ECT, it was not a question, as in the usual intelligence test, whether the person could or could not give the right answer; it was a question only of how *fast* the person could respond.

Response speed (or its converse, reaction time) to various ECTs quickly became of considerable interest to differential psychologists when it was finally established that Galton was right after all: Reaction time, where discrimination or choice is involved, is indeed correlated with IQ or other psychometric indices of mental ability. Research on the experimental psychology of information processing and the measurement of individual differences on various ECTs with chronometric techniques that were related to scores on conventional psychometric tests thus provided a more unified conceptual and methodological framework than we had heretofore possessed for comprehending the empirical phenomena traditionally associated with "learning" and "intelligence."

But before examining the empirical relationship between these domains and the developing theoretical rapproachement between them, I must first define what I mean by each term and note the main semantic blocks to bringing them together in a unified framework.

THE PHENOMENOLOGY OF LEARNING AND INTELLIGENCE

In terms of its subjective phenomenology, learning seems more real, or more directly experiential, than intelligence. A man who grew up in isolation on a tropical island, for example, would very likely induce the concept of learning, as a result of his subjective experience. He would notice that his performance of specific skills, such as bringing down birds by throwing stones, or spearing fish, or climbing trees to fetch fruit, or getting from one part of the island to another, improved with repetition (practice). He would also notice that the rate of improvement was greater when he could perceive the immediate result (reward or reinforcement) of each attempt. He would experience that the attainment of certain goals would become easier with increasing practice; the required tasks would become less difficult, less fatiguing, and less attention demanding (i.e., he could also pay attention to other things while performing the task). If he were so inclined, he could probably discover most of the basic "laws of learning" just by observing his own experiences with practice in a variety of tasks and noting the changes in his performance. By systematic self-observation of his changes in performance with practice, he should be able to induce such concepts as generalization, discrimination, extinction, transfer of training, memory, retroactive interference, and forgetting. (In fact, Hermann Ebbinghaus [1850–1909] did just that, using himself as his only experimental subject.)

It seems doubtful, however, that our hypothetical psychologist, alone on his island, would ever induce the concept of intelligence, or general mental ability. People have no subjective experience of their intelligence. There is nothing an isolated individual could observe in his own behavior that would permit him to induce the concept of intelligence. He would be aware of various abilities to perform particular tasks, and he would notice improvement in performance with practice on specific tasks. Also, he would be conscious of his effort. But the notion of his possessing some level of *general mental ability*, or intelligence, that entered into the acquisition and performance of nearly all of these diverse skills, would never enter his head. The reason, of course, is that the concept of intelligence is an inference, an abstraction, induced from the observation of *differences* between individuals in a certain class of behavior.

If our islander were joined by a number of companions, he would probably induce the concept of "general mental ability" as readily as he had induced the "laws of learning." He might notice that there was no consistent relationship between individuals' proficiency in a variety of tasks and their sheer physical strength or agility or sensory acuity—hence the notion of *mental abilities*, as contrasted with physical abilities. He would also notice that some individuals learned just about every kind of task faster and performed most tasks better than did the majority of other individuals—hence the notion of *general mental ability*. He might also notice certain marked exceptions, where a few individuals learned and performed a certain class of tasks much better than their overall average level of performance on all other tasks—hence the notion of *special abilities*.

In brief, the study of *learning* rests on the analysis of *changes* in a single individual's behavior in relation to certain external conditions that influence these changes. The study of *intelligence* rests on the analysis of *differences* between individuals in level of performance in a variety of tasks that can be described as mental in the sense that individual differences in task proficiency are negligibly correlated with individual differences in sensorimotor functions per se.

DEFINITION OF LEARNING

The concept of *learning* is an inference from the observation of behavior. In terms of the most general operational definition, we say that learning has occurred when we observe a change in the probability or strength of a particular behavior in response to a given stimulus, problem, or situation, where the change cannot be attributed to other causes such as physical maturation of the nervous system, aging, fatigue, illness, brain damage or other physical impairment, drug effects, changes in emotional state, or changes in arousal or drive state.

The behavioral changes from which we infer learning are preceded and followed by changes in the immediate stimuli or external conditions impinging on the organism, which are referred to as the "conditions of learning," and they usually (but not necessarily) involve repetition (or practice) of the particular behavior in the presence of these conditions. The complexity of the behavior that can be learned varies enormously, from relatively simple responses, such as habituation of the orienting reflex, or a conditioned eyeblink or conditioned galvanic skin response, all the way up to extremely complex forms of behavior, such as mastering calculus or composing a symphony.

It will be important in later discussion to distinguish between different kinds of learning. But a caution is needed here. By "kinds" of learning I do not necessarily refer to different forms of learning that correspond to any kind of differences intrinsic to the organism, involving different brain mechanisms or neural structures. In speaking of different "types" of learning, all we can be sure of at the outset are differences in the learning paradigms, that is, the particular experimental conditions of learning. There should be no initial implication of organismic differences underlying the learning that is observed under these different types of conditions. This caveat, of course, in no way rules out the possibility that certain types of learning may engage different neural processes than are involved in certain other types of learning. But that is a separate question that can be answered only through empirical investigation. To avoid confusion, therefore, it is best to think about different types of learning in strictly operational terms, as referring either to the experimental conditions of learning or to the observable characteristics of the particular change in behavior that occurs under the specified conditions.

In discussing the relationship of learning to intelligence, probably the most fundamental distinction is between what has been termed *slow learning* and *fast learning*. These terms do not refer to individual differences in speed of learning, but to how the particular learning comes about.

Slow and fast learning. Most genuinely new learning is usually slow, with improvement in performance taking place gradually throughout the prolonged practice. The acquisition of motor skills is conspicuously of this nature, but so are many cognitive skills. Acquiring proficiency in reading, in writing, and in the basic "number facts" of simple arithmetic are examples of "slow learning." In this type of learning, performance improves with continued practice even long after the learner "knows" the material being practiced.

