Investigating the effect of Mental Set on Insight Problem Solving

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Abstract. Mental set is the tendency to solve certain problems in a fixed way based on previous solutions to similar problems. The moment of insight occurs when a problem cannot be solved using solution methods suggested by prior experience and the problem solver suddenly realizes that the solution requires different solution methods. Mental set and insight have often been linked together and yet no attempt thus far has systematically examined the interplay between the two. Three experiments are presented that examine the extent to which sets of noninsight and insight problems affect the subsequent solutions of insight test problems. The results indicate a subtle interplay between mental set and insight: when the set involves noninsight problems, no mental set effects are shown for the insight test problems, yet when the set involves insight problems, both facilitation and inhibition can be seen depending on the type of insight problem presented in the set. A two process model is detailed to explain these findings that combines the representational change mechanism with that of proceduralization.

Keywords: missing, please supply!

Introduction

Mental set and insight are two elementary processes within problem solving. Both concepts are significant for understanding and explaining a broad range of human problem solving behavior, and yet to date there has been little research that examines both within a single problem solving task. Mental set is the tendency to solve certain problems in a fixed way (Luchins & Luchins, 1959) based on previous solutions to similar problems. Insight is when a problem cannot be solved using conventional stepwise methods (Metcalfe, 1986a,b; Metcalfe & Wiebe, 1987) and the problem solver suddenly realizes (the "aha!" experience, Bühler, 1907; Bowden, 1997; Jung-Beeman, Bowden, Haberman et al., 2004) that the solution involves unconventional methods (the problem solver realizes that the problem needs restructuring, Wertheimer, 1959; Ohlsson, 1984a,b; Ohlsson, 1992; Wagner, Gais, Haider, Verleger, & Born, 2004). Insight is often described as a sudden, unconscious (Sternberg & Davidson, 1995; Bowden, 1997) and unintended (Wegner, 2002) process.

The goal of this paper is to clarify whether there is any interaction between the processes that underlie mental set and insight. First, important studies of mental set and insight will be detailed in order to describe the effects of each. Second, the representational change theory of insight will be introduced as this is a necessary precursor to the manipulations made in the experiments presented, together with the matchstick arithmetic domain as a problem solving task to explore mental set and insight. Third, three experimental studies will examine the interplay between mental set and insight. Fourth, the results will be discussed with reference to the procedural view of mental set and the representational change view of insight.

Studies of Mental Set and Insight

Insight has been examined using various problems. Perhaps the most famous study of insight comes from Duncker's (1945) candle problem where participants were presented with a box of matches, a candle and some tacks, and were asked to create a ledge on a wall to rest the candle on. Problem solvers became fixated on the "container" function of the matchbox and thus reached an impasse on the problem. Subsequent insight only occurred if the problem solver realized that the matchbox could be used in a different way (i.e., as a ledge). Maier (1931) explained the findings of his two-cord problem in a similar way. Two cords hanging from a ceiling had to be tied together but could not actually be held in the hands at the same time. Various implements were also provided (e.g., a pair of pliers), the solution being to tie the pliers to one of the strings to act as a pendulum. Problem solvers reached an impasse when attempting to solve the problem because their prior knowledge led them to see the pliers as a cutting and bending tool rather than as a pendulum.

Luchins (1942) examined mental set effects using the now famous water jug problems. Each problem usually had three jugs of different capacities with the goal being to measure a specific amount of water (by pouring water between the jugs). For example, given three jugs A, B, and

DOI 10.1027/1618-3169.55.4.270

C, having respective capacities of 21, 127, and 3, the goal might be to measure an amount of 100 into one of the jugs. One solution to such a problem would be to pour water into B (127) and then to fill C twice using the water in B, leaving 121 units in B. The final step is then to fill A using the water in B, to leave 100 units in B. Luchins constructed a set of several problems that were all solved by the same solution method (B – 2C – A), after which participants were presented with a so called test problem which could either be solved by the "set" solution or by a simpler alternative solution. For example, given the capacities 23, 49, and 3 in jugs A, B, and C, with the goal of attaining 20 units, the "set" solution of B – 2C – A can be used, but a much simpler alternative of A – C can also be used. Luchins found that the participants under such a set condition hardly ever used the simple method, whereas a control group that only solved the test problems almost always applied the easier solution approach.

Luchins proposed that the repeated application of a successful method makes blind any alternative approach, because of the mechanization of the particular solution method – resulting in what he termed *mental set*.

