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Complex Problem Solving and Intelligence

Empirical Relation and Causal Direction

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INTRODUCTION

The breadth of human problem solving is truly striking. On the one hand, human problem solving makes possible the most wondrous achievements, such as "an 800-seat airliner with wings that blend smoothly into the fuselage instead of protruding from its sides that is scheduled to be in the air by 2006" (AP news from February 9, 2001). Yet, on the other hand, errors in problem solving can lead to catastrophic and near-catastrophic disasters, such as, for instance, the nuclear reactor accident at Three Mile Island, Pennsylvania, in 1979. Whatever "problem solving" is, and scientists disagree vehemently on the proper meaning of the term, there can be little doubt that it has shaped human culture to an extent that is almost unrivaled by any other human ability.

From the inception of the concept of "intelligence," the ability to solve problems has featured prominently in virtually every definition of human intelligence (e.g., Sternberg & Berg, 1986). In addition, intelligence has often been viewed as one of the best predictors of problem-solving ability (e.g., Putz-Osterloh, 1981; Putz-Osterloh & Lüer, 1981). Thus, whatever the causal relation between the two concepts, prevailing theoretical positions strongly suggest that intelligence and problem solving are related. In this chapter we concentrate on complex rather than on simple problem solving. Our main goal is to review the extent to which the ability to solve complex problems is indeed tied, empirically, to intelligence and to discuss which causal direction holds between the two concepts. More specifically, we discuss the extent to which individual differences in complex problem-solving competence can be tied, both theoretically and empirically, to individual differences in global intelligence and/or to individual differences in specific intelligence components.

The chapter is divided into three main sections. In the first section, we briefly describe the history of the mainly European complex

problem-solving research and offer a definition of "complex problem solving." In the second and third sections, we review much of the existing empirical work that relates complex problem-solving competence to intelligence. We distinguish two forms of complex problem solving. In the second section, we focus on explicit complex problem solving, that is, problem solving that is controlled by a problem solver's intentions. In the third section our focus is on implicit, that is, automatic or nonconscious, complex problem solving.

Our main argument throughout the chapter will be that no convincing empirical evidence exists to support a relation between complex, implicit or explicit, problem-solving competence on the one hand, and global intelligence on the other hand. We are aware that arguing the null hypothesis is difficult at best and dangerous at worst. Thus, we do not deny the possibility that a relation between complex problem-solving competence and global intelligence might exist in reality; we argue only that there is no convincing empirical evidence at the present time that supports such a conclusion. On the other hand, however, we believe that a considerable amount of empirical data does suggest that specific components of intelligence, such as processing capacity, might be related to specific components of explicit complex problem solving. On the whole, therefore, we argue that the available evidence suggests that the global concepts of intelligence and problem solving are not related, but that specific subcomponents of intelligence and explicit problem solving might share variance. The existing empirical evidence does not allow us, however, to draw any conclusion on the causal relation between subcomponents of intelligence and subcomponents of problem solving.

DEFINITIONS AND CLARIFICATIONS

As pointed out by Frensch and Funke (1995), researchers in the area of human problem solving have often been quite inconsistent in their use of terms such as "problem," "problem solving," and "intelligence." Although perhaps understandable, different uses of the same term seriously undermine scientific progress. Because the definition of a term affects the choice of experimental tasks and methods, and thus, ultimately affects the conclusions to be drawn (Frensch & Funke, 1995), we make an attempt in this section to delineate what exactly we mean when we talk about "problems" in general and "complex problems" in particular. First, however, we give a brief historical overview of complex problem-solving research.

Simple and Complex Problems

Beginning with the early experimental work of the Gestaltists in Germany (e.g., Duncker, 1935), and continuing through the 1960s and early 1970s,

research on problem solving was typically conducted with relatively simple laboratory tasks (e.g., Duncker's "X-ray" problem; Ewert & Lambert's "disk" problem, 1932, later known as "Tower of Hanoi") that were novel to research participants (e.g., Mayer, 1992). Simple novel tasks were used for a variety of reasons; they had clearly defined optimal solutions, they were solvable within a relatively short time frame, research participants' problem-solving steps could be traced, and so on. The underlying assumption was, of course, that simple tasks, such as the Tower of Hanoi, capture the main properties of real-life problems, and that the cognitive processes underlying participants' solution attempts on simple problems were representative of the processes engaged in when solving real problems. Thus, simple problems were used for reasons of convenience, and generalizations to more complex problems were thought possible. Perhaps the best known and most impressive example of this line of research is the work by Newell and Simon (1972).

However, beginning in the 1970s researchers became increasingly convinced that empirical findings and theoretical concepts derived from simple laboratory tasks were not generalizable to more complex, real-life problems. Even worse, it appeared that the processes underlying complex problem solving (CPS) in different domains were different from each other (Sternberg, 1995). These realizations have led to rather different responses in North America and Europe.

In North America, initiated by the work of Herbert Simon on learning by doing in semantically rich domains (e.g., Anzai & Simon, 1979; Bhaskar & Simon, 1977), researchers began to investigate problem solving separately in different natural knowledge domains (e.g., physics, writing, chess playing), thus abandoning their attempts to extract a global theory of problem solving (e.g., Sternberg & Frensch, 1991). Instead, these researchers frequently focused on the development of problem solving within a certain domain, that is, on the development of expertise (e.g., Anderson, Boyle, & Reiser, 1985; Chase & Simon, 1973; Chi, Feltovich, & Glaser, 1981). Areas that have attracted rather intensive attention in North America include such diverse fields as reading, writing, calculation, political decision making, managerial problem solving, lawyers' reasoning, mechanical problem solving, problem solving in electronics, computer skills, game playing, and even personal problem solving.

In Europe, two main approaches have surfaced, one initiated by Donald Broadbent (1977; see Berry & Broadbent, 1995) in Great Britain and the other by Dietrich Dörner (1975, 1980; see also Dörner & Wearing, 1995) in Germany. The two approaches have in common an emphasis on relatively complex, semantically rich, computerized laboratory tasks that are constructed to be similar to real-life problems. The approaches differ somewhat in their theoretical goals and methodology (see Buchner, 1995, for a more detailed comparison). The tradition initiated by Broadbent

emphasizes the distinction between cognitive problem-solving processes that operate under awareness versus those operating outside of awareness, and typically employs mathematically well-defined computerized systems. The tradition initiated by Dörner, on the other hand, is interested in the interplay of cognitive, motivational, and social components of problem solving, and utilizes very complex computerized scenarios that contain up to 2,000 highly interconnected variables (e.g., the Dörner et al., 1983, Lohhausen project).