"Slow learning" is often preceded by "fast learning." One category of fast learning consists of "getting the idea." Learning to read music is a typical example. A bright adult can learn all the essential principles in reading music within several hours of instruction and study—the learner "catches on" or "gets the idea" rather quickly. But beyond this initial stage of relatively fast learning, it will require some years of continual practice to become able to read music as an accomplished musician does—extremely quickly, virtually automatically, with little conscious mental effort, and with good aural imagery of how it would sound when played on an instrument.

Fast learning is characterized by quickly "catching on," "getting the idea," "grasping a concept," or merely restructuring knowledge that one already

possesses. Learning new names of things for which one already has another name (*sodium chloride* is *salt*) is usually fast learning. Also, there is *insight* learning, which is a form of fast learning. It cannot really be said that one has learned the proof of the Pythagorean theorem, for example, unless one has grasped it through insight, that is, the subjectively sudden perception of a distinctive relationship between separately perceived elements. Another form of fast learning is based on the transfer of prior learned elements to the learning of something new, such as learning the formula for the standard deviation after one already knows the formula for the variance, or learning factor analysis after one has already mastered matrix algebra. Much of the learning that takes place in the course of formal education consists of this type of fast learning.

Rote Learning and Meaningful Learning. These are anchor points on a continuum based on the amount of prior learning that the subject brings to bear on a new task. Rather widely separated points on this continuum would be, for example, the serial learning of a list of Hindi words printed in Devanagari (assuming, of course, that the learner is not a Hindu) versus memorizing a sentence composed of the same number of words in English. In meaningful learning, the learner already possesses overlearned codes for the elements of the task and often also for "chunks" of the task elements, that is, prior learned connections between a number of the elements of the task. Also the task may be perceived in relation to an already familiar context. Older children and adults, already possess many prior learned syntactical connections between words as they normally occur in sentences, so it is much easier to memorize a meaningful sentence than to memorize a list of random words. If the sentence is not highly meaningful, that is, if it is not understood by us because the words (or their peculiar combination) lack appropriate referents to our prior experience and are therefore without context, it is much more difficult to memorize.

When a sentence is fully understood, in the sense that its key elements are assimilated with our prior knowledge, it is much easier to remember the essential *meaning* of the sentence than the exact wording of the sentence itself. We may forget its exact wording, but can accurately paraphrase its meaning in our own words. That is a criterion of comprehension, which is one of the critical differences between good and poor readers.

Another important distinction for understanding the relation of learning to intelligence is *trial-and-error* learning as contrasted with *strategic* problem solving. An example of a strategy for solving a certain class of problems involving logic is the use of Venn diagrams for determining the logical validity of syllogisms. An example of trial-and-error learning is the acquisition of purely random (but consistent) associations between, say, the numerals 1 through 9 and the letters *a* through *i*, when the numbers are presented serially and the learner's guesses of the associated letters are immediately followed by reward or punishment ("Right" or "Wrong"). In general, trial-and-error learning occurs when either (1) the associations to be learned between the elements of the task itself are so random as not to allow any benefit to a planned or systematic approach, or (2) the learner does not bring enough prior experience to the task to be able to adopt an appropriate strategy.

In general, the chief characteristic that distinguishes between all the various types of learning discussed above is the degree to which the learning of a given task benefits from some form of prior learning. This interaction between new learning and prior learning creates one of the main problems in interpreting the observed correlations between individual differences in learning and psychometric intelligence.

Level I and Level II Abilities. Twenty years ago I (Jensen 1968) presented evidence that two distinct classes of cognitive tasks show an interaction with social class and race (i.e., black-white). Individual differences in performance on the two types of tasks were attributed to what was termed Level I and Level II abilities. Briefly, Level I consisted of the registration and recall of information involving little if any transformation of the input; Level II involved transformation and mental manipulation of the input. Examples of Level I tasks are forward digit span memory and serial and paired-associate rote learning that does not depend on mnemonic strategies. Learning the alphabet, or the capitals of the 50 states, or simple arithmetic "facts" is also largely Level I. In contrast, Level II tasks call for reasoning, problem solving, the use of concepts, perceiving abstract relationships, generalization, and the like. Standard IQ tests for the most part typify Level II.

It was discovered that children from high and low socioeconomic status (SES), and especially black and white children, on average, differ very much less in their performance on Level I tasks than on Level II tasks. Only a very moderate correlation of 0.3 to 0.4 was found between Levels I and II, and the correlation was lower among blacks. These findings seemed to suggest that instruction might be able to capitalize on Level I ability to improve the scholastic learning of children who have good Level I ability but are relatively low in Level II, or IQ.

Virtually the entire literature on Level I-Level II has been thoroughly reviewed by Vernon (1981, 1987b). As I have fully explained elsewhere (Jensen 1987g), I have rather drastically revised my own view of the Level I-Level II formulation. In brief, it is theoretically more parsimonious to subsume it under what I have termed "Spearman's hypothesis" (Jensen 1985b, 1987f). This is now the wellsubstantiated empirical fact that the variable size of the average white-black difference on various mental tests is directly related to the degree of the tests' loadings on *g*, the general factor common to all cognitive tasks. Level I and Level II simply represent two classes of tasks that are widely separated on the whole continuum of *g loadings*.

THE MEASUREMENT OF LEARNING

Yet another problematic factor in this connection is the actual measurement of learning. The quantification of learning in individuals is not as highly developed or as standardized in procedures as the technique of psychometric testing.

There is no single measure of an individual's performance in a learning task that is adequate to characterize the individual's learning. Four main parameters must be considered: 1. Initial level of performance on the task prior to the learning trials. In "real life" learning situations, such as schooling, it is rare that all persons begin a learning task with equal levels of performance; they are already at different points on the learning curve when training begins. Therefore it is essential that level of performance on the task be assessed before or during the first learning trial. Only with the specially contrived and usually artificial tasks used in laboratory learning experiments can we reasonably expect that all subjects begin learning at virtually the zero point of the learning curve. At this point, of course, there is no true variance (i.e., individual differences) in performance, only error variance; hence true variance necessarily increases with practice. If the task can be mastered with sufficient practice by all subjects, then, of course, true variance will gradually reduce to zero in the course of learning. Because true variance is essential for correlation between variables, a reliable and valid measure of learning must consist of something other than simply the difference between the initial and final levels of performance.