For about two decades cognitive scientists have started to explain mental set by procedures. Procedures are stated as a collection of rules that specify conditions under which an action is carried out, with a procedure becoming stronger the more often it is used. From a set of procedures that meet a particular condition, the strongest available procedure is always selected. Within this framework, mental set is an artifact resulting from selection processes (Anderson, 1982; Newell, 1990; Lovett & Anderson, 1996; Anderson & Lebiere, 1998), and can be interpreted as a temporary by-product of procedural learning (Ohlsson, 1992).

Lovett and Anderson (1996) investigated the procedural explanation of set by developing an analog to the Luchins water-jug problems that enabled the examination of the relative influence of the current problem context and the repeated selection of the same problem solving procedure. The experiments clearly showed that both the current problem situation and the repeated application of the same solution method influence the selection of a solution procedure. After structural changes to the problem situation, participants were able to immediately select an alternative procedure. However, when the structure of the problem situation remained the same, problem solvers persisted on the well-learned procedure. That is, the current conditions determined the selection of the solution procedure. These results were also successfully simulated in an ACT-R model of the task.

The procedural account does not give a clear indication regarding explanations of insight, but the assumption can be made that prior knowledge makes some procedures more likely for selection than others based on (for example) the usual function of an object. The procedures required for solving insight problems therefore begin with a very low probability of selection. It is through the repeated failure of more high probability solution attempts (and thus a reduction in their probability of selection) that some time later an appropriate solution procedure is selected.

Mental set increases the likelihood of a procedure being selected because it has repeatedly been successful in the immediate past. Prior knowledge, on the other hand, is concerned with the initial likelihood of a procedure being selected, and is thus independent from the effect of set.

The concepts of mental set and insight should be seen as different factors that impinge on problem solving behavior. For mental set, problem solving behavior is affected by factors relating to the given situation e.g., seeing previous problems that can only be solved using a complex procedure and then seeing a problem that can be solved by both a complex and a simple procedure leads the problem solver to continue to use the complex procedure. Thus there has been an external influence involving the previous problems given to the problem solver who accommodates her solution procedures to the invariants of those problems. For insight, problem solving behavior is driven by internal factors e.g., the problem solver restricting the function of an object to what is known from their prior knowledge. In this case there is no pure adjustment of the solution procedure, but a fundamental change of the given knowledge structure is necessary – a new solution is searched and has to be established. Furthermore, mental set effects involve short-term memory processes, because they are created from external factors in the current problem solving scenario, whereas insight effects involve long-term memory processes, because they are created from the problem solver's prior conceptions of the components of the problem. Under these definitions (which fit in with the Gestaltists view of insight and with Luchins' [1942] view of mental set), mental set and insight are two independent processes. However, the two are likely to interact in circumstances where several problems are presented to the problem solver that have both a mental set and an insight nature to them.

Birch and Rabinowitz (1951) were virtually the only Gestaltists to examine mental set and insight together. In a pretest, participants had to complete electric circuits whereby one group repeatedly added a switch and the other group always added a relay. In the test phase, the participants were confronted with the two-cord-problem. In the testing room, participants find the two cords and both the switch and the relay (either can be used as pendulum weights). The group that added switches in the pretest was more likely to select the relay as a pendulum weight – and vice versa for the other group. A control group on the other hand, who did not take part in the pretest, showed no preference for using either the switch or the relay as the pendulum weight. Thus, participants show mental set effects for the insight problem – they do not consider the component that they had used for completing electric circuits in the "set" pretest. Birch and Rabinowitz hence concluded that the perceived function of objects (i.e., prior knowledge) can be influenced by the current problem solving context (i.e., set).

The Gestaltists therefore showed that both long term prior knowledge and short term mental set lead to fixation and as a consequence inhibit achieving insight. Mental set is harmful for attaining insight because fixation on one solution process that is satisfactory for all of the set problems makes the problem solver "blind" to easier or smarter approaches (Koffka, 1935; Luchins, 1942; Duncker, 1945; Köhler, 1947; Luchins & Luchins, 1959; Wertheimer, 1959). Equally, prior knowledge is harmful for attaining insight because it causes fixation on certain aspects of the problem (e.g., the function of an object) and thus hinders successful solution. Mental set and prior knowledge are seen as separate entities that both have an inhibitory effect on the solution of insight problems.

More recent studies have also shown the effect of mental set on problem solving. For example, Smith and Blankenship (1991) illustrated how the display of an inappropriate prime affected performance on the Remote Associate Task (RAT; Mednick, 1962). The RAT involves identifying the linking word (the "associate") between three related words, such as "wheel," "electric," and "high" (the associate being "chair"). By providing an inappropriate prime, such as showing "low" with the word "high," Smith and Blankenship showed that participants had difficulty in finding the associate unless they also had an "incubation" period of five minutes between seeing the three words and being asked for a solution. Furthermore, Smith (1995) proposed that the repeated activation of the same element leads the problem solver into a "mental rut" that makes it impossible to access the information leading to success. Incubation allows the problem solver to leap out of the mental rut and access alternative knowledge that leads to success. Wiley (1998) found similar effects on the RAT for participants with a high level of domain knowledge. One of the three related words was selected to also have meaning within the participant's domain of expertise – when this meaning was inconsistent with the intended associate, performance was impaired.