With these considerations in mind, it is not surprising that there exists a wide variety of definitions of the term "complex problem solving" that have little in common (e.g., Frensch & Funke, 1995). Any general conclusion regarding complex problem solving, however, and any theoretical model of complex problem solving can only be meaningful if all agree on what constitutes a problem and what constitutes complex problem solving. For the remainder of this chapter we define complex problem solving as follows:

Complex problem solving occurs to overcome barriers between a given state and a desired goal state by means of behavioral and/or cognitive, multi-step activities. The given state, goal state, and barriers between given state and goal state are complex, change dynamically during problem solving, and are intransparent. The exact properties of the given state, goal state, and barriers are unknown to the solver at the outset. Complex problem solving implies the efficient interaction between a solver and the situational requirements of the task, and involves a solver's cognitive, emotional, personal, and social abilities and knowledge. (Frensch & Funke, 1995, p. 18)

There are at least two reasons for why we focus, in this chapter, on the relation between intelligence and complex, rather than simple, kinds of problem solving. First several reviews already exist of the relation between intelligence and simple problem-solving competence as displayed when typical laboratory problems are solved (e.g., Sternberg, 1982). The conclusion from these reviews appears to be that if indeed a relation exists between intelligence and problem-solving competence, then it is probably quite modest in size (i.e., correlations around .30). By comparison, the potential relation between intelligence and complex problem-solving competence has been rarely discussed and reviewed in detail (for exceptions, see Kluwe, Misiak, & Haider, 1991a; Kluwe, Schilde, et al., 1991b).

Second, and perhaps more importantly, the external validity of the artificial laboratory tasks typically used to study the relation between intelligence and problem-solving competence is highly questionable. The tasks have little resemblance to the problem-solving situations typically encountered by humans.

As will become apparent later in the chapter, we distinguish between complex problem solving that is dependent upon the intended actions of

a problem solver (i.e., explicit problem solving) and problem solving that occurs, more or less, outside the realm of intention (i.e., implicit problem solving). For both types of problem solving, we will ask to what extent individual differences in CPS competence might be tied to individual differences in intelligence.

Evaluation Criteria

We strongly believe that any theoretical and/or empirical approach arguing for a relation between problem-solving competence and intelligence must meet a number of criteria in order to be taken seriously. We use three criteria to assess and evaluate the research considered:

Criterion 1. Problem-solving competence and intelligence need to be explicitly defined and must not overlap at theoretical and/or operational levels. At a theoretical level, this criterion implies that both intelligence and problem-solving competence need to be defined explicitly and, more importantly, independently of each other. If the latter is not the case, then any attempt to relate problem-solving competence to intelligence is necessarily circular and redundant – one would find what is a priori true (Greve, 2001). At the operational level, Criterion 1 implies that independent and reliable measures need to be used to assess the respective constructs. When overlapping measures (e.g., items that appear on a questionnaire used to measure intelligence also appear on a questionnaire used to measure problem-solving competence) are used, then empirically observed correlations may reflect methodological artifacts rather than theoretically relevant relations.

Criterion 2. The presumed relation between intelligence and problem-solving competence must have a theoretical explanation. This criterion demands that some theory or model exists that specifies the proposed relation between CPS competence and intelligence. In principle, there appear to be at least three main possibilities regarding the relation between complex problem solving and intelligence. First, individual differences in intelligence may cause individual differences in CPS ability. Second, the causal relation might work the other way around; that is, individual differences in CPS ability may cause individual differences in intelligence. Third, individual differences on the two concepts might be not only correlated but also causally related to a third variable. Without an understanding of the direction of the causal link between the two concepts, that is, without a theoretical foundation linking the two concepts, there exists no explanation.

Criterion 3. The direction of the presumed causality must be demonstrated empirically. Whatever the theoretically proposed direction of causality, it needs to be demonstrated empirically. Because a direct experimental manipulation of degree of intelligence is not feasible, indirect assessments of the direction of causality are required. Acceptable approaches might be to (a) use longitudinal research designs or (b) experimentally manipulate

the use of intelligence by varying either instructions or task properties, which requires (c) control of potential third variables that possibly modulate empirically observed relations.

In the next section, we discuss theoretical ideas and empirical research that are relevant to exploring the relation between intelligence and explicit, intention-driven, problem-solving competence for complex problems. In the third section, we focus on the relation between intelligence and implicit, that is, nonintentional problem solving.

INDIVIDUAL DIFFERENCES IN COMPLEX EXPLICIT PROBLEM SOLVING

In this section, we review first some of the research on the relation between complex explicit problem solving (CEPS) and intelligence as assessed by traditional intelligence tests or specific subtests thereof. The assumption underlying this approach is that a person's IQ score reflects some global and relatively stable intellectual ability that might potentially be associated with CEPS. With few exceptions, the tasks used to assess CEPS competence consist of dynamic scenarios presented on a computer, with the number of (independent exogenous and interconnected endogenous) variables ranging from 3 to about 2000. The scenarios are described to research participants with the more or less clearly specified goal to optimize some aspects of the scenario's output (for a review, see Funke, 1995).

Perhaps surprisingly, empirical support for a relation between intelligence and problem-solving ability is poor. Typically, the reported correlations are low or even zero, at least when the problem situation is nontransparent and/or the goal to be achieved is poorly specified (for detailed reviews, see Kluwe et al., 1991a, b; Beckmann & Guthke, 1995). The probably best-known study producing zero correlations was conducted by Dörner and colleagues (Dörner et al., 1983) using the Lohhausen system. Participants' task was to take care of the future prosperity of a small town called Lohhausen over a simulated 10-year period. About 2,000 variables were involved in this system (e.g., number of inhabitants, earnings of the industry, etc.). Participants interacted with the system through an experimenter. Problem-solving competence on this task did not correlate with Raven's Advanced Progressive Matrices (APM; Raven, Court, & Raven, 1980) scores, nor did it correlate with scores on the Culture Fair Intelligence Test (CFT; Cattell & Weiss, 1980).

Results such as these have been interpreted and discussed quite controversially by different groups of researchers. One group of researchers (e.g., Dörner & Kreuzig, 1983; Putz-Osterloh, 1981) has argued that zero correlations between problem-solving competence and general intelligence reflect the fact that traditional IQ measures tend to be ecologically less valid than CEPS measures. More specifically, these researchers claim

that in dynamic scenarios (a) the goals are often ill specified, (b) information in needs to be actively sought after, and (c) semantic/contextual embeddedness (i.e., a meaningful cover story) is almost always present, and that traditional intelligence tests do not measure the intellectual abilities (such as the so-called operative intelligence; Dörner, 1986) required for successful problem-solving performance in highly complex and ecologically valid environments.