2. Final level or asymptote of performance at the end of practice. This can be a reliable measure of individual differences only if practice is not carried on to a level of mastery of the task for any subject in the study, or if the nature of the task is such that there is effectively no intrinsic ceiling to proficiency on the task. There is probably no ceiling for skill in chess, for example.

3. Rate of change between the initial trial and final trial. Because a learning trial is an arbitrary unit, it is preferable to convert trials to an appropriate unit of *time* measurement. (Time has the advantage of a physical measurement with units constituting a ratio scale.) This can be easily done because learning trials, whether experimenter-paced or subject-paced, occur in time, and we obtain some measure of the level of the subject's performance at each point in time. Hence rate of learning can be expressed as amount learned per unit of time.

However, this type of measure of rate of change is not without serious problems when there are true individual differences in the level of task performance at the beginning of training or practice. Subjects who excel at the beginning or during the first trial of learning often appear as slow learners in terms of gain scores, because they have less far to go to reach peak performance on the task to be learned. Therefore they are necessarily constrained to show a low *rate* of improvement with practice. A person who cannot type at all, for example, can show a much greater gain in typing proficiency after three hours of practice than can a person who already has some skill in typing.

There is also the problem that gain scores (or change scores) are notoriously unreliable. This is so because the reliability of a difference between, say, variables x and y is a function not only of the separate reliabilities of x and y, but of the correlation between x and y. The higher the correlation between x and y (e.g., levels of performance in the initial and final trials of learning), the lower is the reliability of the difference between them. This mathematical necessity plays havoc with attempts to correlate gain scores with other variables. These psychometric and statistical problems of measuring change have been well explicated elsewhere (Cronbach & Furby 1970; Cronbach & Snow 1977).

4. Oscillation in performance level throughout the course of practice. Learning curves show a directionally consistent and smooth change in level of performance with practice only when they are group curves based on the average of a number of individual learning curves. Changes in an individual's performance throughout practice are comparatively erratic, yielding a rather saw-toothed record of gains and losses from trial to trial, although a smoothed curve can usually be fitted to these erratic data points to reveal an overall gradual improvement in performance as a function of amount of practice. Oscillation is the up-and-down variation in performance around the smoothed curve. There are reliable individual differences in the degree of oscillation, which are related to other parameters of the learning curve and possibly to intelligence, although research on individual differences in oscillation is too scanty for any worthy conclusions. It is not yet certain whether individual differences in oscillation involve any reliable variance that is independent of individual differences in other parameters of the learning curve. The phenomenon of oscillation may well reflect what cognitive psychologists now refer to as "attentional resources." It seems as if the nervous system varies from moment to moment in its capacity to respond to external events, and this inherent intraindividual variability may be a fundamental phenomenon related to individual differences in learning and intelligence. It is known, for example, that trial-to-trial intraindividual variability in reaction time (RT) is at least as highly correlated with IQ as is RT itself (Jensen 1982a, 1987c).

Developmental Factors. When we study forms of learning in which instruction and practice continue over an extended period, such as a school semester, it is important to avoid confusing learning with maturation, or the spontaneous development of abilities in children as a function of chronological age. In order to assess the extent of maturational effects on task performance in studies of this type, one needs a longitudinal study in which a noninstructed control group is matched with the instructed experimental group on age, gender, and IQ. Some tasks that are exceedingly difficult and require training and prolonged practice for a child to learn to do at an early age become surprisingly easy if they are postponed to a slightly older age. Children who have great difficulty learning to copy the shape of a diamond at age 6, for example, usually find this an easy task by age 7 or 8.

The effects of maturational readiness were seen most dramatically in the famous case of Isabelle, who, from birth to age 6.5, was reared in a semidarkened attic by her deaf-mute mother, without any other social contacts (Davis 1947). When she was finally discovered by the authorities (age 6.5), she was incapable of speech, acted much like an infant, and had a Stanford-Binet mental age of 1 year 7 months. Once she was placed in a normal social environment, however, her rate of learning was far in excess of that of the average child of the same mental age. She quickly learned to talk and acquired vocabulary with phenomenal speed, in fact, at about the rate that would be expected for a child with an IQ of 300! But this incredible rate of learning lasted only until her mental age caught up with her chronological age, or maturational level, at about age 8. Within two years she had advanced from a mental age of 1 year 7 months to a mental age and level of scholastic performance on par with her 8-year-old classmates. Obviously, a great

amount of learning had occurred during those first two years following Isabelle's rescue from the attic. But the *rate* of knowledge acquisition was highly confounded with Isabelle's stage of maturation, or "readiness" (to use an old-fashioned term).

Similarly, normal children, all of exactly the same chronological age, reared under normal conditions, also differ from one another in "readiness" for various kinds of learning. These differences are related to differences in intelligence as indexed by conventional IQ tests.

DEFINITION OF INTELLIGENCE

Intelligence has never had, and most probably never will have, a generally agreed on definition among psychologists (Sternberg & Detterman 1986). It can be argued that intelligence is not a scientifically useful concept. (The long history of this concept has been detailed elsewhere [Jensen 1987d].) Because it lacks any operational meaning that is not just the arbitrary choice of any given psychologist, I have urged that the term intelligence be abandoned in all future scientific discussions of human abilities (Jensen 1987a). Intelligence will of course continue in popular parlance to mean whatever the speaker may want it to mean. I do not propose a new definition because whatever scientifically worthy construct we may refer to as "intelligence" will be fraught with all the scientifically unmanageable connotations that this word has accrued since its origin in ancient Greece. Also, to substitute a new word for intelligence would only be a circular futility. Whatever "intelligence" or any of its synonyms may mean to psychologists or to lay persons, one thing seems certain: it does not represent any operationally knowable phenomenon and therefore is not amenable to scientific study. So there is absolutely no need for another definition of *intelligence*. We should talk about something else-something that meets the requirement of being the kind of natural phenomenon that is amenable to investigation by empirical science.