There are, however, few studies that have systematically examined mental set and insight. Birch and Rabinowitz (1951) showed that mental set and insight can interact together, but did not show the precise nature of this interaction. Luchins (1942), Smith and Blankenship (1991) and Wiley (1998) showed that mental set has an effect on problem solving, but they did not use an insight task in their studies. Hitherto, there is no systematic examination of the precise interaction between mental set and insight.

The Representational Change Theory of Insight and the Matchstick Arithmetic Domain

The Representational Change Theory (RCT; Ohlsson, 1992) has been successfully used to explain insight problem solving (Knoblich & Wartenberg, 1998; Knoblich, Ohlsson, Haider & Rhenius, 1999; Knoblich, Ohlsson & Raney, 2001; Jones, 2003; Kershaw & Ohlsson, 2004; Reverberi, Toraldo, D'Agostini, & Skrap, 2005). The theory supposes that the problem solver begins with an incorrect representation of a problem (due to prior knowledge), with the insight process involving the re-representation of the problem.

When a problem solver is confronted with an insight problem, there is an initial (often unconscious) activation of prior knowledge that was useful for solving apparently similar (noninsight) problems in the past, but is a hindrance for solving the insight problem. As a consequence a "biased" problem representation is established making it very difficult to access the operators that are necessary to transform the problem state into a proper solution. Without an appropriate solution procedure the problem solver gets stuck in an impasse. Within this impasse, problem solving behavior ceases (or the same useless solution attempts are repeatedly carried out) and the problem solver is left with the impression that the problem is unsolvable. Following the Ohlsson account, a representational change is the key to overcoming impasse. During the impasse phase, there are unconscious processes that enable the possibility that a change in problem representation will reach the threshold of awareness. This is the moment of "AHA! I have found it." It is plausible to assume that during impasse the activation of the repeatedly accessed solution procedure(s) decrease(s) and thus less active procedures can be accessed. This assumption fits quite well with findings of the incubation research (e.g., Smith, 1995; Smith & Blankenship, 1991; Wagner et al., 2005; Wallas, 1926**[not in refs]**). The RCT suggests that there are at least two possibilities to change a problem representation. First, the relationship between the constituents of a given problem can be changed – for example, a problem entity may be perceived as a whole when in fact it can be broken down into further subcomponents. This is termed *chunk decomposition*. Second, the initial representation of the problem may place unnecessary constraints on the problem itself, and thus constraints need to be relaxed. This process is termed *constraint relaxation*.

The matchstick arithmetic domain can be used to illustrate the processes of chunk decomposition and constraint relaxation. In matchstick arithmetic, an incorrect initial equation, represented by matchsticks, is given in Roman numerals. The task for the problem solver is to solve the equation by moving only one matchstick. For example, IV = III + III requires the "I" before the "V" to be placed after the "V," creating VI = III + III. This provides an example of a simple chunk to decompose – the fact that "IV" can be seen as the numeral "4," but can also be decomposed into further numerals, "1" and "5." This problem is fairly simple and can be solved by applying the well known prior school knowledge that changing values in an equation lead to success. However, consider the equation XI = III + III, which contains a much more difficult chunk to decompose. Here, the "X" can be broken down into two slanted matchsticks, which can then form a "V" to make VI = III + III.

Matchstick arithmetic can impose unnecessary constraints that problem solvers' implicitly place on their initial representation of the problem. For example, prior knowledge informs people that in general, equations involve changes to values, and hence when beginning to solve matchstick arithmetic problems, problem solvers' begin by only considering the matchsticks that make up values as being valid moves. If the problem requires a change to an operator (e.g., IX = VI–III requires interchanging one horizontal stick between the "=" and "–" to attain IX–VI = III), then problem solvers' get stuck in an impasse until finally relaxing such a constraint. Hence the initial problem representation can be overconstrained by problem solvers' self imposed assumptions and so a solution becomes impossible.

