DIMITRIOS STAMOVLASIS* and GEORGIOS TSAPARLIS

COGNITIVE VARIABLES IN PROBLEM SOLVING: A NONLINEAR APPROACH

ABSTRACT. We employ tools of complexity theory to examine the effect of cognitive variables, such as working-memory capacity, degree of field dependence–independence, developmental level and the mobility–fixity dimension. The nonlinear method correlates the subjects' rank-order achievement scores with each cognitive variable. From the achievement scores in organic-synthesis problems of various mental demands, rank-order sequences of the subjects, according to their scores, were generated, and in the place of each subject, his/her score was replaced by the value of the corresponding cognitive variable. Then each sequence was mapped onto a one-dimensional random walk, and when treated as a dynamic flow, was found to possess fractal geometry, with characteristics depending on the complexity of the problem. The findings were interpreted using concepts from complexity theory, such as order, correlation exponents, and entropy. The method provides meaningful results and adds to the understanding of information processing and the role of cognitive variables within the frame of predictive models in problem solving. Although the method is applied to a particular kind of problems (chemical, organic-synthesis problems), it can be generalized to other problems, not only in chemistry, but also in other sciences and in mathematics. Finally, the educational implications are discussed.

KEY WORDS: cognitive variables, complexity theory, degree of field dependence–independence, developmental level, mobility–fixity dimension, nonlinear methods, problem solving, working-memory capacity

Researchers in science education are mainly concerned with students' cognitive structure and conceptual learning. They study students' ideas about science concepts, and deal with practical issues in relation to instruction. In addition, research is seeking to bridge the gap between the cognitive structure of learners' science knowledge and their problem solving ability (Gabel & Bunce, 1994; Lee, 1985; Lee, Goh, Chia & Chin, 1996; Niaz, 1989a, 1989b, 1994). On the other hand, advances in neuroscience and neuropsychology, during the last two decades, have provided and supported information-processing models that have as central concept that of *working memory* (Baddeley, 1986, 1990). With respect to problem solving in science education, research has shown that, in certain cases, working-memory capacity, mental (or M-space) capacity, and/or other *cognitive* (or *psychometric*) variables [such as *disembedding ability* (degree of field dependence–independence), *developmental level* and the *mobily–fixity di-*

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mension] can be predictive of the student performance (Johnstone, Hogg & Ziane, 1993; Johnstone & Kellet, 1980; Niaz, 1988; Niaz & Logie, 1993; Tsaparlis & Angelopoulos, 2000; Tsaparlis, Kousathana & Niaz, 1998).

A characteristic model involving cognitive variables is the working-memory model (Johnstone & El-Banna, 1986). It states that a student is likely to be successful in solving a problem if the problem has a mental demand (M-demand or Z-demand) which is less than or equal to the subject's working-memory capacity (X) ($Z \leqslant X$), but fail for lack of information or recall, and unsuccessful if $Z > X$, unless the student has strategies that enable him/her to reduce the value of Z to become less than X (Johnstone & El-Banna, 1986, 1989). That is, as the problem increases in complexity (in terms of what has to be held and what process has to be performed), there must be a decrease in achievement; moreover, if the holding/thinking space has a finite limit, the decrease of achievement may be rapid after the limit has been reached (Pascual-Leone, 1974; Scandarmalia, 1977). Note that in order for the model to be valid, a number of necessary conditions must be fulfilled: (a) the logical structure of the problem must be simple; (b) the problem has to be non-algorithmic; (c) the partial steps must be available in the long-term memory and accessible from it; (d) the students do not employ chunking devices; (e) no 'noise' should be present in the problem statement (Tsaparlis, 1998; Tsaparlis & Angelopoulos, 2000).

All the above research work has implemented linear methods in data treatment. From the methodological perspective, linear statistical methods and models have been the cornerstones in quantitative science-education research as in other social sciences, for most of the past century. Nevertheless, a lesson learned from physical science is that there are a large number of situations in which nonlinear effects play a prominent and fundamental role. Nonlinear effects have been observed in biological systems (Cramer, 1993) in all scales. At the psychological level, nonlinear effects have been invoked to account for some perceptual illusions such as the Necker cube, while phase transitions have been described in motor behavior (Kelso, 1999; Port & Van Gelder, 1995). At the social level, there has been extensive discussion of the possible role of nonlinear processes in politics and economic systems (Kiel & Elliott, 1996). Science education research, which deals predominately with nonlinear phenomena, has to foster such methodologies in order to develop more rigorous descriptive and predictive models.

Recently, nonlinear methods have been developed to analyze the effect of working-memory capacity on chemistry problem solving (Stamovlasis & Tsaparlis, 1999, 2000, 2001a, 2001b, 2003a, 2003b; Tsaparlis & Stamovlasis, 1999). The work correlates the rank order of the subject achievement scores in problem solving with working-memory capacity and shows how the effect of this variable on problem solving can be observed with means and tools of complexity theory. The current paper describes the general framework for the application of this nonlinear approach, the Random Walk method, in studying the effect of cognitive variables on problem solving. In addition, it provides an exploration of the effect on student performance of: (a) the degree of field dependence–independence; (b) the developmental level; and (c) the mobility–fixity dimension. Finally, it reviews relevant recent work The above cognitive variables, and the particular corresponding psychometric tests, were chosen because they have been used in a considerable amount of recent research in science education. The present study adds to these endeavors by revisiting the role of these variables, and describing their effects by means of complexity theory.

The Cognitive Variables and the Psychometric Tests

Working-Memory Capacity. The concept of working memory, that has been widely used in cognitive science, refers to the human limited capacity system, which provides both information storage and processing functions (Atkinson & Shiffrin, 1968), and is necessary for complex cognitive tasks, such as learning, reasoning, language comprehension, and problem solving. The model was extensively developed by Baddeley and his coworkers (Baddeley, 1986, 1990). The working-memory capacity of the students was assessed by means of the digit backward span (DBS) test, which is part of the Wechsler Adult Intelligence Scale (Wechsler, 1955). This test involves both storage and processing and has been used as measure of working-memory capacity in relevant works (e.g., Johnstone & El-Banna, 1986, 1989).