According to a second group of researchers (e.g., Funke, 1983, 1984; Kluwe et al., 1991b), low correlations between IQ and CEPS are due to methodological and conceptual shortcomings. Kluwe et al. (1991a, b) have pointed out, for instance, that it is impossible to derive valid indicators of problem-solving performance for tasks that are not formally tractable and thus do not possess a mathematically optimal solution. Indeed, when different dependent measures are used in studies with the same scenario (i.e., Tailorshop; e.g., Funke, 1983; Putz-Osterloh, 1981; Süß, Kersting, & Oberauer, 1991), then the empirical findings frequently differ for different dependent variables.

Second, the reliability of the performance indices is often low (e.g., Funke, 1983, 1984; Kluwe et al., 1991b), ranging between .2 and .7, depending on the dependent variable used (see, e.g., Müller, 1993; Putz-Osterloh & Haupts, 1989; Strohschneider, 1986). Other quite serious methodological criticisms concern the narrow sampling of IQ in most of the studies just mentioned (e.g., Funke, 1991) and the ecological validity of the scenarios.

However, the empirical picture is far more complicated and less clear than might have been suggested thus far. Although zero correlations between test intelligence and complex problem-solving competence are frequently obtained, this is not always the case. For example, Putz-Osterloh (1981; Putz-Osterloh & Lüer, 1981) has argued that the relation between global intelligence and complex problem-solving competence is mediated by the transparency of the problem-solving task. Like Dörner et al. (1983), Putz-Osterloh (1981) failed to find significant correlations between problem-solving competence and Raven's APM in a nontransparent experimental condition with the Tailorshop scenario, a scenario simulating a small company in which shirt production and sales are controlled by purchasing raw materials and modifying the production capacity in terms of the number of workers and machines. The participant's goal in the study was to maximize the company's profit, either in a transparent condition, in which they had access to a diagram depicting the relations between the system variables, or in a nontransparent condition in which no diagram was shown.

Putz-Osterloh (1981, see also Putz-Osterloh & Lüer, 1981; Hörmann & Thomas, 1989) found a statistically reliable relation (*Tau* = .22) between IQ and problem-solving competence (operationalized by the number of months with increasing capital assets) in the transparent experimental condition (but see Funke, 1983, for different results).

A different moderator variable affecting the link between global intelligence and complex problem-solving competence has been suggested by Strohschneider (1991). The author, using the Moro system in which participants are asked to improve the living conditions of nomads in the Sahel zone, manipulated the specificity of the to-be-attained goals. In the specific-goal condition, participants were asked to reach specified values on critical variables (e.g., number of cattle, number of inhabitants, etc.). In the unspecific-goal condition, the participants' task was to take actions that guaranteed long-term improvements of the Moro living conditions.

In the unspecific-goal condition, problem-solving performance did not correlate with general intelligence as measured by the Berlin Intelligence Structure (BIS) test (Jäger, 1982; Jäger, Süß, & Beauducel, 1997); however, substantial correlations (up to $r = -.59$) were found in the specific-goal condition.

Yet another variable affecting the relation between global intelligence and complex problem-solving ability may be the semantic context of a problem-solving task. Hesse (1982) investigated the impact of the semantic embeddedness of the problem-solving task on the relation between IQ and CEPS. In the semantic condition, participants were asked to solve the Dori problem, a computerized system involving ecological variables and relations. In the semantic-free condition, a system with an isomorphic problem structure but without the cover story and without meaningful variable names was presented to the participants. In addition, transparency was manipulated in the same way as had been done in the Putz-Osterloh (1981) experiment described earlier. Hesse (1982) obtained moderate correlations between problem-solving performance and APM scores only in the semantic-free condition ($r = .38$ and $r = .46$ for the transparent and the nontransparent condition, respectively).

On the whole, these empirical findings do not support a strong link between global intelligence and complex problem-solving competence when goal specificity and transparency are low and when the semantic content is rich; the link appears to be somewhat stronger when the intelligence-testing conditions more closely resemble the problem-solving testing conditions. We agree with Kluwe et al. (1991a, b) that on the basis of these results, it cannot be determined whether low correlations are due to invalid intelligence testing (i.e., their failure to assess real-world intellectual abilities necessary for dealing with complexity) or are due to a lack of reliability of the CEPS measures. The heterogeneity of the scenarios and IQ tests used further complicates the interpretation of the existing results.

Evaluation of Approach

Criterion 1. Problem-solving competence and intelligence need to be explicitly defined and must not overlap at theoretical and/or operational levels. Because

independent tasks are typically used to assess problem-solving competence and intelligence, the measures used in the described research do not overlap at an operational level. However, the fact that significant correlations between complex problem-solving competence and IQ are obtained when goal specificity is high and/or semantic embeddedness is missing suggests an overlap at the level of task requirements.

Criterion 2. The presumed relation between intellectual ability and problem-solving competence must have a theoretical explanation. Apart from general statements, it is not obvious how exactly intelligence should contribute to CEPS. This is so because (a) to date researchers have not agreed on the nature of intelligence (see, for example, Kray & Frensch, 2001, for an overview of different accounts of the nature of g), and (b) no models exist that theoretically link intelligence to (specific aspects of) complex problem-solving behavior. The latter problem may partly be due to the difficulty to define an objective problem space for mathematically intractable scenarios. For that reason, some researchers recommend the use of formally tractable scenarios like finite-state automata or linear structural equation systems (see Buchner, 1999; Funke, 2001).

Criterion 3. The direction of the presumed causality must be demonstrated empirically. To our knowledge, no longitudinal or training designs have been used to assess the direction of causality. Some empirical studies have manipulated task properties such as transparency, but only Funke (1983) used a between-group design (sampling from the extremes of the IQ distribution). Furthermore, it is questionable whether potential moderator variables have been adequately controlled for. For instance, when both semantic embeddedness and transparency are varied, as in the study by Hesse (1982), then transparency does not affect problem-solving performance in the semantic-free condition. Hence, the direction of causality (if any exists) remains unclear.

To summarize, correlating global IQ scores with complex problem-solving performance does not seem to be particularly useful when the goal is to understand the potential link between intelligence and complex problem-solving competence. Our main concern with this approach relates to a lack of theoretical explanation. In the next part, we review research that goes beyond correlating global IQ with CEPS performance by singling out individual components of intelligence that may affect problem-solving competence.