Abilities. The term *ability*, as used here, does not refer to a potential, a capacity, an enduring characteristic of an individual, or a latent trait or factor inferred from behavior. It refers only to manifest behavior itself.

To be termed an *ability*, the behavior must meet two main criteria: (1) It must be an observable response to a task, a problem, or challenge offered by the environment; and (2) the adequacy of "goodness" of the response must be of such a nature as to be classified or graded in terms of an objective standard.

Abilities are said to be *mental*, as contrasted with *physical*, when individual differences in performance on the tasks in which the ability is observed are negligibly correlated with individual differences in independent measurements of sheer sensory acuity or muscular strength or dexterity.

A single item on a typical IQ test, aptitude test, or achievement test is an example of a task. An individual's response to the item, when scored, indicates the degree of his or her *ability* to perform that *particular task*. To use the term *ability* in any other sense than as an observable response to a particular task is to turn it from a datum into an abstraction, an inference, a "factor of the mind," or a hypo-

thetical construct. It is best not to risk confusing raw observations with inferences about them. So "abilities" are the raw observations as here defined.

To speak of abilities with such a high degree of specificity may seem so molecular and chaotic as almost to preclude our understanding them in any systematic way. Fortunately, there is one fact of nature that makes it possible to have a science of human abilities. That is the fact that the correlations among virtually all mental abilities are nonzero positive in any large, unrestricted sample of the general population. Although the positive correlations among mental abilities have not been empirically demonstrated. L.L. Turstone (1974: 341-343) termed this phenomenon *positive manifold*, when it is seen in a matrix of all positive correlations.

Factor Analysis. The existence of a positive manifold has the important implication that some large part of the total variance in a number of different abilities can be accounted for mathematically in terms of some much smaller number of underlying sources of variance (termed *factors*) than the total number of abilities. Hence one can speak of *common factor* variance that different tasks, test items, or whole tests may have in common. The *reliable* variance in total scores on any mental test composed of a number of items consists of the total common factor variance among all the items, or twice the sum of all the item covariances.

A variety of mathematical techniques known as *factor analysis* makes it possible to decompose the total common factor variance on a number of diverse tests into some smaller number of factors, either correlated (*oblique*) factors or uncorrelated (*orthogonal*) factors, depending on the method of factor analysis.

It is theoretically preferable to perform a factor analysis in such a way as to make all significantly nonzero factor loadings positive on every factor because it makes little sense psychologically to speak of a negative ability. Also, it is an artificial mathematical constraint to make all of the primary factors in a factor analysis orthogonal (i.e., uncorrelated) to one another. These first-order, or primary, factors can be correlated with one another, and these correlations, in turn, can themselves be factor analyzed to yield a smaller number of higher-order (in this case, second-order) factors. These factors in turn may be correlated and factor analyzed to yield (in this case) third-order factors. This procedure of extracting uncorrelated factors at different levels that represent increasingly more general sources of variance is termed *hierarchical* factor analysis. When applied to a large collection of diverse mental tests, it affords the clearest, most easily interpretable, and theoretically most compelling picture of what psychometricians refer to as the structure of mental abilities. Procedures for doing this type of factor analysis have been explicated by Schmid and Leiman (1957) and by Wherry (1959).

The well-established primary (or first-order) factors are described by such terms as word fluency, verbal comprehension, reasoning, numerical operations, spatial visualization, memory, and perceptual speed. The best established second-order factors are variously named crystallized and fluid ability (Cattell 1971), or v:ed (verbal-educational) and k:m (spatial-mechanical) Vernon 1950). The single

highest-order factor in a hierarchical analysis of any large and varied selection of mental ability tests is conventionally labeled g (for *general factor*), the symbol coined by Charles Spearman (1927), the inventor of factor analysis and discoverer of g.

Psychometric *g*. The *g* factor derived from psychometric tests differs from all other factors in that it cannot be described at all in terms of the information content or other surface characteristics of the tests in which it is loaded. It is so general that it cannot be described at the level of tasks or tests or at the level of behavior. Factor analysis permits us to identify the tests that are the most and the least loaded with *g*, but it does not tell us what *g* is. One should not mistake the mere descriptions of tests that are found to be highly *g* loaded as a *definition* of *g*.

The belief that individual differences in *g* reflect nothing other than differences in knowledge, or what individuals have previously learned, is clearly disproved by the fact that some tasks that involve no prior learning or knowledge content also show some *g* loading.

Distinctions such as "academic intelligence" as contrasted with "practical intelligence" or "everyday intelligence" do not necessarily reflect different psychological processes or constructs, but simply refer to various criterion tasks that may differ in their *g* loadings as well as in certain group factors. It happens that most "academic" tasks are more highly *g* loaded than most "everyday" tasks. But, in general, novel and complex tasks of any kind are more highly *g* loaded than routine or simple tasks.

The well-established high heritability of g (Plomin 1988) suggests that its explanation will have to be understood ultimately in neurophysiological terms. But whatever the essential nature of g is finally discovered to be, there is presently little argument that it is a most important factor in individual variation in human mental abilities (Gustafsson 1988; Jensen 1987b). It is by far the major component of the validity of tests for predicting scholastic performance and occupational level, and it is correlated with many other personally, socially, and economically important variables (Gottfredson 1986; Jensen 1984; Thorndike 1985, 1986).

I have argued extensively (Jensen 1986, 1987b, e) that a hierarchical *g* is highly similar when extracted from different collections of mental tests, provided only that the tests are numerous and varied in form and content (also see Thorndike [1987]).