Cognitive Style/Disembedding Ability. Disembedding ability refers to the degree of field dependence/field independence, and represents the ability of a subject to dissembed information in a variety of complex and potentially misleading instructional context (Pascual-Leone, 1989; Witkin, Dyk, Paterson, Goodenough & Karp, 1974). This ability is also connected with the ability of the subject to separate *signal* from *noise*; thus, learners who use some of their memory capacity to process irrelevant data (noise) appear to posses lower working memory capacity, and are categorized as field dependent. Disembedding ability is usually assessed by means of the Group Embedded Figures Test, GEFT) (Witkin, 1978; Witkin, Oltman, Raskin & Karp, 1971). In our work, a similar test was used, which has been devised and calibrated by El-Banna (1987) from Witkin's original test materials, using hidden figures (the 'Hidden-Figures Test,' HFT).

Developmental Level. Developmental level is a Piagetian concept and refers to the ability of the subject to use formal reasoning (Lawson, 1978, 1985, 1993). It was assessed by the Lawson test, a pencil–paper test of formal reasoning (Lawson, 1978).

The Mobility–Fixity Dimension. The mobility–fixity dimension is associated with the theories of Werner (1957), Witkin & Goodenough (1981) and Pascual-Leone (1989), and has been shown to be a good predictor variable in problem solving. According to Werner (1957), during individual development, perception is first global, i.e., field-dependent (FD), and later analytical, i.e., field-independent (FI), and finally, in the mature individual, synthetic, i.e., field-mobile. The characteristic of FI subjects to function consistently in a FI fashion (i.e., *fixity*) and of others to vary more according to circumstances (i.e., *mobility*) has been referred to as the '*mobility–fixity dimension*' by Witkin (1965) and as a '*Mobile/fixed cognitive style*' by Pascual-Leone (1989). The classification (Niaz, 1989b; Niaz & Saud De Nunez, 1991; Niaz, Saud De Nunez & Ruiz De Pineda, 2000; Stamovlasis, Kousathana, Angelopoulos, Tsaparlis & Niaz, 2002) involves the Figural Intersection Test, FIT (Pascual-Leone & Burtis, 1974) and the test for field dependence/independence.

More information about the administration of the psychometric tests, and the classification of the subjects as mobile or fixed is provided in the Appendix.

Complexity Theory

Complexity theory (CT) is developed to address complex systems and emergent phenomena. CT is associated with Dynamical Systems Theory, which employs nonlinear mathematical methods. It includes two twin subjects, Fractals and Chaos. Fractals are a class of geometric forms, dealing with geometric patterns and quantitative ways of characterizing these patterns. Chaos is a class of dynamical behaviour, dealing with the evolution of systems in time and the underlining characteristics (Williams, 1997). Fractal and chaos are closely intertwined. Chaotic behaviour, when mapped into geometrical forms, can exhibit fractal characteristics. An essential characteristic of fractals is *self-similarity or scale invariance*. A fractal appears self-similar under varying degrees of magnification; in effect, it possesses symmetry across scale, with each small part of the object replicating the structure of the whole (Mandelbrot, 1982).

CT uses concepts, such as, fractal dimension, entropy, complexity, information, order, or disorder to describe qualitatively and quantitatively a complex system. A fractal structure is characterized by its *own fractal dimension*, which is usually (but not always) a non-integer number and less than its Euclidean dimension. The fractal dimension quantifies the scaling of pattern or complexity over a range of scales (Peitgen & Saupe, 1988). CT approaches have been effectively used in physical sciences, but the last decade they also make important contributions to social science.

In the present work, we created spatial arrays or sequences of symbols from students' rank-order achievement scores. These symbolic sequences take the form of stochastic fractals possessing a varying degree of randomness, disorder or *entropy*. The amount of *order* determines the correlation with the mental task, which the students' achievement scores were taken from.

Rationale and Method

The data set in the present research consists of achievements scores in chemistry problem solving and the psychometric tests that 'measure' the cognitive variables. Instead of comparing average scores, as in usual statistical treatments, we correlate the cognitive variable with the rank-order achievement. There are two reasons for that: (1) by rank-ordering the data, *dynamics* is introduced, allowing the application of nonlinear tools; (2) subjects are selected rather on the basis of the rank-order achievements than on an absolute achievement score (as, for instance, in university entrance examinations); and (3) the applied nonlinear method is nonparametric, that is, it is independent of the score distribution.

Rank-order sequences of subjects, according to their scores, are generated, and each score is then replaced by the value of the subjects' corresponding cognitive variable. The produced symbolic sequences, corresponding to the various problems of different complexity (Z-demand and logical structure), are treated as dynamical flows. The proper method to study the properties of these *dynamic* sequences is to apply concepts and tools of complexity theory. An example of these sequences is of the type:

HHLLMMHLMLHMMHHLLMHMLMLHHHMLHMMHLLLLL . . . ,

where H refers to the high level, M refers to the intermediate level, and L refers to the low level of a cognitive variable.

The basic hypothesis, which is behind the nonlinear treatment, is an interesting statistical physics type of question. That is, whether each of these dynamic sequences (which are strings of symbols) in all cases of different problems with varying complexity behaves like a one-dimensional 'ideal gas' (where the density fluctuation of certain particles obeys the Gaussian law) or whether there exist scale-invariant, long-range correlations. In the language of physics, these correlations are in the 'vicinity of a critical point,' where a 'phase transition' is observed.

In this approach, a core concept is *entropy*, which is a measure of the *disorder* of the dynamic sequence. If a sequence possesses high *entropy,* it implies a random sequence. On the contrary, low entropy or high *order* implies that there is 'memory' in the sequence or that the sequence possesses a 'structure.' This 'structure' or *order* signifies the correlation of the cognitive variable being examined with the mental task, and is demonstrated by determining the scale-invariant, long-range correlations. In order to study such correlations in a dynamic sequence, we applied the Random Walk (RW) method. This is a mathematical approach which is analogous to the one used in analyzing DNA sequences (DNA walk; Bunde & Halvin, 1994; Peng, Buldyrev, Goldberger, Halvin, Simons & Stanley, 1993). The description that follows will make clear the way the RW method was applied in our case.

We introduce a graphical representation of the above dynamic sequence, which is termed a *psychometric random walk.* Depending on the psychometric variable used, we have a *working-memory random walk*, a *field dependence–independence random walk*, etc.

We define the function $\Psi(i)$ of the random walk as follows:

(1)
$\Psi(i) = -1$, for low level;
$\Psi(i) = +1$, for intermediate level (RW L/M);

(2)
$\Psi(i) = -1$, for intermediate level;
$\Psi(i) = +1$, for high level (RW M/H);

(3)
$\Psi(i) = -1$, for low level;
$\Psi(i) = 0$, for intermediate level;
$\Psi(i) = +1$, for high level (sequence T)

with $i = 1$ to N representing the number of subjects, while L, M, and H denote the level (low, intermediate, or high) of the corresponding cognitive variable. In this way, the generated sequence becomes a spatial array of -1s, or $+1$s (or -1s, 0s or $+1$s for sequence T), so that it is possible to map the dynamic sequence onto a one-dimensional random walk.