CEPS and Specific Intelligence Components

In the research reviewed next, IQ subtests such as those inherent in the BIS or learning-test scores were correlated with complex problem-solving performance. For example, Süß et al. (1991, 1993; see also Hussy, 1991) had problem solvers work on a nontransparent version of the Tailorshop.

The authors hypothesized that to successfully control this system, problem solvers needed to infer the relations among critical variables and to deduce meaningful goals and actions. Therefore, reasoning ability, as assessed by the BIS K-factor (processing capacity, capturing the ability to recognize relations and rules and to form logical inferences in figure series, number series, and verbal analogies) was predicted to be the single most predictive ability of problem-solving ability. This is indeed what the authors found. Overall problem-solving performance correlated substantially with K ($r = .47$). In addition, *knowledge* (specific system knowledge as well as general economic knowledge) was found to be a predictor of problem solving (see also Putz-Osterloh, 1993).

Similar findings have been reported by Hörmann and Thomas (1989), who administered the Tailorshop under two different transparency conditions. When problem solvers' system knowledge, as assessed by a questionnaire, was high, then the K-factor ($r = .72$) and the G-factor (indicating memory performance, $r = .54$) correlated with CEPS performance in the nontransparent condition, whereas the B-factor (processing speed) was the best predictor in the transparent condition. However, when system knowledge was not considered, then significant correlations only emerged in the transparent condition.

Hussy (1989), on the other hand, found the K-factor to be the single most predictive operative factor, regardless of transparency condition and system knowledge. The scenario used by Hussy was the Lunar Lander, a mathematically well-defined system with only six variables and a very specific goal, which makes it difficult to compare this study directly to those using the Tailorshop. Nevertheless, it is interesting to note that Hussy (1989) also found the G-factor (memory) to be significantly correlated with problem-solving performance in the nontransparent condition. This finding is similar to Hörmann and Thomas's result (1989) and points to the possibility that nontransparent problems may pose particularly high memory demands when problem solvers attempt to develop internal models of the task (cf. Buchner, 1995).

In general, these results appear to be inconsistent with Strohschneider's (1991, see previous section) finding of high correlations between almost all BIS operative factors and problem-solving performance in the specific-goal condition of the Moro system. But then again, Strohschneider's study differs substantially in terms of task demands, such as system complexity and operationalization of goal specificity, from these studies, making direct comparisons difficult.

A different "componential" approach has been taken by Beckmann (1995; for a comprehensive overview see Beckmann & Guthke, 1995). Beckmann and colleagues argue that successful problem-solving performance involves the ability to learn from success and failure. The authors therefore use learning tests (e.g., Guthke, 1992) that assess problem solvers'

learning potential, in addition to the reasoning subtests of traditional intelligence tests (Intelligence Structure Test, IST; Amthauer, Brocke, Liepmann, & Beauducel, 1973; and Learning Test Battery "Reasoning," LTS 3; Guthke, Jäger, & Schmidt, 1983) to predict problem-solving performance and knowledge acquisition. Diagrams for which the relevant relations need to be filled in assess the latter. The authors' six-variable system is based on a linear equation system and was administered in either an abstract Machine version or in a semantically meaningful version (Cherrytree, for which water supply, warmth, etc., had to be manipulated in order to control the growth of cherries, leaves, and beetles).

In the abstract Machine version, problem solvers acquired substantial system knowledge, and learning-test scores correlated substantially with the system knowledge measure as well as with problem-solving performance measures, whereas traditional intelligence subtest scores only correlated (albeit to a smaller degree) with problem-solving performance. In contrast, in the Cherrytree version, problem solvers did not demonstrate system knowledge nor did test scores (regardless of type) correlate with problem-solving performance (see also Hesse, 1982). Interestingly, the two experimental groups (i.e., Machine vs. Cherrytree) did not differ in terms of the quality of their CEPS performance, that is, in their control of the system. This and similar results have led several researchers (e.g., Berry & Broadbent, 1984) to propose different modes of learning and of problem solving; we return to this issue in the third section when we discuss implicit problem solving.

To summarize, when specific intelligence components are correlated with problem-solving performance in complex systems and when the problem-solving goals are clearly specified, then moderate to substantial correlations are obtained, even under nontransparent task conditions. The most important intelligence components predicting problem-solving competence appear to be processing capacity/reasoning ability and learning potential. Semantic content appears to be an important mediator of the relation between abilities and CEPS (e.g., Hesse, 1982), implying that the content may activate prior knowledge and affect the problem representation. Furthermore, inconsistent results have been obtained regarding the relation between system knowledge (i.e., knowledge about the relations among variables) and problem-solving performance.

Evaluation of Approach

Criterion 1. Problem-solving competence and intelligence need to be explicitly defined and must not overlap at theoretical and/or operational levels. Regarding operational overlap, much the same can be said as in the previous section. There is little reason to expect much overlap at the operational level although task requirements may overlap to some extent. Concerning

theoretical overlap, the situation is even more satisfying. Learning and reasoning are better defined than is global intelligence, and the overlap between the theoretical concepts appears to be low.

Criterion 2. The presumed relation between intellectual ability and problem-solving competence must have a theoretical explanation. Although interesting with regard to hypothesis generation, the approach just discussed suffers from a lack of theoretical explanation. Demonstrating that a person's reasoning ability is related to problem-solving competence, for instance, does not tell us much about the specific reasoning processes and representations that may be required for successful problem solving. Thus, the theoretical foundation of the link between the proposed ability and problem-solving performance remains rather unclear at the level of mechanisms. A closer task analysis (plus the use of mathematically tractable tasks) as well as a more systematic variation of task properties may be needed to better understand how specific intelligence components might be related to complex problem-solving competence.

Criterion 3. The direction of the presumed causality must be demonstrated empirically. Largely the same conclusions can be drawn regarding this criterion as in the first part of the present section. In our view, a causal link between intellectual ability and specific intelligence components has not been demonstrated within this line of research.

On the whole, the approach of correlating specific intelligence components with CEPS performance is theoretically much more interesting than correlating CEPS performance with global IQ. However, to theoretically understand CEPS in terms of the underlying intellectual abilities, three things are needed: (1) more detailed models of knowledge acquisition processes in CEPS situations, (2) more detailed theoretical accounts of the links between the proposed abilities and CEPS performance, as well as (3) research designs that allow inferences about the direction of causality.