Chunk decomposition and constraint relaxation have both been shown to affect insight in the matchstick arithmetic domain. Longer solution times are found for insight problems that consist of constraints that are difficult to relax (or chunks that are difficult to decompose) compared to easier constraints/chunks (Knoblich et al., 1999). Furthermore, eye movement data also support the two theoretical constructs (Knoblich et al., 2001). Problem solvers fail to fixate on the appropriate problem elements (i.e., the elements related to the constraint to relax, or chunk to decompose) when they begin the problem, which is consistent with the idea that the relevant problem elements are not being considered as possible moves in the initial representation of the problem. Knoblich et al. (2001) demonstrated, when beginning a problem, problem solvers only fixate on the matchsticks that comprise the values of the equation because it is values in equations that normally change. After an impasse, solvers spend more time fixating on the relevant problem elements than nonsolvers, further cementing the idea that constraint relaxation and chunk decomposition are critical factors in solving matchstick arithmetic insight problems.

Within the matchstick arithmetic domain, there are different problem types that differ in their problem difficulty (Knoblich et al., 1999; Knoblich et al., 2001). Problem difficulty is not determined by the number of moves (i.e., the size of the problem space) but by the degree of the necessary representational change (i.e., the necessary constraint relaxation or chunk decomposition). That is, problem difficulty is determined by the level of difficulty in decomposing a chunk or relaxing a constraint. The simplest problem is one that only involves manipulating a so-called "loose chunk" that conforms to prior knowledge. One such example is the equation VIII = VI + IV that can be solved by manipulating a value and moving the vertical stick from the VI to the left side (IV), producing the solution VIII = IV + IV. Although the VI needs to be decomposed into the numerals I and V, this is a simple chunk to decompose and does not require any detailed representational change. This type of noninsight problem is labeled the standard type (ST) and can serve as a baseline for the other problem types.

Table 1. Problem difficulty. Column one displays the task. Column two gives the corresponding solution. Column three indicates the necessary degree of chunk decomposition. "+" indicates loose, "++" intermediate, and "+++" tight chunk decomposition. Column four indicates the degree of necessary constraint relaxation. 0 is assigned to standard goal representation that is supported by prior knowledge. "+" is assigned to a goal representation that assumes one operator is constant. "++" is assigned to a goal representation that assumes that both operators are constant. "+++" is assigned to a goal representation that assumes operators are constant plus the more fundamental assumption that equations always consist of two different operators. The last column assigns the abbreviations of the problem type labels. ST: standard type, CR1–CR3: constraint relaxation type – the ascending degree of the attached number should indicate the degree of necessary constraint relaxation, CD: Chunk Decomposition. The bold font in column two indicates the sites where a manipulation occurred.

Problem	Solution	CD	CR	Type
VIII = VI + IV	VIII = **IV** + IV	+	0	ST
VI = VI + I	VI = **VII** – I	++	+	CR1
IX = VI – III	IX – VI = III	++	++	CR2
VI = VI + VI	VI = VI = VI	++	+++	CR3
VI = VI + V	**XI** = VI + V	+++	0	CD

There is a clear hierarchy in problem difficulty based on the type of chunk to decompose. Participants find it more natural to manipulate loose chunks, rather than intermediate chunks (=, +), or so called tight chunks (X, V) (see Knoblich et al., 1999). Therefore a problem where one has to decompose a tight chunk is more difficult than a problem with an intermediate chunk, which in turn is more difficult than a problem where a loose chunk is involved (see Table 1).

The same hierarchy of difficulty is seen for the type of constraint that needs relaxing. For example the problem type CR3 (constraint relaxation 3) uses equations of the type VI = VI + VI. The problem solver not only has to overcome the constraint that operators in equations are constant, but she also has to relax the more fundamental constraint that an equation always consists of two different operators. The solution is to transform the + into = by moving one matchstick, thus the solution is attained (VI = VI = VI). CR1 and CR2 problems require weaker forms of constraint relaxation (see Table 1). Counterintuitively, Reverberi and colleagues (2005) found that patients with a lesion at the dorsolateral prefrontal cortex (DLPFC) did better in solving this tautological task than healthy controls. They conclude that DLPFC might be one possible candidate that is responsible for imposing constraints on one's problem representation.

Knoblich and colleagues (1999, 2001) have consistently shown that chunk decomposition and constraint relaxation are two independent sources of problem difficulty for matchstick arithmetic problems, using the same types of problem that are used in the stimulus set here. There is growing evidence from neuro-physiological and cognitive studies that justify the cognitive concept of a representational change. Physiological evidence is provided by some eye tracking studies (for an overview see: Knoblich, Öllinger, & Spivey, 2005). Investigating eye-movement patterns in the matchstick arithmetic task, Knoblich et al. (2001) divided the problem solving process into three phases (before, within, and after an impasse). When solving insight problems requiring constraint relaxation, problem solvers focused significantly longer and more frequently at values than at operators prior to reaching impasse. Within an impasse there was no systematic eye-movement pattern. After an impasse (the representational change having now occurred) solvers of the problem gazed significantly longer at the operator than nonsolvers. Jung-Beeman et al. (2004) investigated insight problem solving with fMRI and EEG. The authors found significantly more activation in the right anterior superior temporal gyrus, a key region for linking unrelated concepts together, when people had insightful solutions in contrast to noninsight solutions. With EEG they detected a sudden burst of high frequency neural activity immediately before insight solutions, possibly indicating the occurrence of a representational change.