The statistical quantity characterizing any walk is the root mean-square fluctuation $F(L)$ about the average displacement at the position L (Hurst, 1951; Peitgen, Jurgens & Saupe, 1992; Peng et al., 1993). For any random walk, the following relation holds: $F(L) \propto L^H$, with H (the correlation or Hurst exponent) being the slope of the diagram $\log F(L)$ versus $\log L$. If $H = 0.5$, the sequence is a normal random walk or Brownian motion (Addison, 1997; Bunde & Halvin, 1994). On the other hand, if $0.5 < H < 1$, there exist scale-invariant, long-range correlations (*power-law* correlations) with persistent behavior. Such correlations reject the null hypothesis that the sequence is random ($H = 0.5$): there is 'memory' in the sequence, which then possesses higher *order* (low *entropy*) or lower *disorder*. When we map the sequence onto a one-dimensional random walk, its graphical representation is found to possess a value of Hurst exponent, depending on the complexity (schemata and/or Z-demand) of the corresponding problem.

To test the null hypothesis of randomness, that is whether a sequence is random, surrogates were developed for each sequence of symbols, by taking the original data set and randomizing it completely by shuffling. In this way, the surrogates maintain the same statistical characteristics as the original data set, but with all dynamics being erased. For each sequence the average of twenty surrogates was calculated and standard deviations along with the confidence limits were estimated. The same confidence limits were kept also for the original data. In all cases, none of the surrogates had a higher Hurst exponent than the original sequence. Thus the (non-parametric) level of statistical significance of our results would be at least $p = 1/20 = 0.05$. More details, about the method and the mathematics employed, are given by Stamovlasis & Tsaparlis (2001a). An outline of the calculation procedure for working memory is given in Figure 1. The same procedure is used for the other cognitive variables. By creating plots of Hurst exponent for the different problems, we actually create a picture of how the *entropy* of the rank-order achievement scores changes with the complexity of the problem. The notion of *low entropy* or *order* has the meaning of *correlation*.

Taking the examination can be seen as the process that generates these *dynamic* sequences and selects subjects with preference to a certain cognitive variable level. When the sequence possesses high entropy (close to surrogate data), there is no preference as to who comes first. There is randomness in the rank order of achievements because everybody solves the problem. When we observe a statistically significant decrease of the *entropy*, meaning that long-range correlations exist, a 'structure,' appears in the sequence. With values of Hurst exponent greater than the surrogate value, long-range correlations demonstrate persisted behavior. Subjects with higher values of the cognitive variable outscore subjects with lower values. Thus the 'structure' is the 'phase separation' between sub-

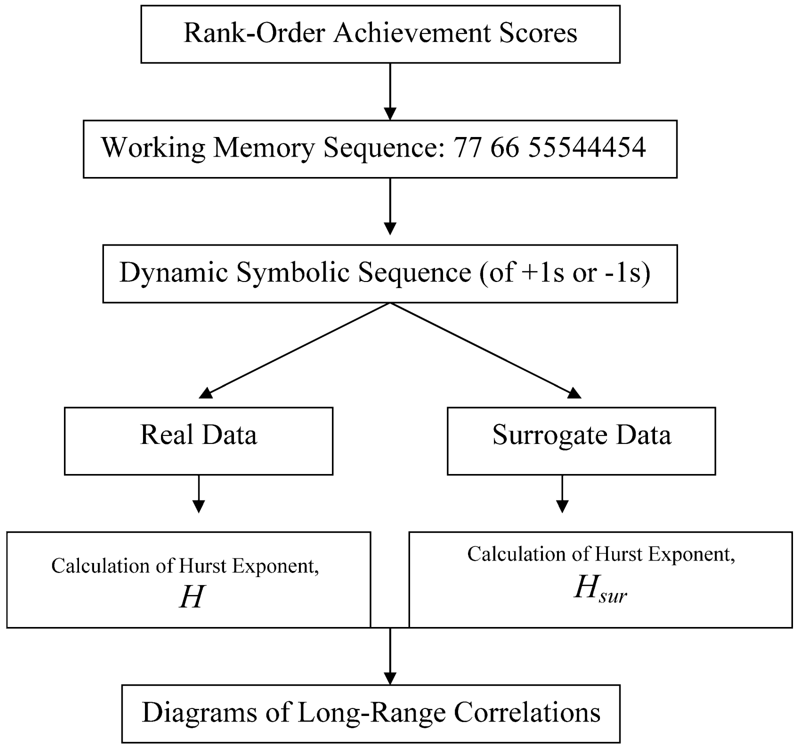

Figure 1. Summary of the procedure for a working-memory random walk. See text for details.

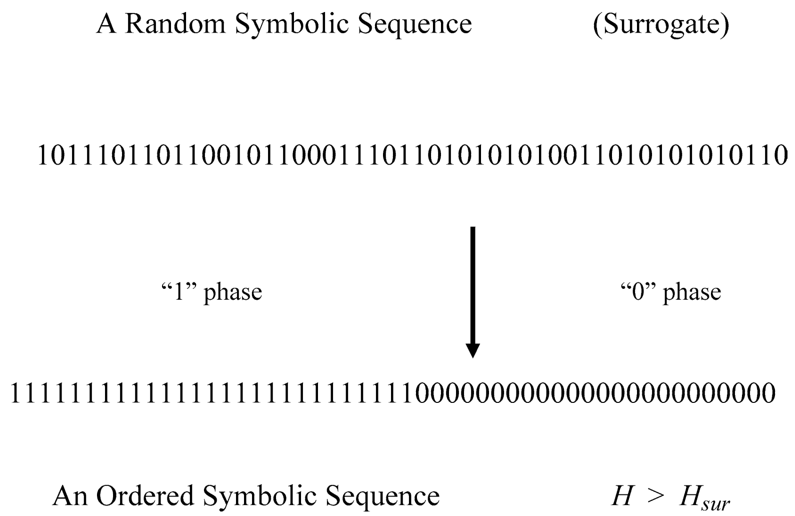

Figure 2. A picture of an ordered sequence with low entropy, 'structure,' and long-range correlations.