Most important, in the same articles, I have shown that *g* is not merely an artifact of the method of constructing psychometric tests, or of the mathematical manipulations of factor analysis, as some critics have claimed, but exists as an objectively real phenomenon independently of psychometrics and factor analysis. For example, the degree to which various psychometric tests are *g* loaded is highly related to their degree of correlation with numerous other variables that have no connection with psychometrics or factor analysis, such as the heritability of individual differences in test scores, the spouse correlations and various genetic kinship correlations, the effects of inbreeding (and its counterpart, heterosis) on test performance, reaction time to visual stimuli, inspection time (i.e., the speed

of visual or auditory discrimination), and certain features of the brain's evoked electrical potentials. Also, the highly variable magnitude of the mean difference between representative samples of the black and white populations on various mental tests is found to be directly related to the tests' *g* loadings (Jensen 1985a, b, 1987f; Naglieri & Jensen 1987).

Measurement of g in Individuals. Estimates of g in individuals are best obtained by means of factor scores. An individual's g factor score is a composite score consisting of the weighted average of the individual's standardized scores on all of the various tests that had entered into the factor analysis, each weighted by its g loading. Good approximations to g factor scores can be obtained by averaging the unitweighted standard scores on three or four tests that are already well established as being highly g-loaded. Even the score on a single test, provided the test has a high g loading that approaches its true-score variance, or reliability, can serve as an approximation to g.

It so happens that the total score, or IQ, on most of the well-known standardized tests of intelligence is invariably found to be among the most highly gloaded in factor analyses of any fairly large collection of diverse mental tests. This is fortunate from the standpoint of the present review because IQ tests have been the most frequently used in studies of the relationship between learning and intelligence, or IQ. It is essentially the relationship of learning to g that has been observed. IQ in these studies is best viewed from a theoretical standpoint as a stand-in for g.

It should be clearly realized, however, that *g* itself is not a product of the IQ tests. We can measure *g* without using IQ tests at all, by means of techniques that scarcely resemble IQ tests, such as inspection time, reaction time, evoked potentials, and other laboratory techniques. The high *g* loadings of conventional IQ tests in factor analyses simply fall out as a fact of nature; the *g* is not created by the IQ tests. Because of the central importance of *g* in individual differences in performance on every kind of task requiring mental ability, especially in tasks involving novelty and increasing complexity, as in scholastic learning, IQ tests, which were originally devised to assess scholastic aptitude, have been shaped by the nature of *g*, usually unknowingly, but occasionally by intention.

CORRELATIONS BETWEEN LEARNING AND IQ (OR g)

The relationship between learning and g can be discussed on two levels: (1) In terms of the empirically observed correlations between measures of learning and measures of g, and (2) in terms of a theoretical system that comprehends the observed empirical phenomena of individual differences in both realms, learning and g, within a common conceptual framework.

Simple correlational studies of the relationship between learning and IQ, if their results are taken at face value, have produced a rather inconsistent picture that contributes little to our understanding. Learning tasks and subject populations have both been extremely diverse in these studies, and the obtained correlations between learning measures and IQ vary over an extremely wide range, although the vast majority are on the positive side of zero when the learning parameters are measured in such a way that higher scores represent superior performance.

However, a detailed review or a meta-analysis of all the correlational studies ever reported in the literature would have almost no scientific value because the precise magnitudes of all the observed correlations do not represent estimations of a single true value, as do, for example, various estimates of the speed of light. The correlations are so complexly determined by so many conditions, many of them not explicit in the particular studies or often not even known for sure to anyone, that any particular correlation coefficient, or even the mean of all of them, would scarcely be meaningful. There are already so many excellent detailed reviews of this literature that it would be otiose to review it again here; readers are referred elsewhere for more detailed discussion of this material (Estes 1970, 1974, 1981, 1982; Gagné 1967; Zeaman & House 1967).

A few empirical generalizations from all the studies are essential at this point, however. Above all, there can be little question of a positive correlation between learning and IQ when learning is measured as absolute level of performance after a given amount of time (or number of trials) spent in practice of the task to be learned, or the speed with which a given level of performance is attained through practice (e.g., Dickenson 1941; Garrison 1928; Peterson 1920; Pyle 1919).

This generalization may seem to be contradicted by the conclusion that is often drawn from a highly influential series of studies by Woodrow (1938a, b, c, 1939a, b, c, 1940, 1946). The Woodrow studies, unfortunately, created a misleading impression that has dominated many discussions of learning and IQ for at least two decades. Woodrow claimed that intelligence is not the same as the ability to learn. He based this claim on the small, often nonsignificant, and at times even negative, correlations he found between IQ and a variety of simple laboratorytype learning tasks. What is essential to note, however, is that Woodrow operationally defined learning in terms of gain scores, that is, the difference between performance in early and late trials, and in the learning tasks he used there were usually significant individual differences in task performance in the very early trials. Hence Woodrow's gain measures were not base-free and therefore manifested all the statistically intractable problems of change scores (or difference scores) that necessarily arise whenever the two points of measurement are correlated (Cronbach & Furby 1970). By using gain scores as the measure of learning on learning tasks in which there were initial individual differences, Woodrow, in effect, unwittingly partialed out much of the variance in the performance of any given task that it has in common with other learning tasks and with IQ. In other words, he largely partialed out g. This has led to the common but false conclusion that individual differences in learning have little, if any, connection with individual differences in g.

A number of studies (Allison 1960; Duncanson 1964; Edgerton & Valentine 1935; Perl 1934; Stake 1961) indicate that when individual measures of parameters such as learning rate, overall performance level, and asymptotic level are obtained from a wide variety of learning tasks and are factor analyzed, there is found a modest general factor along with a number of smaller group factors. The general factor of a battery of learning tasks is almost invariably smaller (i.e., it accounts for less of the total variance) than is the general factor typically found in a battery of psychometric tests. There are two main reasons for this: (1) learning measures are generally less reliable or less temporally stable than scores on psychometric tests, and (2) more important, the simple learning tasks typically used in the reviewed studies have much more *specificity* (i.e., variance not shared with other tasks) than do psychometric tests composed of a large number of items. Single learning tasks are much like single test items in their degree of specificity. The usual psychometric test, however, is composed of a large number of items, so the specificity of the single items is, in effect, averaged out in the total score, leaving a substantial source of variance in the total scores that is common to all the items. For example, if we factor analyze conventional IQ tests at the item level, the g loadings of the single items are even smaller than the loadings of any particular parameter of single learning tasks on the general factor extracted from a variety of learning tasks (e.g., McNemar 1942).