In cognitive studies the most prominent indicator for representational change is a sudden drop in solution rates (Knoblich et al., 1999; Wagner et al., 2005). Solution rate graphs of insight problems often show a plateau, demonstrating for the majority of people an inability to find a solution, but then suddenly solution rates strongly increase. Taken together there are good reasons to assume the existence of a representational change in insight problem solving. For the remainder of the article, we distinguish between "two types of insight": One type of insight that requires chunk decomposition as a representational change and another type of insight that requires constraint relaxation.

The Goals of the Study

The representational change theory clearly shows how insight may be explained and the matchstick arithmetic domain provides an insight problem where both the chunk decomposition and constraint relaxation processes can be manipulated. The goal of the present study is to investigate how the repeated use of a particular solution procedure (i.e., mental set) affects the process of representational change (i.e., insight). This research uses three experiments to attempt to answer several specific questions regarding the interplay of mental set and insight. First, does the repeated solution of set problems that are noninsight problems (problems that don not require a representational change) inhibit the solution of test problems that are insight problems? We expect no mental set effects, because prior knowledge problems do not affect representational change. Second, do set problems containing insight problems that constantly promote the need for chunk decomposition inhibit the solution of test problems that involve constraint relaxation? We expect mental set effects, because the strong activation of chunk decomposition procedure makes "blind" for constraint relaxation. Third, how will the above questions be affected when the set involves constraint relaxation problems yet the test problems involve a combination of noninsight, constraint relaxation and chunk decomposition problems? For the noninsight and the chunk decomposition problems we expect mental set effects, because constraint relaxation makes "blind" for value manipulation. For the constraint relaxation problem we expect a strong positive transfer.

Experiment 1

The first experiment asks whether the repeated use of a particular solution procedure that does not require a representational change (i.e., noninsight problems) can hamper the solution of problems that require a representational change (i.e., insight problems). Participants solved a set of ST (standard type = noninsight problems) problems before a test problem was given. The test problems either required a constraint relaxation representational change (problems CR1, CR2, CR3 in Table 1) or a chunk decomposition representational change (problem CD in Table 1). Two experimental groups were used to investigate the influence of the activation of the mental set procedures. The Same-Procedure Group (SPG) was always given ST set problems where the same type of move was applied to achieve solution. In contrast, the Different-Procedure Group (DPG) was given ST set problems that required different moves to achieve solution. The performance of a control group served as a baseline. The controls exclusively solved the test problems, with anagrams being given in place of the set problems.

Method

Participants

108 paid participants (26 male; age range: 18–47) were recruited by advertising at the University of Munich and in local newspapers and received €7. Using 108 participants and assuming a medium effect size ($w = .5$) with an α level of .05 gives a statistical power of .995 for χ^2 tests ($df = 1$), .995 for McNemar tests (N.B. power is based on 1.6 multiplied by the power given for a within-subjects *t*-test, Clark-Carter, 2004) and .995 for ANOVA tests ($df = 1,36$). Participants were screened beforehand for familiarity with Roman numerals. Each participant was randomly assigned to one of the two experimental conditions, or to the control group.

Materials and Apparatus

The material consisted of matchstick arithmetic tasks that could be solved by moving a single matchstick. Each participant worked on 31 problems. 27 were set problems (ST problems) and 4 were test problems (CR1–3, and CD, as shown in Table 1).

In the Same-Procedure Group (SPG), half of the participants worked on set problems that were solved exclusively by transforming either "VI" into "IV" or "XI" into "IX." The other half worked on problems that were solved exclusively by transforming either "IV" into "VI" or "IX" into "XI." The Different-Procedure Group worked on set problems that could be solved by procedures that apply different value transformations. This included all transformations previously mentioned and additionally transformations that require moving a stick from one numeral to another (e.g., I = II + I into II = I + I). A randomization procedure ensured that different problems occurred in roughly equal proportions in each of the four blocks of set problems.

The control group solved anagrams for an amount of time that had been determined in a pilot study as the mean solution time participants needed for solving the different blocks of set problems (two blocks of four minutes and two blocks of five minutes). Anagrams should not be seen as insight problems because the central involvement in anagrams is that of search – searching through one's vocabulary until the correct word to fit the anagram is found (Weisberg, 1995; for a different view see Bowden, 1997).