Expertise and Intelligence

Instead of assessing complex problem-solving competence with the aid of computerized systems, researchers have also explored the relation between intelligence and problem-solving competence in a more natural context, namely by correlating global intelligence with expertise. Arguably the best-known work in this regard has been performed by Ceci and his colleagues (e.g., Ceci & Liker, 1986a, b; Ceci & Ruiz, 1992, 1993), who claim that expertise is unrelated to global IQ. Ceci and Liker (1986a, b), for instance, compared experts and novices in terms of their ability to handicap races and in the cognitive complexity underlying their handicapping performance. Furthermore, the relation between expertise and IQ, as measured by the WAIS, as well as between cognitive complexity and IQ was examined.

Experts differed from novices in terms of their ability to correctly predict post-time odds for the top three horses in ten actual races on the basis of a priori factual information about the horses although the two groups were comparable in terms of their factual knowledge about races (as assessed by a screening questionnaire), years of track experience, years of education, and, most importantly, IQ. That is, both groups contained high-IQ as well as low-IQ individuals.

Experts as well as novices subsequently handicapped 50 experimentally contrived races, in which an "experimental" horse had to be compared to a "standard" horse. For the former, values on potentially important variables (such as lifetime speed, claiming price, trace surface condition, etc.) were systematically varied. To model how experts and novices arrived at their odds predictions, Ceci and Liker used multiple-regression analyses.

The results of the study can be summarized as follows. First, the modeling results showed that a simple additive model was not sufficient to predict performance, at least not for experts. Rather, quite complicated interactive terms needed to be included. Second, experts gave more weight to higher-order interactions than did novices, suggesting a higher degree of cognitive complexity in their reasoning. Third, the weight of the higher-order interactions correlated highly with handicapping ability, but did not correlate with IQ. The latter finding is particularly important because it suggests that global intelligence is unrelated to cognitive complexity in real-life complex problem solving such as handicapping races.

Interestingly, similar results have been obtained in very different areas of expertise. For example, in their recent work on practical intelligence (i.e., situational-judgment tests that present work-based problems for participants to solve), Sternberg and colleagues have repeatedly found no correlation between performance and IQ. In their most recent article, Sternberg et al. (2001) describe work done with 85 children between the ages of 12 and 15 in a rural village in western Kenya. The main dependent variable of interest was children's scores on a test of tacit knowledge for natural herbal medicines used to fight illnesses. Sternberg et al. found that scores on the tacit knowledge correlated trivially or even significantly negatively with measures of IQ and achievement, even after controlling for socioeconomic status.

Even if it is true that global intelligence is not related to expertise, it might still be related to the acquisition of expertise. To explore the latter possibility, Ceci and Ruiz (1992, 1993) conducted a follow-up case study in which they investigated the acquisition of expertise on a novel task of two race-handicapping experts with different IQ levels. The new task was constructed such that it had the same underlying "problem structure" as the race-handicapping task. That is, the authors constructed a stock market game that included just as many variables as were included in

the handicapping task. In the new task, an experimental stock had to be compared to a standard stock. The two handicapping experts were asked to decide which of the two stocks would yield a better future price/earnings ratio. Experimental trials were constructed such that the equation modeling handicapping performance held for a subset of the stock market variables.

The results of this study showed that the two experts did not spontaneously transfer the "handicapping" rule to the new task before they were informed that the task-relevant variables could be weighed and combined in the same manner as they had done in predicting post-time odds. After receiving this hint, performance increased considerably for both experts. Modeling indicated that the experts had not developed a model as complex as the equation they used for handicapping. Rather, they appeared to work with models containing only lower-order interactions. Consequently, performance never reached impressive levels, although both experts managed to eventually perform above chance. Most importantly, the high and low IQ experts did not differ in their performance nor in terms of the cognitive complexity they brought to bear on the new task.

Ceci and colleagues interpret their results as indicating that (a) intelligence always manifests itself as an interaction between underlying intellectual abilities and experience in particular domains, and is therefore context/content dependent, (b) multiple intelligences exist, and (c) IQ tests measure only a specific type of intelligence, namely one developed in academic settings.

The Ceci studies have not remained without criticism. Detterman and Spry (1988; see also Ceci & Liker, 1988, for a reply), for instance, argued that sampling procedure, sample size, and questionable reliabilities (but see Ceci & Liker, 1988) might have led to an underestimation of the "true" correlations. Ceci and Ruiz (1993) themselves made the point that the difficulty of the novel task might have prevented transfer to occur.

Regardless of the validity of the criticisms, it is important to acknowledge that the Ceci and Liker and Ceci and Ruiz studies are two of the very few studies that have related global intelligence to expertise and to the acquisition of problem-solving competence. The empirical result is both intriguing and consistent with the European research reviewed earlier: IQ does not seem to predict expertise (i.e., CEPS competence), nor does it predict the acquisition of CEPS competence.

Evaluation of Approach

Criterion 1. Problem-solving competence and intelligence need to be explicitly defined and must not overlap at theoretical and/or operational levels. Except for possibly similar task demands, no overlap appears to exist at the operational level. That is, the measures used to assess level of expertise

and global intelligence differ. In addition, the reliability of the prediction performance scores may be better than has been pointed out by critics (e.g., Detterman & Spry, 1988).

The argument Ceci and colleagues are pushing is that global intelligence and expert problem-solving competence do not overlap theoretically. As for separately defining expertise and global intelligence, some effort has been made to define critical (cognitive) characteristics of expertise. The problem concerning the nature of g discussed in the first part of the present section remains unsolved, however.

Criterion 2. The presumed relation between intellectual ability and problem-solving competence must have a theoretical explanation. While an overall correlation between global intelligence and expertise was not expected, Ceci and Liker (1986b) state that "each of us possesses innate potentialities for achievement in abstract reasoning, verbal analysis, creative expression, quantification, visual-spatial organization, and so on" (Ceci & Liker, 1986b, p. 139) that are funneled into specific expressions of intelligence according to experience and motivation. Thus, a more stringent test of the existence of independent context-specific manifestations of intelligence would be to correlate prediction performance/complexity with (IQ) subtest scores. For example, it would be interesting to see whether people with different learning test scores differ with respect to learning and transfer on the stock market task.

Criterion 3. The direction of the presumed causality must be demonstrated empirically. Because a number of potential moderator variables, such as age, years of experience, and preexisting knowledge, have been taken into account, the Ceci and Ruiz training study can be considered a first step in demonstrating (the lack of) a causal relation between IQ and the acquisition of complex problem solving. Of course, methodological shortcomings such as small sample size and possible floor effects regarding learning and problem-solving performance demand replication. Moreover, the empirically demonstrated lack of a global IQ effect does not tell us much about (a) whether more specific abilities would have had predictive value and (b) how much overlap in content is required for two "ability measures" to be correlated.