The most important finding, from my perspective, is that when a number of learning tasks and a number of psychometric tests of abilities are factor analyzed together, they all share a large common factor which is statistically indistinguishable from psychometric g (Allison 1960; Garrett, Bryan, & Perl 1935). Factor scores derived from the general factor in each domain are about as highly correlated as reliability permits. Virtually all recent reviewers of the evidence in this field have reached the same conclusion, that there exists no general factor of learning ability independently of what we have here termed psychometric g (Ackerman 1986, 1987; Estes 1982; Kyllonen 1986). Whatever general factor is found among the parameters of the learning curves derived from a number of diverse learning tasks is essentially the same general factor, g, that is found among any large number of diverse tests of mental abilities.

It is to be expected, therefore, that the *g* loadings of various types of learning tasks, and consequently their degree of correlation with IQ, will follow the same pattern seen with psychometric tests. As Spearman (1927) had originally discovered, those tests are more highly *g* loaded that require the "eduction of relations and correlates" (in short, reasoning) and involve some degree of abstraction. The same is also true for various learning tasks. Concept learning, for example, is more *g* loaded (and more highly correlated with IQ) than are rote learning and the acquisition of perceptual-motor skills (Ackerman 1987).

But there is probably no point on the continuum of complexity and abstractness of tasks at which g is completely absent. For example, on a simple trial-anderror selective learning task, with consistent reinforcement of correct responses, in which all learners began without any knowledge of the six stimulus-response connections to be learned and in which the particular S-R associations to be acquired were strictly random, thereby ruling out the efficacy of logical strategies or any kind of reasoning, groups of mildly retarded, average, and gifted junior high school pupils all showed clearly different mean learning curves over the course of 200 trials; the total number of correct responses is positively correlated with IQ both between and within groups (Jensen 1963). Also, on serial and paried-associate verbal rote learning tasks, children of average intelligence (mean IQ 105) showed significantly faster learning than retarded (mean IQ 58) young adults who were matched with the children on Stanford-Binet mental age (Jensen 1965).

Probably the simplest form of learning is *habituation*. It is usually ranked even below classical conditioning in the hierarchy of cognitive complexity, and some experts do not even include habituation in the category of learning. Habituation is the weakening of a response following repeated stimulation not followed by reinforcement. It is observed even in such neurologically simple species as flatworms and protozoans. Yet it has been shown in young adult persons in the upper half of the IQ distribution that individual differences in the habituation of the amplitude of the brain's electrochemical reaction (i.e., the evoked potential) to a repeated auditory stimulus ("click") is correlated (about +.50) with Full Scale IQ on the Wechsler Adult Intelligence Scale (Schafer 1985). Even more interesting is the fact that the correlation is entirely attributable to the g factor of the Wechsler scales; none of the subtests shows an iota of correlation with habituation of the evoked potential when g has been partialed out. Also, the relative magnitude of the correlations of the 11 WAIS subtests with the measure of habituation is correlated .80 with the subtests' g loadings. Strictly behavioral (as contrasted with electrophysiological) measures of habituation have not yet been studied in relation to g. It would be surprising, however, if they approached anything like the degree of correlation for the habituation of the evoked potential.

In reviewing the then entire literature on the relation of learning to IQ, I (Jensen 1979) arrived at a number of empirical generalizations regarding the conditions that seem most clearly related to the magnitude of the learning-IQ correlations, or the degree to which various learning tasks are g loaded. To summarize: *Learning is more highly g loaded when*:

- 1. learning is intentional and calls forth conscious mental effort;
- 2. the learning or practice trials are paced in such a way as to allow the subject *time to think;*
- 3. the material to be learned is *hierarchical* in the sense that the learning of later elements depends on mastery of earlier elements;
- 4. the material to be learned is *meaningful* in the sense of being related to other knowledge or experience already possessed by the learner;
- 5. the learning task permits *transfer* from somewhat different but related past learning;
- 6. the learning is *insightful*, that is, it involves "catching on" or "getting the idea";
- the material to be learned is of moderate difficulty and complexity, in the sense of the number of elements that must be integrated simultaneously for the learning to progress;
- 8. the *amount of time* for learning a given amount of material to a specified criterion of mastery is fixed for all students;
- the learning material is positively *age-related*, that is, some kinds of material are more readily learned (hence the concept of "readiness") by older than by younger children; and
- 10. performance gains are measured at an *early stage* of learning something "new" than at a late stage of practice on the same task.

Continued practice, or overlearning, on a given task leads to some degree of *automatization* of performance, and as performance becomes more automatized it also becomes less *g* loaded. Individual differences in the speed with which performance becomes automatized during the course of practice may well be correlated with *g*, but the research on this point is yet insufficient to warrant a strong conclusion.

It is especially noteworthy that all these conditions that positively influence the correlation between learning and IQ are highly characteristic of school learning. Thus the common impression of teachers that IQ is indicative of learning aptitude is quite understandable. Low IQ children are indeed "slow learners" in school compared with high IQ children, not because the IQ test measures what is taught in school, but because it measures mostly *g*, individual differences in which are reflected to some degree in every kind of cognitive performance, including school learning.

THEORETICAL ADVANCES ON THE RELATION BETWEEN LEARNING AND g

The conceptual bridge between individual differences in learning and g is *time*. Specifically, it is the amount of time required for information processing. In recent years, both learning and abilities have been viewed theoretically in the context of an information processing system (e.g., Ackerman 1986, 1987; Kyllonen 1986; Thorndike 1984). Each of the components or processes involved in this system operates in time, and there are large and reliable individual differences in the time required for the various processes.