TABLE I

Examples of tasks from the organic-synthesis test

Suggest synthesis routes for the preparation of the following organic compounds, with starting material the organic compound given in each case:
1. Formaldehyde, HCHO, from sodium acetate, CH_3COONa.
2. Propyne, $CH_3C{\equiv}CH$, from 2-propanol, $CH_3CH(OH)CH_3$.
3. Pentane, $CH_3CH_2CH_2CH_2CH_3$, from 1-propanol, $CH_3CH_2CH_2OH$.
4. 3-hydroxyproprionic acid, $HOCH_2CH_2COOH$, from formaldehyde, HCHO.

jects with different values of the cognitive variable. This separation, the implied 'structure' of a low entropy sequence, can be visualized in Figure 2.

All calculations were carried out by the appropriate software *Chaos Data Analyzer* (Sprott & Rowlands, 1995).

DATA

The method was applied to data taken from organic-synthesis problem solving (Tsaparlis & Angelopoulos, 2000). The subjects ($N = 281$) were students in the twelfth grade. The problems were simple chemical, organic-synthesis problems with varying mental (Z-) demand from two to eight. Some examples of the organic-synthesis problem-solving test are given in Table I.

The problems suggest preparation of organic compounds, with starting material a given organic compound in each case. All proposed reactions were standard reactions having a good yield and leading predominantly to the required compound. The solver/subject had to recall these reactions and combine them to a certain order so that a total synthesis is produced. These problems exclude numerical or algebraic calculations, they have a unique chemical logical structure, and in addition they have a unique non-algorithmic character. The elementary steps of the suggested synthetic routes are standard reactions included in school textbooks. Content validity of the test was established by having it scrutinized by the two researchers plus an experienced chemistry teacher. As a check for reliability, we used two different sets of problems for each Z-demand. In addition, the Kuder–Richardson coefficient of reliability was calculated and found to be 0.74.

One definition of mental demand is "the maximum number of thought steps and processes which have to be activated by the least able, but ultimately successful candidate in the light of what had been taught" (Johnstone & El-Banna, 1986, 1989; Johnstone, Hogg & Ziane, 1993; Johnstone

& Kellet, 1980). The assignment of Z-demand for each problem was based on the judgment of two researchers, and followed directly from the minimum number of partial (the individual) steps required to accomplish the synthesis; the assigned Z-demands were further confirmed by *post-factum* analysis of students' answers. This method is consistent with the four-step procedure for the evaluation of the Z-demand known as 'dimensional analysis' (Niaz, 1989a, 1989b; Tsaparlis & Angelopoulos, 2000).

For the nonlinear treatment, two scores of achievement in each problem have been used for each student (Stamovlasis & Tsaparlis, 2001a). In the first score (*independent marking*), two marks were given for an entirely correct synthesis route; one mark for a correct overall route, but with some minor omissions or errors; and zero marks for wrong answers. In the second score (*accumulated marking*), an accumulation of the current mark (according to the first score) with the marks of all problems of lower Z-demand was implemented; for instance, if a student had achieved marks 2, 2, 2, 2, 1, 1, 0 in the seven problems of increasing Z-demand, his/her accumulated scores would be 2, 4, 6, 8, 9, 10, 10 respectively. Independent marking shows only whether the subject succeeded to solve the particular problem, while accumulated marking takes into account the history of achievement in all previous problems.

The two marking schemes lead to the same conclusion, but accumulated marking contributes to eliminating to a certain degree the problem of ties in the rank-order achievement scores (Stamovlasis & Tsaparlis, 2001). Irregularities in the equivalent independent marking, such as "0102202" and "0021202," did not exist because the subjects who were capable of solving the problem with $Z = 4$ were also capable of solving the problems with $Z = 3$ and 2. There existed though a few cases such as, "2222000" and "2221100," or "2222220" and "2222211." These were not specially treated, and they were considered as ties. In this paper, only accumulated marking scores for the organic-synthesis problems are used.

Results and Interpretation

The Effect of Working Memory

In order to study the *entropy* of the rank-order achievement scores, the *working-memory random walk* is used. The definition of the random walk function $\Psi(i)$ is as follows:

$$(4) \qquad \begin{aligned} \Psi(i) &= -1, \quad \text{for } X = 4; \\ \Psi(i) &= +1, \quad \text{for } X = 5; \quad \text{(RW 4/5)} \end{aligned}$$

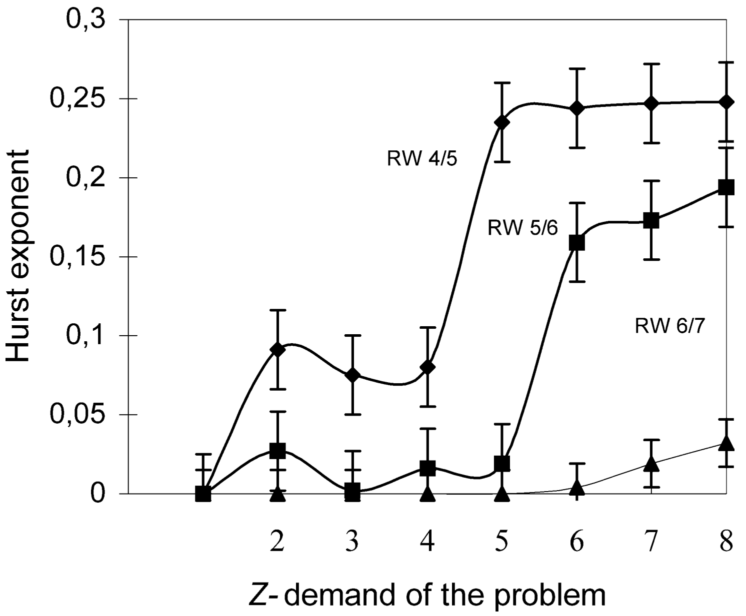

Figure 3. Long-range correlations of working-memory capacity with the rank-order achievement scores: Hurst exponent versus Z-demand for random walks, RW 4/5, RW 5/6, and RW 6/7.

$$(5) \quad \begin{aligned} \Psi(i) &= -1, \quad \text{for } X = 5; \\ \Psi(i) &= +1, \quad \text{for } X = 6; \quad \text{(RW 5/6)} \end{aligned}$$

$$(6) \quad \begin{aligned} \Psi(i) &= -1, \quad \text{for } X = 6; \\ \Psi(i) &= +1, \quad \text{for } X = 7; \quad \text{(RW 6/7)} \end{aligned}$$

X being the working-memory capacity.