The experimental program was implemented in JAVA (SDK 1.3) and run on a PC (Windows 98). The problems were displayed on a 17-inch monitor (Belina). The display consisted of two areas. The upper area presented the problem. The lower area was used to type in the solutions.

Design

There were two experimental groups, the Same-Procedure Group (SPG) and the Different-Procedure Group (DPG), and in addition the control group. A block of set problems was always finished off by a test problem. The number of set problems in a block varied from five to eight in order to avoid anticipations of the position at which a potential test problem might appear, and the experiment was finished by a single set problem that followed the last test problem. The order of the given test problems was randomized. The two dependent variables were the frequency of solutions distributed across 90 s intervals for each test problem and the solution times for set problems.

Procedure

Upon entering the lab, all participants received instructions which stated (1) that all problems could be solved by moving one matchstick; (2) that matchsticks could not be removed; and (3) that the only valid symbols were Roman numerals and the arithmetic operators "+," "–," and "=." Participants in the control group received a further instruction for solving anagram problems. In addition, they were told that a matchstick arithmetic problem would appear once in a while. Before the experiment started, the controls solved one practice ST problem to acquire some familiarity with the matchstick arithmetic task. The results on this problem were discarded as the problem was only used for familiarization purposes.

During the experiment participants were seated in front of a computer screen. In the beginning of each trial a problem appeared. As soon as participants thought they had found a solution, they entered it into the text field. For this purpose they used six particular keys on the keyboard that were labeled "I," "V," "X," "+," "–," and "=." After proposing a solution they received immediate feedback. If the proposed solution was incorrect, they continued to search for the correct solution until an upper time limit was reached (120 s for set problems and 360 s for test problems). If a set problem was not solved, the participants were told the solution. However, if the participants failed to solve a test problem, they would not receive the solution in order to minimize possible transfer effects for the remaining test problems. The same display was used when presenting anagrams to the control group. Participants in this group used the common keyboard mapping for typing in the solution to the anagrams.

Results

Solution Frequencies for Test Problems

Figure 1 displays the cumulative frequency of solutions for the test problems divided into 90 s intervals and by group. There was a clear pattern of problem difficulty (see Figure 1a). Across all intervals problem type CR3 was solved less often than problem type CR2, and problem type CR2 less often than problem type CR1. McNemar tests (with significance values reduced to cater for familywise error rates) confirmed significant differences between problem types CR3 and CR2, χ^2 (1, N = 108) = 32.07; p < .0005, and problem types CR2 and CR1, χ^2 (1, N = 108) = 9.26, p < .01.

Pairwise χ^2-analyses were conducted between groups based on solution rates after 360 s (i.e., final solver/nonsolver rates). The analyses did not reveal significant effects for any of the problem types. For the CR1 problem, there was no difference in solution rates for controls and the SPG group, χ^2 (1, N = 36) = 2.37, p > .10, or for controls and the DPG group, χ^2 (1, N = 36) = .59, p > .30. Similarly, there were no differences for the CR2 problem (χ^2 (1, N = 36) = 1.03, p > .30, and χ^2 (1, N = 36) = .46, p > .30), the CR3 problem (χ^2 (1, N = 36) = .00, p = 1.00, and χ^2 (1, N = 36) = .59, p > .30), or the CD problem (χ^2 (1, N = 36) = .00, p = 1.00, and χ^2 (1, N = 36) = .00, p = 1.00). In the next step, we conducted standard pair-wise χ^2-analyses to compare the solution rates between the experimental groups.