In summary, Ceci and colleagues have undertaken an impressive attempt to demonstrate that expertise, defined as people's ability to reason complexly in one domain (i.e., race handicapping), is independent of general intelligence. Expertise has been relatively clearly defined and an attempt has been made to study the cognitive processes involved in successful performance by careful task analysis. Moreover, the training study is the first attempt at assessing causality. However, as amply discussed earlier, correlating global intelligence with CEPS is not particularly informative as to the exact nature of the intellectual abilities underlying problem solving.

IMPLICIT PROBLEM SOLVING

Some recent findings with artificial grammar-learning, sequence-learning, and complex problem-solving tasks all suggest that people are capable of successfully solving problems even when they are not able to verbally express the knowledge they are utilizing (e.g., Frensch & Rünger, 2003). Such findings have led some researchers (e.g., Berry & Broadbent, 1984, 1987; Nissen & Bullemer, 1987; Reber, 1967, 1969) to propose independent learning systems that might underlie performance in a problem-solving task: an explicit learning system and an implicit learning system. The former is thought to be based on deliberate hypothesis testing, to be selective with respect to what is learned, and to lead to consciously accessible and verbalizable knowledge. Implicit learning, on the other hand, has been characterized as involving "the unselective and passive aggregation of information about the co-occurrence of environmental events and features" (Hayes & Broadbent, 1988, p. 251). Thus, implicit learning is assumed to take place irrespective of the intention to learn, to not rely on hypothesis testing, and to lead to implicit (tacit) knowledge that cannot or can only partially be accessed (Frensch, 1998). Furthermore, it has been argued (Reber, Walkenfield, & Hernstadt, 1991; see also Anderson, 1998) that implicit learning is an evolutionarily older, less variable, and more robust ability, suggesting that problem-solving performance that is based on implicit learning might not be correlated with intelligence.

In this section of the chapter we address whether or not this suggestion is correct. Before we do so, however, we briefly describe the tasks that have been used to demonstrate the existence of implicit problem solving and the arguments that have been exchanged between proponents and opponents of the implicit-learning assumption.

The Tasks Used

The dynamic scenario most often used in the studies reported below consists of a simple linear equation relating one input variable to an output variable, also taking into account the previous output. In addition, in most studies a random component is added on two-thirds of the trials, such that on these trials the system changes to a state one unit above or below the state that would be correct according to the deterministic equation. The system is frequently used in one or both of two semantic versions, the Sugar Factory and the Computer Person. When controlling the Sugar Factory, problem solvers are required to reach and maintain specified levels of sugar output by varying the number of workers employed. In the Computer Person task, problem solvers enter attitude adjectives (e.g., "friendly" or "polite") from a fixed adjective set in order to get the computer person to display a specified behavior (e.g., "very friendly").

A second task that is frequently used is the City Transportation system. This task is similar to the linear equation systems described in the previous section in that two variables (free parking slots and number of people taking the bus) need to be adjusted by varying two exogenous variables (time schedule for buses and parking fee). In the majority of studies, problem solvers are asked to control the system from the beginning (i.e., there is no exploration phase). In addition, instructions and/or system features are varied. After controlling the system for a while, problem solvers are probed for their structural knowledge. This is usually done with the help of multiple-choice questionnaires that require problem solvers to predict outcomes, given a specified previous output and novel input. The experimental approach thus differs from the standard procedure of the studies discussed in the previous section in that (a) the systems are usually less complex in terms of the underlying variables and relations, (b) problem solvers are typically not allowed to explore the system before they are asked to reach specified target values, and (c) problem solvers are usually not probed for their structural knowledge before they have completed the experiment.

Empirical Evidence Supporting the Assumption of an Implicit Learning System

Empirical evidence supporting the existence of an implicit learning system mainly comes from two types of dissociations: (1) dissociations between problem-solving performance and questionnaire answers and (2) differential effects on problem-solving performance when systems are controlled that are assumed to engage different learning systems.

For instance, Berry and Broadbent (1984), using both the Sugar Factory and the Computer Person task, found that problem-solving performance improved with practice (two vs. one block of practice), but that structural knowledge was unaffected. Furthermore, correlations between problem-solving performance and knowledge tended to be negative. In contrast, informing problem solvers about the rules of the system after the first practice block improved structural knowledge but did not affect performance. Again, no positive correlations between problem-solving performance and knowledge emerged.

Berry and Broadbent (1987, 1988) demonstrated that this type of dissociation critically depends on the salience of the relations among variables. In their 1988 study, salience was manipulated by varying feedback delay in the Computer Person task. In the salient version, the output depended on the input of the current trial. In contrast, in the nonsalient version, the output was determined by the problem solver's input on the preceding trial. Berry and Broadbent assumed that nonsalient tasks would induce implicit learning, whereas the easier salient task would be learned explicitly. The authors

reported that performance improved with practice for both task versions, although performance on the salient task was generally better than on the nonsalient task. More interestingly, instructions to search for systematic relations between variables improved performance for the group working on the salient task, but impaired performance in the nonsalient group. Moreover, structural knowledge scores were higher in the salient group than in the nonsalient group, and correlations between knowledge and problem-solving performance tended to be somewhat higher in the salient group (yet none of the correlations reached significance).

The nature of the underlying relations also seems to affect the ability to transfer knowledge to novel situations (Berry & Broadbent, 1988; Hayes & Broadbent, 1988). Hayes and Broadbent found that a change in the equation after an initial learning phase impaired problem-solving performance in the nonsalient condition of the Computer Person, but not in the salient condition. More dramatically, however, this pattern of results reversed when problem solvers worked under dual-task conditions (i.e., when they performed a concurrent random letter generation task). That is, when a secondary task had to be performed concurrently, relearning was impaired in the salient but not in the nonsalient condition. Based on these and similar results, Berry and Broadbent concluded that two independent learning systems exist, and that the unselective and unintentional implicit-learning mechanism is particularly well suited to dealing with highly complex situations in which deliberate hypothesis testing has little chance of being successful.