In the hypothetical one-dimensional space of the rank-order achievement scores, we take a random walk among the subjects with working-memory capacity $X = 4$ and $X = 5$. This walk is named RW 4/5. The results for the Hurst exponent H for the *accumulated-marking* case are shown in Figure 3. It is observed that for low values of Z-demands (2, 3, and 4), H takes low values, close to the surrogate exponent, which corresponds to theoretical randomness: $H = 0.5$, a normal random walk. The sequence has high entropy close to the entropy of a random sequence, because everybody solves the problem (more precisely, everybody is *capable* of solving it).

At Z-demand 5, the value of Hurst exponent increases, showing long-range correlations. The increase of Hurst exponent is interpreted as departure from randomness. The entropy decreases and long-range correlations appear in the sequence. That is because subjects with working-memory ca-

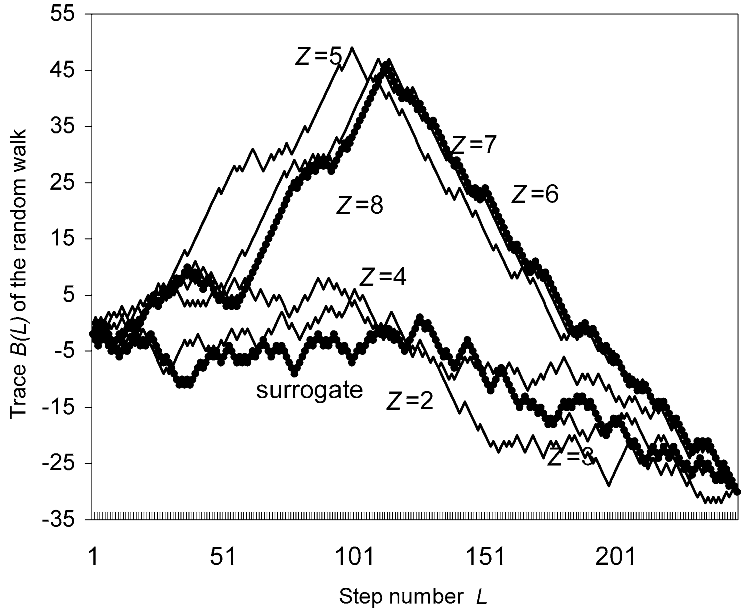

Figure 4. Working-memory random walks: the trace $B(L)$ for random walk RW 4/5 versus the step number L.

pacity 5 outscore subjects with working-memory capacity 4, and a simple 'structure' of two separated phases appear in the sequence. This 'structure' is demonstrated in Figure 4, the graph of the *space trace* $B(L)$ as a function of the *step number* L [Equation (7)]. $B(L)$ is the net displacement after L positions, or the sum of the unit steps $\Psi(i)$ for each step i:

$$B(L) = \sum_{i=1}^{L} \Psi(i). \qquad (7)$$

The space trace follows a trajectory which for the problem with $Z = 5$ (corresponding to a large H value) possesses high order and displays long-range correlations with persistent behavior. At the beginning of the random walk, $B(L)$ increases, and then drops. Subjects with $X = 5$ outscore subjects with $X = 4$. This means that at the threshold of $Z = 5$, the population of the subjects in the one 'dimensional space' of rank-order achievement scores tends to split into two separate 'phases,' the phase of $X = 5$ and the phase of $X = 4$. Thus the problem of Z-demand 5 is the 'critical point' mentioned above. This sudden separation of phases, occurring after a $\Delta Z = 1$, could also be interpreted as a 'catastrophe.'

The same pattern is observed for the random walk among the subjects with $X = 5$ and $X = 6$ (RW 5/6, Figure 3). The threshold appears at $Z = 6$, where subjects with $X = 6$ outscore subjects with $X = 5$. The same holds for RW 6/7, where subjects with $X = 7$ outscore subjects with $X = 6$, but the change is not pronounced as in the other cases because the length of this random walk (RW 6/7) is relatively short (a smaller number of students, 71, was involved). Note that the application of the random-walk method requires about at least one hundred points (Stamovlasis & Tsaparlis, 2001a, 2001b). In all cases, the departure from randomness occurs at *threshold values* of Z-demand, X, where subjects with a working-memory capacity X outscore subjects with working-memory capacity $X - 1$.

The existence of threshold Z-demands, where the rank-order sequence demonstrates long-range correlations, verifies the role of working-memory capacity in problem solving. The Hurst exponent of the long-range correlated sequences does not assume very high values, close to unity, or the rank-order sequences are not highly ordered, because some subjects with a working-memory capacity X manage to outscore subjects with working-memory capacity $X + 1$, by employing *chunking devices* to keep $Z < X$. For educational implications see Conclusions.

The Effect of Disembedding Ability

We have also used the random-walk method in an attempt to reveal any effects of disembedding ability. To this end, we took the dynamic sequence of rank-order achievement scores, and then each subject's score was replaced in the sequence by the value of his/her degree of field dependence. The following coding is used:

$$\Psi(i) = -1, \quad \text{for field dependent subjects;}$$
$$\Psi(i) = 0, \quad \text{for field-intermediate;}$$
$$\Psi(i) = +1, \quad \text{for field-independent students} \quad (\text{sequence } T).$$

Figure 5 shows the long-range correlations of the degree of field dependence in the rank-order achievements score sequence. We observe that for all problems, the Hurst exponent of the sequences is close to the surrogate value. The whole pattern suggests that correlations of rank-order achievement with the field-dependence variable do not exist. Exceptions are small increases of long-range correlations that appear at $Z = 3$ and $Z = 4$. An interpretation of this finding is that the role of disembedding ability is evident only in the case of lower-demand problems, before the working-memory-overload phenomenon appears.

When we divide the sample into three groups (field independent, field-intermediate and field-dependent students), and apply separately for the three groups the working-memory random walk method, we observe (Figure 6) that in the rank-order sequences corresponding to field-independent

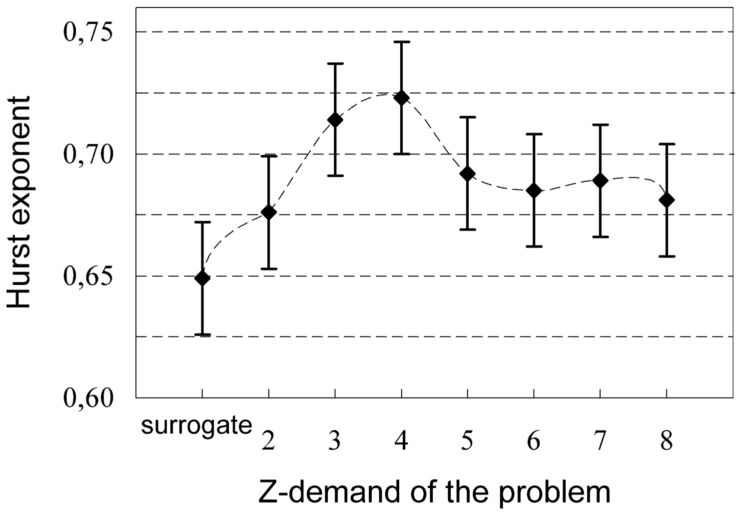

Figure 5. Long-range correlations of disembedding ability with the rank-order achievement scores: Hurst exponent versus Z-demand of the sequences T.

subjects, long-range correlations appear stronger than for the field-intermediate or field-dependent case. That is, the working-memory model applies better to field-independent than the field-intermediate or field-independent students.