Individual differences in the time taken by certain elemental processes can be studied by means of various *elementary cognitive tasks* (ECTs), which are generally so simple that reliable individual differences can be obtained only chrono-metrically, in terms of the subject's reaction times, or response latencies (Jensen 1985c). Because these time intervals are extremely short, often less than one second, they are typically measured in milliseconds. As mentioned previously, these time measures have been shown to be correlated (negatively) with scores on conventional psychometric tests and with factors derived from them, such as *g*, and verbal and spatial factors, depending on the information content of the ECTs (Brebner & Nettelbeck 1986; Hunt 1976; Jensen 1982a, b; Levine, Preddy, & Thorndike 1987; Pellegrino & Kail 1982; Vernon 1987a).

How does it come about that there is a negative correlation between the reaction time to an ECT and scores on a nonspeeded psychometric test, in which the subject's response to each test item is scored as "right" or "wrong"? Leaving aside the question of the basic cause of individual differences in speed of information processing (a question that will have to await being answered in terms of neurophysiology), the answer is suggested by appeal to several well-established findings of experimental cognitive psychology.

First, the conscious brain acts as a one-channel or *limited-capacity* information processing system, which can deal simultaneously with only a very limited amount of information. The limited capacity also restricts the number of opera-

ations that can be performed simultaneously on the information that enters the system from external stimuli or from retrieval of information stored in short-term or long-term memory (STM or LTM). Quickness of mental operations is advantageous because more operations per unit of time can be executed without overloading the system.

Second, there is *rapid forgetting* of stimulus traces in the sensory buffers and of information in STM, so there is an advantage to speediness of any operations that must be executed on the information while it is still available.

Third, to compensate for limited capacity and rapid forgetting of incoming information, the individual resorts to rehearsal and storage of information into LTM, which has relatively unlimited capacity. But the process of storing information in LTM itself uses up channel space, so there is a "trade-off" between the storage and the processing of incoming information. The more complex the information and the operations required on it, the more time that is necessary, and consequently the greater the advantage of speediness in all the elemental processes involved. Loss of information to overload interference and forgetting of traces that were inadequately encoded or rehearsed for storage or retrieval from LTM results in "breakdown" and failure to grasp the essential relationships between the elements of a complex problem needed for its solution. Speediness of information processing should therefore be increasingly related to success in dealing with cognitive tasks to the extent that their information load strains the individual's limited channel capacity. The most discriminating test items would be those that "threaten" the information processing system at the threshold of "breakdown." In a series of items of graded complexity, this "breakdown" would occur at different points for various individuals. Hence measurements of individual differences in the speed of the elemental components of information processing could be obtained on tasks that are so simple as to rule out "breakdown" failure, as in the various ECTs on which response latencies are found to be correlated with scores on complex psychometric tests, such as the Wechsler Scales and the Raven Matrices. In general, a faster rate of information processing means that more information is processed per unit of time, and because all knowledge and skill acquisition involve information processing, those who process information faster acquire more knowledge and skill from a given amount of experience. Although individual differences in the exceedingly brief reaction times to elementary cognitive tasks are very slight, often amounting to no more than a few milliseconds, they become of considerable consequence when multiplied over extended periods of time. The seemingly slight but real differences in reaction times between average and gifted children are, by about age 12, correlated with quite extreme differences in amounts of general knowledge, vocabulary, and academic skills (Cohn, Carlson, & Jensen 1985).

All the same principles also apply to learning; the very same cognitive processes are involved. Hence it is not surprising to find, as Gettinger (1984) reports in her important review, that individual differences in the amount of time needed for learning is very substantially correlated with IQ, and this is especially true in learning scholastic subjects, probably because of their greater complexity than the learning tasks typically used in experimental studies of learning.



FIGURE 1

Hypothetical schema of information processing components, with arrows showing direction of information flow.

The main information processing components most frequently mentioned in the recent literature are shown schematically in Figure 1. Each of the components (represented in rectangles) requires a certain amount of time. For example, just the first two, which can be measured by simple reaction time to an external stimulus, require about 200 to 300 milliseconds for young adults. The time required just to attain conscious awareness of an external stimulus is, on average, about 500 milliseconds (Libet 1965). Each additional component of information processing required by a cognitive task adds more time between stimulus (input) and response (output). Short-term memory consists of primary memory (which is a passive, limited capacity, rapid decay storage system) and working memory (which is a limited capacity, rapid decay system for manipulating information received from primary memory; it has been aptly termed the mind's scratch-pad). In most learning and problem solving, the Working Memory retrieves from long-term semantic memory whatever information is needed to interpret the recently input information in STM. The semantic memory includes past-learned meanings, relationships, and rules or strategies for operating on certain classes of symbols, such as words, syntax, numbers and arithmetic operations, musical notation, chess moves, and the like. The Working Memory brings the products of past learning from LTM into conjunction with novel inputs to arrive at problem solutions or to encode and rehearse the perceived relationships of the "new" information to the "old" information in preparation for its storage in Semantic LTM. Episodic LTM is a store of nonsemantically encoded spatial-temporal experiences, which may later be semantically encoded for storage in Semantic LTM.

Many kinds of learning, and school learning in particular, consist of transferring newly input information (which, besides specific knowledge, includes skills, strategies, and general heuristics) from Primary STM to Semantic LTM through the agency of Working Memory. In computer terminology, the Working Memory is analogous to a computer's central processor.

The efficiency of the operations performed in a given individual's Working Memory, however, is not constant, but can vary markedly according to the processing strategies adopted and the amount of prior practice and overlearning the individual has had on a particular type of information input. Single bits of information can be "chunked" into larger units, which can then be dealt with as single bits by the Working Memory, which thereby, in effect, increases its capacity for retaining information long enough to execute operations in it.

Controlled and Automatic Processing. A now important concept in cognitive psychology is the distinction between *controlled* and *automatic* processing, developed by Shiffrin and Schneider (1977), and recently applied by Ackerman (1986, 1987) specifically to a theoretical formulation of the relation between individual differences in learning and intelligence.