Unfortunately, however, not all researchers have empirically obtained such clear-cut dissociations between problem-solving performance and questionnaire answers supporting the existence of two independent learning systems as have Berry and Broadbent (1987, 1988), nor do all researchers agree with Berry and Broadbent's interpretation. For example, Green and Shanks (1993), in an attempt to replicate the Hayes and Broadbent (1988) study, found that problem solvers in the salient and nonsalient conditions were similarly impaired by an equation reversal (transfer), as well as by an equation change under dual-task conditions. Moreover, under dual-task conditions, initial learning was better in the salient than the nonsalient group. Green and Shanks concluded that feedback delay may simply influence task difficulty and hence the amount of knowledge acquired, instead of tapping into two functionally distinct learning systems. When problem solvers who learned nothing or very little during the initial learning phase were included in the analysis, Green and Shanks found that the performance of nonlearners in the nonsalient/dual-task condition improved after the equation change. However, Berry and Broadbent (1995) re-analyzed the Hayes and Broadbent data and could not confirm this latter pattern in their data analysis. Instead, they raised the possibility that differences in instructions may have contributed to these obviously contradictory results.

Although results such as these have led researchers to doubt the existence of two truly independent and possibly antagonistic learning systems, most researchers (e.g., Berry & Broadbent, 1988; Buchner, Funke, & Berry, 1995; Dienes & Fahey, 1995, 1998; Frensch & Rünger, 2003; Stanley et al., 1989) now seem to at least agree that complete and adequate explicit knowledge is not a necessary condition for successful problem solving in complex systems.

Implicit Learning and Intelligence

If indeed, as argued by Reber et al. (1991), implicit learning is an evolutionarily old, less variable, and more robust ability, then it is conceivable that problem-solving performance that is based on implicit learning might not be correlated with intelligence. Reber et al. (1991) were among the first to empirically explore the relation between implicit learning and intelligence.

Reber et al. compared participants' performance on an explicit letter series completion task (i.e., requiring an explicit search for underlying rules) with implicit learning (i.e., a well-formedness judgment) following an artificial grammar learning task. During the learning phase of the artificial grammar learning task, participants were instructed to memorize letter strings produced by a finite state grammar. They were informed about the existence of rules underlying the strings only after the learning phase had ended, that is, before the test phase took place. During the test phase, participants were asked to judge whether a given string corresponded to the rules (i.e., well-formedness task). In order to ensure a common metric for the series completion task and the well-formedness task, performance on the series completion task was assessed via 2-choice response alternatives. In addition, participants were required to explain their choices.

Reber et al. found relatively small individual differences on the well-formedness task as compared to much larger individual differences on the series completion task. This result could be corroborated by a re-analysis of former studies (e.g., Reber, 1976) in which implicit versus explicit learning was manipulated by varying the instruction for the artificial grammar task.

More to the point and much more interesting was the fact that Reber et al. (1991) could show that participants' WAIS scores correlated only weakly and nonsignificantly with performance on the well-formedness task ($r = .25$). Thus, implicit learning did not correlate significantly with IQ.

Recently, McGeorge, Crawford, and Kelly (1997) replicated and extended the earlier findings from Reber et al. (1991) in interesting ways. First, a factor analysis showed that while the correlation between performance on the implicit task and overall IQ was not significant ($r = .12$), there was a small but statistically reliable correlation between implicit learning and the perceptual organization factor ($r = .19$). Interestingly, this factor is the one most clearly associated with fluid intelligence. Second, there were no differences in performance on the implicit task with increasing age.

Using a somewhat different implicit-learning type task, Zacks, Hasher, and Sanft (1982) reported no difference in frequency encoding for students from a university with median verbal Scholastic Aptitude Test (SAT) scores of 610 and those from a school with median verbal SAT scores of 471.

Furthermore, Maybery, Taylor, and O'Brien-Malone (1995) found that performance on an implicit contingency detection task was not related to IQ ($r = .02$ and $.04$ for children in grades 1–2 and 6–7, respectively). Also, the children in these studies showed no association between their success on the implicit task and actual verbalized knowledge of the contingency tested ($r = .05$ for both groups). Interestingly, the low correlations between implicit learning and IQ seem not to have been due to lack of variation in implicit functioning. That is, there were individual differences in implicit learning, but these were not related to the differences obtained on the IQ measure. Also of interest is the fact that performance on the implicit tasks increased systematically with age.

Unfortunately, in more recent work, Fletcher, Maybery, and Bennett (2000) were not able to replicate their earlier findings. Comparing twenty children with intellectual disability (mean mental age = approximately 5.8 years) with intellectually gifted children (mean mental age = approximately 12.4 years) of similar chronological age (approximately 9.5 years), the authors found that implicit learning varied with intellectual level. It is unclear at present why the earlier and the more recent studies using essentially the same methodology yielded conflicting results.

In a somewhat different and yet related area of research, Ellis and colleagues found that individuals identified as retarded often display intact incidental learning. In the first of their studies, Ellis, Katz, and Williams (1987) found that mildly retarded adolescents, normal children, and normal adults were all equivalent in incidental learning of location. As with the studies discussed before, individual differences were obtained but were unrelated to gross measures of high-level cognitive functioning.

Ellis and Allison (1988) painted a more complex picture. Incidental learning of frequency of occurrence was equivalent for mildly retarded adolescents and college students, but only for visual information. While many individuals with a diagnosis of retardation displayed normal incidental learning of verbal-semantic material, several such individuals did not. The findings suggest that uncontrolled, unintentional learning processes show little age and IQ variation when visual-spatial or noncomplex materials are used, but that individual differences might emerge in processing of verbal or complex materials. Anderson (1998) recently reviewed research into related phenomena, arguing that variation in IQ is associated primarily with variations in mechanisms that are amenable to conscious control and reflection.

On the whole, although the implicit learning tasks used by Reber and colleagues cannot necessarily be considered CPS tasks, the typically obtained null findings are nevertheless interesting because they point to the

possibility that implicit and explicit problem-solving competence might rely on different intellectual abilities.

Evaluation of Approach

Criterion 1. Problem-solving competence and intelligence need to be explicitly defined and must not overlap at theoretical and/or operational levels. In most studies using implicit learning tasks, structural knowledge was assessed separately from problem-solving performance. Concerning theoretical independence, the concepts of implicit and explicit learning were defined independently of each other; thus, one may argue that – at least according to the original assumptions – no theoretical overlap exists.