The Effect of Developmental Level

Next we use the random-walk method to examine the effect of developmental level. In this case, we took the dynamic sequence of rank-order achievement scores, and then each subject's score was replaced in the sequence by the value of his/her developmental level. The following coding is used:

$$\Psi(i) = -1, \quad \text{for students at concrete level;}$$
$$\Psi(i) = 0, \quad \text{for subjects at transitional level;}$$
$$\Psi(i) = +1, \quad \text{for students at formal level} \quad \text{(sequence } T\text{).}$$

Figure 7 shows the long-range correlations of the developmental level in the rank-order achievements score sequence. We observe that Hurst exponent of the sequences increases gradually with Z-demand of the problem. No sudden increase is observed. The changes are smooth but the trend is clear. Students at higher developmental level are more likely to outscore students at lower developmental level. Their differences are becoming more pronounced as the Z-demand of the problem increases. The organic-synthesis problems require more information processing capac-

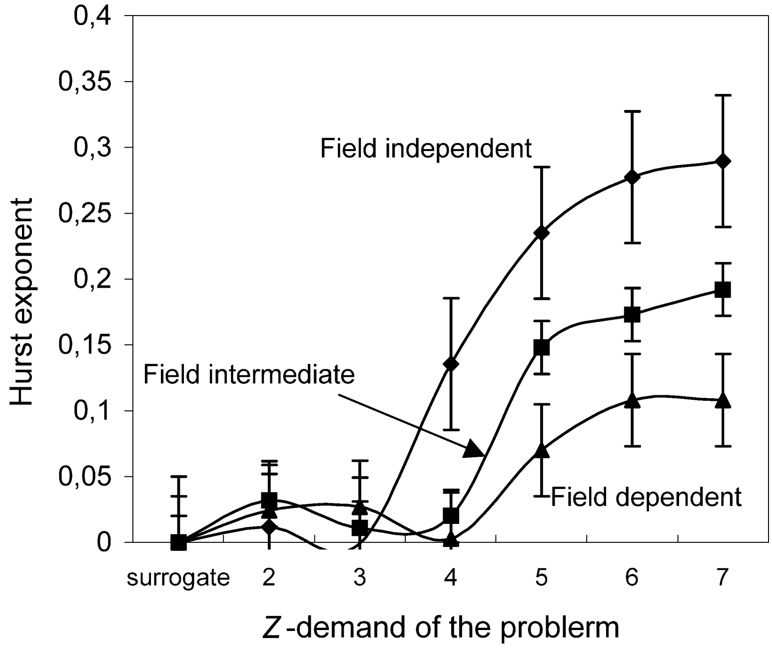

Figure 6. Long-range correlations of working-memory capacity with the rank-order achievement scores at the three levels of disembedding ability: Hurst exponent versus Z-demand for the sequences T.

ity than formal operation reasoning. Though, long-range correlations appeared to be statistically significant as ΔZ becomes larger. This pattern could be attributed to the fact that working memory capacity and developmental level are not totally independent variables, but they are correlated ($r = 0.38$).

The Mobility–Fixity Dimension

We followed the rationale and the random walk methodology developed above, introducing in this case the *Mobility–Fixity Random Walk* (MFRW), by defining the function $\Psi(i)$ as follows:

$$\Psi(i) = -1, \quad \text{for fixed subjects} \quad \text{and}$$
$$\Psi(i) = +1, \quad \text{for mobile subjects.}$$

Figure 8 shows the Hurst exponent of the dynamic sequences of rank-order achievement scores as a function of the Z-demand of the problem. For problems with low Z-demand, H is close to surrogate data and increases as the Z-demand of the problem increases. Long-range correlations with persistent behavior appear and became stronger at the problem of Z-demand 6. After the local maximum H has tendency to decrease again.

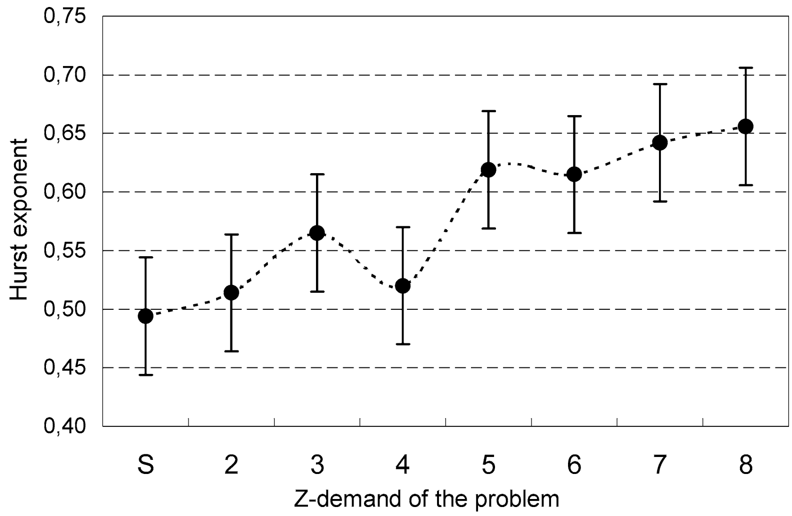

Figure 7. Long-range correlations of developmental level with the rank-order achievement scores: Hurst exponent versus Z-demand for the sequences T.