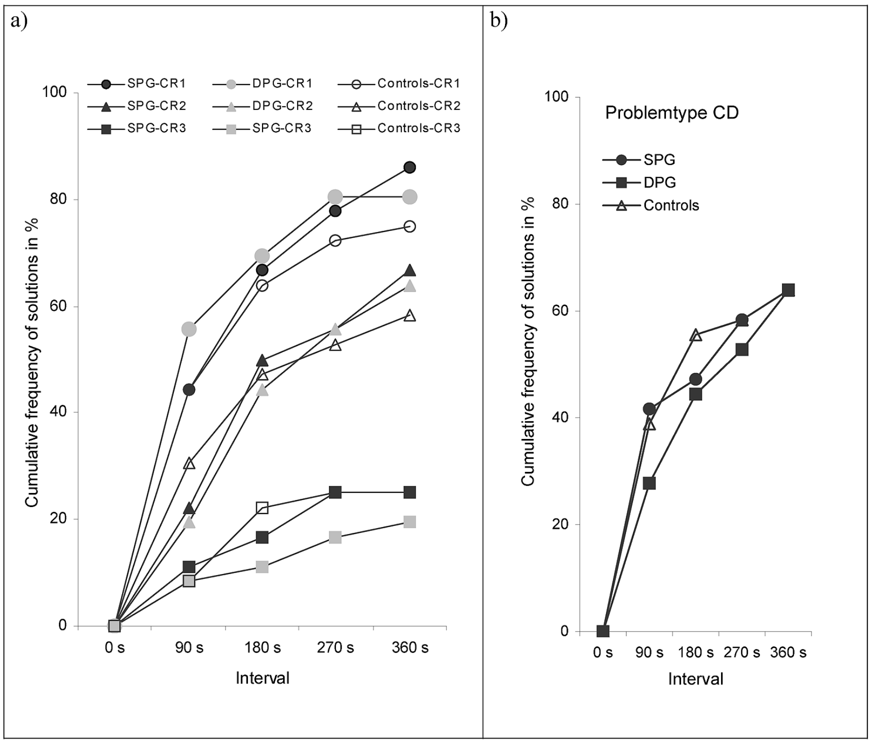

Figure 1. Cumulative frequency of solutions in Experiment 1 for test problems CR1, CR2, CR3 and CD across 90 s intervals. The figure displays the constraint relaxation problems on the left (panel a) and the chunk decomposition test problem on the right (panel b).

Table 2. Solution time in seconds assigned to the serial position (SP) of set problems, averaged over the four blocks. Standard deviations are in parentheses

Exp	Group	SP1	SP2	SP3	SP4	SP5	SP6
1	SPG	50.2 (18.0)	40.5 (16.2)	33.8 (17.2)	34.9 (20.5)	28.6 (16.4)	–
1	DPG	62.6 (22.5)	57.2 (23.8)	54.4 (17.9)	49.8 (18.9)	47.0 (19.3)	–
2	Exp. Gr.	61.5 (17.9)	51.4 (20.2)	44.1 (19.6)	42.5 (17.7)	36.8 (12.4)	–
3	SPG	90.1 (31.9)	63.3 (36.3)	48.9 (36.6)	41.7 (30. 6)	34.7 (28.1)	33.2 (27.2)
3	DPG	74.0 (34.7)	64.1 (31.1)	57.2 (35.2)	51.5 (34.4)	48.6 (33.4)	41.8 (28.7)

These analyses also revealed no significant effects (the closest to significance being for the CR1 problem, χ^2 (1, *N* = 36) = .40, *p* > .50).

Solution Time for Set Problems

We analyzed whether participants became faster for consecutive problems during each mental set block. Only the first five set problems are included in the analysis, because this was the minimum number of set problems presented in each block. The solution time for problems that were not solved (11.7%) within the given time limit were replaced with the maximum solution time of 120 s. Naturally, this substitution overestimates performance, but this overestimation is less troublesome than computing the analyses with missing data. To learn more about how the errors were distributed across the participants we conducted further statistics. We found that 13 out of 36 participants solved each of the presented set problems. There was an average of 3.3 unsolved set problems (range 0–10; median = 3).

The mean time spent working on set problems in the SPG condition was 15.2 min, with 22.7 min for the DPG group and 18.0 min for the controls.

As can be seen from Table 2, the solution times of both experimental groups became faster across consecutive set problems. A 2 × 5 mixed ANOVA with the between factor Group and the within factor serial position revealed a highly significant main effect for Group, $F(1, 70) = 23.82$, $p < .001$, where solution times were longer for DPG than SPG. There was also a highly significant main effect for serial position, $F(4, 280) = 17.94$, $p < .001$[1], with posthoc analyses indicating that problems in the first serial position were

[1] Log transforming the data prior to analyses revealed highly significant main effects (Group, $F(1, 70) = 28.5$; serial position, $F(4, 280) = 20.65$; $p < .001$) and a significant interaction between Group and serial position ($F(4, 280) = 3.01$, $p < .05$).

solved much more slowly than problems in the fifth serial position ($p < .001$).

Solution Time for Set Problems Preceding and Succeeding a Test Problem

We analyzed whether working on a test problem that requires a representational change influences the solution time of the set problem appearing after the test problem. We compared the solution time of the set problem that immediately preceded the test problem with the solution time of the set problem that immediately succeeded the test problem. As can be seen from Table 3 set problems before a test problem were solved more quickly than set problems after a test problem. A 2 × 2 mixed ANOVA with the between factor Group and the within factor Position revealed a highly significant main effect for Group, $F(1, 70) = 25.66$, $p < .001$, with SPG solving more quickly than DPG, and a highly significant main effect for Position, $F(1, 70) = 15.06$, $p < .001$, with set problems before a test problem being solved significantly more quickly than those after a test problem.