In brief, *controlled processing* of information demands the individual's focused attention, requires conscious mental effort, is relatively slow, and deals with information input sequentially, being able to handle only very limited amounts of information simultaneously, or in parallel. Controlled processing may crowd the full capacity of Working Memory. It is characteristic of novel problem solving and the learning of new knowledge or skills.

Automatic processing, in contrast, does not demand the individual's entire attention, is relatively effortless, and can deal with relatively large amounts of information simultaneously.

The degree to which performance on tasks can become automatic in the course of learning or practice depends on how consistent, predictable, or routine the information processing demands of the task are. The more consistent the required sequence of operations between input and output, the easier it is to automatize task performance by means of *overlearning*, that is, practice continued beyond initial mastery. In the Morse code, for example, there is an invariant relationship between the letters of the alphabet and their corresponding dot-and-dash codes. In highly practiced telegraphers, the act of sending or receiving messages has become completely automatic. Automatic processing removes most of the burden from Working Memory, which is virtually bypassed when a high degree of automatization has been attained. The Working Memory then is available for the controlled processing of other information.

A corollary of the present theory of the relationship between learning and intelligence is that performance on cognitive tasks becomes less *g* loaded to the extent that the performance becomes overlearned and automatic, because *g* largely reflects the controlled processing operations of Working Memory. Each new step in learning complex knowledge or skills makes great demands on the limited capacity of Working Memory. More of its capacity is left available for processing new material when the prerequisite knowledge and skills are highly

automatic, so that operations with them do not encumber the Working Memory. It is largely automatization of prerequisite knowledge and skills that make it possible for experts to learn something new in their field of expertise much easier and faster than would be possible for novices, regardless of their IQs.

Individual differences in the rate at which performances having regular and consistent information processing demands can become automatic are probably also related to g, although the empirical evidence on this point is still sketchy. (For the most complete discussion of individual differences in automatic and controlled processing available in the literature, see Ackerman and Schneider [1985].) Whatever is the relation of individual differences in automatization to g, a convincing case has been made that failure to automatize certain elementary skills is one of the features of some scholastic learning disabilities (Sternberg & Wagner 1982).

Failure to automatize elementary skills can seldom be detected by means of ordinary paper-and-pencil tests, especially if they are given without time limit. It is possible, for example, that two children could obtain perfect scores on a test of simple addition, but one child's performance would have manifested *automatic* processing and the other's *controlled* processing of the simple addition problems. A chronometric test of addition, however, would highlight the difference between the two children, who would display gross differences in their speed of responding and in the variability of their response times for different problems. Response latencies to very simple arithmetic problems, for example, can be highly revealing of the specific nature of the subject's mental processing of them (Groen & Parkman 1972). I have suggested elsewhere (Jensen 1988) how a variety of chronometric techniques could aid in the study and diagnosis of specific learning disabilities (Jensen 1987h).

The relatively unexplored relation of individual differences in rate of automatization of cognitive skills to *g*, and especially to children's scholastic progress, promises to be a fruitful subject for future research. As a logical extension of task analysis, its principal aims would be threefold: To discover those components of school learning that depend most heavily on automatization of information processing, to devise methods for detecting individual learning difficulties that are associated with automatization failure, and to develop instructional techniques for improving automatization of the specific skills that are essential for pupils' progressing to more advanced levels of reading comprehension, written expression, and quantitative problem solving.

SUMMARY AND CONCLUSIONS

Recent theory and research related to the topic of this article generally support the conclusion that the early phase of investigation of the relation between individual differences in learning and intelligence, which has focused on the correlation between measures of intelligence (which are usually defensible) and measures of learning (which are often questionable), has run its course. Most of the resulting evidence, particularly the more recent and methodologically soundest studies,

converge on the conclusion that learning and intelligence are not essentially independent factors (i.e., sources of individual differences), although they are legitimately distinguishable concepts in terms of the specific psychometric and experimental paradigms by which they are studied. Individual differences in both psychometric g and in quickness of original learning of novel material seem to reflect one and the same general factor of cognitive ability. Both original learning and g reflect the efficiency of the construct known as Working Memory in information processing models.

The often apparent disparity between *g* and learning ability, I suggest, results from the fact that the general source of individual differences in cognitive abilities that we know as *g* becomes manifested in multifarious ways through the agency of learning, especially through overlearning that results in the automatization of particular skills and rapid access to information stored in long-term memory. Although the *g* construct itself is content-free and can even be measured to some extent on a physiological level, its behavioral manifestations necessarily involve context and content in terms of specific cognitive skills and knowledge. The *g* factor of mental abilities is extremely diffuse and therefore especially predominates in contexts, like formal schooling, in which the variety and range of original learning are extremely broad and in which time constraints permit only some fraction of what is learned to become automatic.

The particular knowledge and skills that eventually become automatic in a given individual are probably determined partly by some innate advantage in the elementary cognitive processes on which the original acquisition of a particular skill depends, but also by the frequency and strength of positive reinforcements accorded to successful performance, and by opportunity interacting with interests and values. Undoubtedly, mere chance and serendipity also play a part.

Because of these different proclivities and influences, different things are overlearned and automatized by persons who are equal in g. In a sense, we can say that learning transforms the "raw material" of g (and also probably the major group factors) into the achievements in terms of which individuals manifestly differ and for which their capabilities are differentially valued by society. Intellectually and behaviorally, an individual's conspicuously strongest capabilities and achievements, that is, the individual's areas of special expertise, largely reflect the individual's repertoire of overlearned and automatized skills and rapidly accessible knowledge. This aspect of the individual's capability is usually much more exceptional than the individual's level of g and could be scarcely predicted by a pure measure of g. This seems to be invariably true of recognized experts, accomplished scientists, artists, writers, musicians, and the like, who manifest outstanding performance or achievement. The same thing, to some degree, is probably true of nearly everyone.

Future research could well be fruitfully directed toward understanding just how individual differences in the interaction of g with the specific context and contents of learning eventuate in various forms of intellectual competence, expertise, and achievement, with their phenomenal range of individual differences.

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