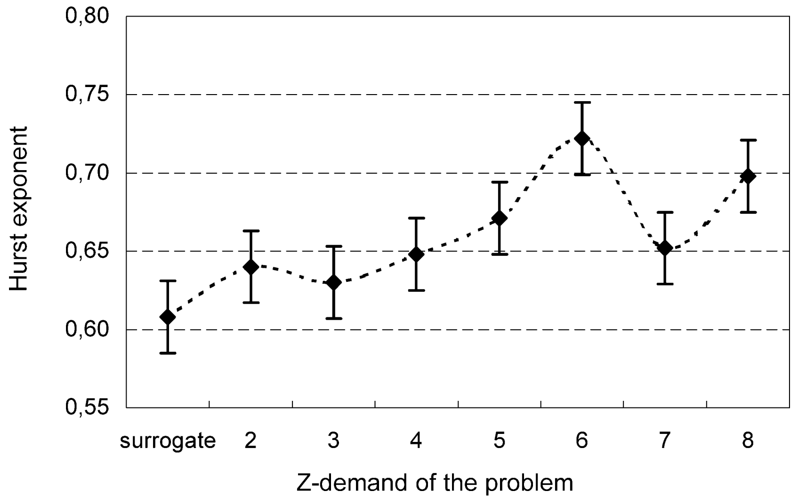

Figure 8. Long-range correlations of the mobily–fixity dimension with the rank-order achievement scores. Hurst exponent versus Z-demand.

The organic-synthesis problems, being non-algorithmic, require high mental demand and can cause working memory overload, which produced a decline in subjects' performance (more pronounced in fixed subjects), introduced noise and increased the entropy of the dynamic sequences of rank-order achievement scores.

CONCLUSIONS AND EDUCATIONAL IMPLICATIONS

The main issues of the present work are, on the one hand, the methodological issues developed and implemented, which are related to the nonlinear approach; and on the other hand, issues concerning the role of cognitive variables in science education. By employing tools of complexity theory, we re-examined the role of a number of select cognitive variables in problem solving. These variables were: (i) working-memory capacity; (ii) cognitive style/disembedding ability (that is, degree of field dependence–independence); (iii) developmental level; and (iv) the mobility–fixity dimension.

The nonlinear methodology correlated the subjects' rank-order achievement scores with each cognitive variable. Data were taken from achievement scores in organic-synthesis problems. Correlation of a cognitive variable with the subjects' performance was measured as the decrease of *entropy* or *disorder* of the symbolic sequence representing the one-dimensional space of rank-order achievement scores. Correlation exists when a 'structure' appears in those dynamic sequences. This 'structure' results from the separation of phases, which represent the different levels of the cognitive variables. In this study, this *order* was measured as change of the Hurst exponent of these dynamic sequences. The decrease of *entropy* or *disorder* could also be observed as drop of the *fractal dimension* of the *random walk*, that is a decrease of the degrees of freedom. Further details and main methodological issues concerning the used nonlinear approach are addressed in Stamovlasis and Tsaparlis (2001a, 2001b, 2003a, 2003b).

We must emphasize that by using linear conventional statistical analysis we can observe that the Pearson correlation coefficient between achievement scores and the cognitive variables follows the same patterns as the Hurst exponent. If a sequence is not rank-ordered, it looses the long-range correlations, but its linear correlation is maintained. However the two approaches (linear and non-linear) provide different insights. By rank-ordering the data and applying a non-linear method, we learn something more. The random-walk approach reveals that the sequence of rank-order achievement scores displays *power-law correlations*. It calculates the correlation exponent (*Hurst exponent*) and establishes a non-linear relation between achievement scores in problem solving and subjects' cognitive variables.

Diagrams showing the appearance of long-range correlations as a function of the complexity of the problem provide pictures of interactions between the examined cognitive variable and the mental demand of the problem. Interactions also may exist between the cognitive variable and the logical structure of the problem, thus providing support to the dynamic hypothesis in problem solving, which Pascual-Leone (1989) and Niaz (1991) have explicitly referred to.

It is the concepts of complexity theory, such as *order* and *entropy,* perceived as *correlations* in the rank-order achievements, that provide a meaningful picture and the context for drawing the conclusions. On the contrary a (linear) Pearson correlation coefficient r is the slope of the regression of the achievement-score variable on working-memory capacity, when both are in standard units. This is evidence of a correlation between the two variables, without them being connected in fact by a linear relationship. Linear correlation presents an analogous behavior, but does not provide the context for rigorous patterns to be revealed.

The application of nonlinear methodology has added to science education research by providing a tool and a framework to describe changes observed in educational data. That is, the statistically significant differentiation in achievements between student groups were observed in our data in the rank-order achievement scores as 'phase transitions' from *randomness* to *order*, demonstrating long-rage correlations. This nonparametric method, which is actually an application of statistical physics to science education data, could be a starting point in science education research for introducing and fostering nonlinear approaches. Following the new trends in social science, the nonlinear methods will affect the way of stating our hypotheses and in addition they could provide our theories with more powerful exploratory tools.

Predictive-explanatory models that are based on cognitive variables can provide a rigorous and quantitative basis for the study of the factors that affect the general problem-solving ability of students, as well as of the structure of the problems themselves. The present work correlates individual differences, such as cognitive variables, with students' performance in science education, and has mainly explanatory functions. The work supports the findings of previous research (Johnstone et al., 1993; Johnstone & Kellet, 1980; Niaz & Logie, 1993; Tsaparlis & Angelopoulos, 2000; Tsaparlis et al., 1998), and has also important implications for the educational process.

The limitation of the information-processing ability can result in students' significant fall in performance when the mental demand of the problems exceeds their working-memory capacity. In addition, low disembedding ability (that is, field dependency) can cause students to loose a significant portion of their working-memory capacity, especially when 'noise' is present in the data. Based on the above, one can expect that students who are high processors, and at the same time are field-independent, have an advantage in problem solving.

The working-memory overload phenomenon could occur in problem-solving situations and also during learning. On the other hand, there is evidence in the literature (Johnstone & Selepeg, 2000; Stamovlasis & Tsaparlis, 2003b) that even in mental tasks that do not require high processing capacity, such as memorizing algorithms or recalling of learned schemata, high processors had higher achievement, that is, the science material to be learnt seemed more familiar to the high processors.

According to a general information-processing model, familiar or interesting catching components are admitted through the sensory filter. However, the judgment of what is familiar must be controlled by what has already been established in long-term memory (LTM). Thus, there exists evidence that what has been established in LTM (learnt material) is correlated to information processing capacity. During the learning period, the material (input) to be learnt is recoded/changed in short term memory (STM) and stored in LTM (Johnstone & Selepeg, 2000). We have learned from information processing models that the human processor is not increasing its information-processing abilities by expanding its STM, that is, by increasing the number of *chunks* processed. The number of *chunks* of information, which can be processed, is constant (Simon, 1974). What actually happens is that the human processor can become more efficient when the number of *bits* per *chunk* increases. The role of education/training is thus focused on this matter.