Unfortunately, none of the studies reviewed in the present section reported reliabilities, neither for performance indicators nor for the questionnaires. Given the assumptions regarding the nature of the two learning mechanisms and the evidence regarding changes in learning/knowledge with practice, it would not make much sense to assess retest reliability. There is indirect evidence, however, that parallel-test reliability may not be very high. For example, several researchers (e.g., Stanley et al., 1989) have reported that problem solvers are better at controlling the Computer Person than the Sugar Factory task although the structure of the two tasks is identical. This, again, points to the impact of semantic embedding and of prior knowledge that is brought to the task, which may differ across individuals and domains.

Criterion 2. The presumed relation between intellectual ability and problem-solving competence must have a theoretical explanation. The proposal that an implicit learning mechanism might contribute to complex problem solving and is functionally dissociable from explicit learning is an exciting one because most work on abilities and individual differences has exclusively concentrated on explicit/conscious cognition. Unfortunately, however, convincing evidence for truly independent learning mechanisms does not exist at the present time (Frensch & Rünger, 2003). Rather, recent work suggests that what differs might not be learning per se, but the processing of study episodes. It may well be the case that the processing induced by different task demands correlates with different subtests of traditional intelligence tests and/or learning tests. Clearly, better definitions of critical task-related concepts such as "salience" and more thorough accounts of which processing requirements and abilities are afforded by certain task characteristics are needed in order to gain a better understanding of the abilities underlying implicit complex problem solving.

Criterion 3. The direction of the presumed causality must be demonstrated empirically. Evidence for a causal influence of an implicit learning mechanism on complex problem solving does not exist at the present time. However, some work (e.g., Geddes & Stevenson, 1997; Stanley et al., 1989; Vollmeyer,

Burns, & Holyoak, 1996) suggests that task demands encourage the use of particular strategies, which in turn affect what is being learned (see Wenke & Frensch, 2003, for a more extensive discussion of this argument). Of course, more work including experimental strategy induction as well as training, in combination with between-group designs, is necessary to gain a more complete understanding of strategic abilities. In addition, these study should address the issues of (a) semantic embeddedness and its influence on the mental models problem solvers bring to the task and (b) factors that lead to potential strategy shifts in the course of practice (e.g., chunking), or when working with enlarged solution spaces.

SUMMARY AND CONCLUSIONS

The main goal of the present chapter was to discuss to what extent, if indeed at all, individual differences in complex problem-solving competence are related to individual differences in intelligence. In the first section of the chapter we provided a definition of "complex problem solving." In the second and third sections, we evaluated much of the empirical work that relates complex problem-solving competence to some measure of intelligence with regard to three evaluation criteria. Two forms of problem solving were distinguished. In the second section, we focused on explicit problem solving, which is controlled by a problem solver's intentions. In the third section, our focus was on implicit, that is, automatic or nonconscious, complex problem solving.

Our main conclusions are as follows. First, no convincing empirical evidence exists that would support a relation, let alone a causal relation, between complex explicit or implicit problem-solving competence, on the one hand, and global intelligence on the other hand. It is important to emphasize, again, that this conclusion is one that is based upon a lack of evidence, not necessarily a lack of theoretical relation. That is, we do not deny the theoretical possibility that a relation between global intelligence and CPS competence might exist; we argue only that there exists no convincing empirical evidence to date that would support such a relation. Nevertheless, the evidence reviewed in this chapter is consistent with a wealth of empirical findings on the relation between intelligence and simple problem solving that suggest that even when a relation between intelligence and problem-solving competence is obtained, it is quite modest in size (e.g., Sternberg, 1982).

Second, however, a considerable amount of empirical data suggest that specific components of intelligence, such as processing capacity, might be related to specific components of explicit complex problem solving. To what extent a similar conclusion might be warranted for implicit complex problem solving remains to be seen; the available research has thus far not addressed this specific question.

On the whole then, the available evidence suggests that the global concepts of intelligence and problem solving are not related, but that specific subcomponents of intelligence and explicit problem solving might share variance. The existing empirical evidence does not speak, unfortunately, to the issue of whether subcomponents of intelligence predict subcomponents of problem solving or whether the opposite causal relation holds; the empirical designs used simply cannot answer this question.

The conclusions have two important consequences. First, the intellectual abilities investigated thus far are frequently too coarse, too general, and too abstract to allow a prediction of inter-individual differences in complex problem-solving competence; what is clearly needed in future research is a focus on much more specific and narrower intellectual abilities that more closely capture the cognitive system's architecture and functioning.

Second, from the empirical evidence that is currently available, it appears that the relation between intelligence and complex problem-solving performance might be moderated by a complex interaction between individuals, tasks, and situations. Thus, the future task will not be to find correlations between intelligence and problem solving, but rather to find out when which kind of relation holds. More exact experimental assessments of specific subcomponents of the relevant concepts along with longitudinal designs that assess causal directionality are a sine qua non if we will ever have a chance to find out whether individual differences in intelligence cause individual differences in complex problem-solving ability or whether the opposite is true.

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Cognition and Intelligence

Identifying the Mechanisms of the Mind

Edited by

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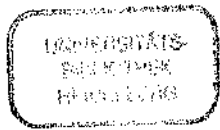*Yale University*

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Contents

Preface

COGNITION AND INTELLIGENCE

How did the study of cognition and intelligence get started? Although some psychologists in the nineteenth century were interested in cognitive processing (e.g., Donders, 1868/1869), the connection between information processing and intelligence seems first to have been explicitly drawn by Charles Spearman (1923), the same individual known for initiating serious psychometric theorizing about intelligence with his theory of the general factor of intelligence (Spearman, 1927).

Spearman (1923) proposed what he believed to be three fundamental qualitative principles of cognition. The first, *apprehension of experience*, is what today might be called the encoding of stimuli (see Sternberg, 1977). It involves perceiving the stimuli and their properties. The second principle, *eduction of relations*, is what today might be labeled inference. It is the inferring of a relation between two or more concepts. The third principle, *eduction of correlates*, is what today might be called application. It is the application of an inferred rule to a new situation.

Spearman was not the only early psychologist interested in the relationship between cognition and intelligence. Thorndike et al. (1926) proposed a quite similar theory based on Thorndike's theory of learning. According to this theory, learned connections are what underlie individual differences in intelligence. Some early researchers tried to integrate cognition and biology in studying intelligence. For example, the Russian psychologist Alexander Luria (1973, 1980) believed that the brain is a highly differentiated system whose parts are responsible for different aspects of a unified whole. In other words, separate cortical regions act together to produce thoughts and actions of various kinds. Luria (1980) suggested that the brain comprises three main units. The first, a unit of arousal, contains the brain stem and midbrain structures, including the medulla, reticular activating system, pons, thalamus, and hypothalamus. The second unit of the brain is a