Finally, this study also provided evidence, by means of nonlinear methods, that the mobility–fixity dimension is an important predictor variable of high school students' performance in chemistry. This reinforces previous research findings (Niaz, 1989b; Niaz & Saud De Nunez, 1991; Niaz, Saud De Nunez & Ruiz De Pineda, 2000; Stamovlasis et al., 2002). Problem solving in chemistry requires flexibility of functioning and potential for adapting to a wide spectrum of experiences, and this is facilitated by mobility.

Guided by the findings of research, we are able to construct a series of problems in a science topic with the same reasoning pattern (logical structure) and different Z-demand. We can then facilitate student success by introducing first problems of low Z-demand, and leaving problems of high Z-demand for later use in the course, when the students have acquired experience and motivation or have developed efficient strategies. Clearly the demand of problems must be carefully controlled for novices to built confidence with success. Only when strategies have been learned, should complexity be allowed to increase so that students can learn to keep the value of Z (not the actual, but their modified value of Z by '*chunking*') well within their capacity (X). In this way, confidence can be maintained while complexity increases, leading novices towards the expert state. To make this transition in students efficient and satisfying, teachers cannot leave strategies to chance, but must emphasize and consciously teach them throughout their teaching.

On the other hand, the incorporation in teaching of methods that contribute to the acceleration of the development and the improvement of general cognitive abilities, such as developmental level, information processing and field independence, should not be ignored. One example is the intervention programme *Cognitive Acceleration through Science Education* (CASE) (Adey & Shayer, 1994). In addition, the design of teaching strategies that can facilitate conceptual understanding (beyond the algorithmic strategies), plus the use of a variety of problems of variable logical structure and of demand for information processing, and in particular the extended use of novel problems, can provide a means for the development of various cognitive abilities, and for effecting the transition from lower- to higher-order cognitive skills (Tsaparlis & Zoller, 2003; Zoller & Tsaparlis, 1997).

It is obvious that our findings are of paramount importance to science and mathematics education. Although our data came from organic-synthesis problems, the findings can be transferred and/or generalized to other types of chemistry problems, as well as to problem in physics and mathematics. These problems are not algorithmic, do not require algebraic manipulations and/or numerical computations. One could argue that problems in other disciplines, for instance Euclidean geometry, share common features, so this work can indeed have far-reaching consequences. Note that the role of cognitive variables has also been demonstrated in physics problem solving (Johnstone et al., 1993). Some interesting applications of cognitive theory to designing multimedia-learning environments have also been reported (Kirschner, 2002).

In conclusion, we maintain that the present work has added to the research on the effect of cognitive variables in problem solving. It has demonstrated how complexity theory could be applied to science education, by developing and implementing a research tool, which is suitable for modeling nonlinear phenomena. It is such phenomena which science education research predominately deals with.

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APPENDIX: THE ADMINISTRATION OF THE PSYCHOMETRIC TESTS

The Digit Backward Span (DBS) test (for Working Memory Capacity)

Subjects listen to sequences of variable number of digits, from two to eight, at a speed of about one digit per second, and have to hold them before writing them down on a sheet of paper. This involves storage only, and is given as a practice. Following that, the same procedure is followed, but this time subjects have to write down the numbers in reverse order, for instance the sequence 472 is written as 274. In our administration of this test, there were three sequences of digits with two digits each, three sequences with three digits each, and so on until three sequences of eight digits each. To avoid the possibility of cheating (writing the digits in reverse order from right to left, and in particular simultaneously with listening), students had to write the digits by filling in printed grids, with one digit in each square; in addition, there was not a progressive increase in the complexity of sequences (as used in other studies), but some alteration was made, as follows: 222–334–344–556–566–778–788. The value for working-memory capacity was taken to be the maximum number of digits which were successfully written for at least two out of the three corresponding sequences. *Reliability* issues related to reproducibility of the measurements of working memory capacity were faced by careful collection of data: High processors were double-checked by administering to them the digit backward span test privately. The Kuder–Richardson reliability coefficient was 0.79 for the sequences of five and six digits.

The 'Hidden-Figures Test,' HFT (for Disembedding Ability/Degree of Field Dependence–Independence)

This test has been used by the Johnstone group as measure of the degree of field dependence/independence in all relevant work, while Niaz has used GEFT in his work. Students were given a timed (20 minutes) test, consisting of eighteen items. In each item, they had to locate a hidden figure inside a complicated figure. Subjects with 13 or more successes were classified as field independent; with 7 to 12 successes as field intermediate; and with 6 or fewer successes as field dependent. The split-half reliability coefficient was 0.68 for the present sample.

The Lawson Test of Formal Reasoning (for Developmental Level)

The Lawson test is a pencil–paper test of formal reasoning (Lawson, 1978). The test consists of 15 items that examine the following cognitive abilities: weight conservation, volume conservation, numerical analogies, control of

TABLE II

Classification (bivariate frequency distribution) of students ($N = 281$) in the mobility–fixity dimension, on the basis of working-memory-capacity and field dependence/independence

	Working-memory capacity			
	4	5	6	7
Field-independent	Mobile 20	Mobile 25	Mobile 20	Fixed 6
Field-medium	Fixed 82	Fixed 66	Mobile 31	Mobile 6
Field-dependent	Fixed 16	Fixed 6	Fixed 3	Mobile 0

variables, combinations and probabilities. The students had to justify their answers. In a scale of a hundred, students with scores of 0–25 were classified as concrete operational; with scores of 26–50 as transitional; and with scores of 51–75 as formal operational. A Kuder–Richardson reliability coefficient of 0.74 was obtained for the present sample.

The Mobility–Fixity Dimension

The procedure for classifying subjects as mobile or fixed was the same as that used in previous studies by Niaz (Niaz, 1989b; Niaz & Saud De Nunez, 1991; Niaz et al., 2000; Stamovlasis et al., 2002). An alternative mobility–fixity classification can be postulated on the basis of the data from the DBS test in place of the Figural Intersection Test (FIT). The two constructs must share a common space, as is evidenced also by the high correlation between DBS and FIT: $r = 0.66$ (Stamovlasis et al., 2002). This explains the success of working-memory capacity as an alternative measure for defining the mobility–fixity dimension. We must be aware, however, that mobility–fixity is conceptually connected with mental capacity rather than working-memory capacity. This postulation is supported by the fact that both tests provide a measure of information-processing capacity, and in other studies (Stamovlasis et al., 2002) appear to have high association coefficient (Yule's Q is 0.867). Table 2 shows this alternative classification.

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