Table 3. Solution time in seconds of set problems appearing before and after test problems

Experiment	Group	Before test problem	After test problem
1	SPG	23.9	32.2
1	DPG	40.1	50.1
2	Exp. Group	31.8	42.4
3	SPG	26.4	48.8
3	DPG	38.4	34.2

Discussion

Experiment 1 indicates that the repeated solution of noninsight set problems, which were supported by prior knowledge, did not inhibit the solution of test problems that required a representational change. Furthermore, manipulating the variation of the set problems (i.e., varying the solution procedure or keeping it constant for the problems in the set) revealed no differences in the subsequent solving of the insight problems. Problem solvers did however become more familiar with the set problems and therefore produced faster solutions in the course of the experiment. In addition, a clear hierarchy was found concerning the relative difficulty of the insight problems (CR3 > CR2 > CR1), which supports previous research (e.g., Knoblich et al., 1999, 2001; Reverberi et al., 2005).

Even when participants were given standard matchstick arithmetic problems that required exactly the same solution procedure (SPG), there were no detectable mental set effects inhibiting the solution of insight test problems. Why do we not find mental set effects? Were the ST problems too easy to solve? This cannot be the case for two reasons. First, about 2/3 of the problem solvers failed to solve some (11.7%) of the set problems. Second, as Table 2 illustrates, although problem solvers became faster with serial position, they always needed time to solve the problem (for example, 28.6 s for serial position 5 of the SPG group). Additionally, there was evidence that working on a test problem slowed down the reaccessing of the set procedure. That is, changing the solution procedure decreases the activation of the formerly preferred procedure (Lovett & Anderson, 1996).

We can conclude that the repeated solution of noninsight problems did not hamper the solution of insight problems. That is, the processes that drive a representational change are not affected by the repeated use of procedures that are consistent with prior knowledge.

Experiment 2

Experiment 2 will investigate whether insight set problems that require chunk decomposition prevent the solution of insight test problems that require constraint relaxation.

Method

Participants

36 paid participants (9 male, age range: 20–36) were recruited by advertising at the University of Munich and in local newspapers and received €7. Participants were screened beforehand for familiarity with Roman numerals. The control group was the control group from Experiment 1; no procedural details will be given here regarding controls, but their data from Experiment 1 will be used in the results section.

Material and Apparatus

Again, the participants worked on 31 problems. There were 27 set problems and 4 test problems. All set problems required the decomposition of a tight chunk (see above) into its constituent parts in order to compose a new chunk. For example, “X” could be decomposed into its constituent parts “\” and “/” in order to compose a “V” (or vice versa, a “V” into an “X”).

The test problems were the same as for Experiment 1 (CR1, CR2, and CR3), with one exception: a CD problem type could not be used (because they are used as part of the set) and so instead of a CD problem type, the participants solved an ST problem type in order to keep the number of test problems consistent with the control group. The ST problem type for the experimental group and the CD problem type for the control group were discarded from analyses.

Procedure and Design

The same procedure from Experiment 1 was used.

Results

Solution Frequencies for Test Problems

Figure 2 displays the cumulative frequency of solutions for the test problems divided into 90 s intervals for the experimental group and the control group. At all intervals, CR3 problems were solved less often than CR2 problems (χ^2 (1, N = 72) = 26.28, $p < .001$), and CR2 problems were solved less often than CR1 problems (χ^2 (1, N = 72) = 4.35, $p < .05$).

For the CR1 test problem, there was no significant difference in final solution rates between the control group and the experimental group, χ^2 (1, N = 36) = .59, $p > .30$. The same is true for the CR2 problem, χ^2 (1, N = 36) = .11, $p > .70$. However, as Figure 2 shows, there is a clear initial difference across the two groups. An analysis of solution rates at the 90 s interval shows that the control group has significantly higher solution rates than the experimental group for the CR2 problem at this time interval (χ^2 (1, N = 36) = 4.71, $p < .05$).

The final solution rates for the CR3 problem shows that people in the control group were significantly more able to solve CR3 problems (χ^2 (1, N = 36) = 7.26, $p < .01$).

Solution Time for Set Problems

The results indicate that the set problems were not too easy for participants, with only 4 out of 36 participants solving all of them, with 11.9% of set problems failing to be solved (average = 3.1 unsolved set problems; range = 0–10; median = 3). Participants in the experimental group became faster for consecutive set problems (see Table 2). A one-way ANOVA with the factor serial position revealed a highly significant effect, $F(4, 140) = 18.25$, $p < .001$[2]. A posthoc test between the first and the fifth serial positions showed the fifth problem was solved significantly more quickly than the first problem ($p < .001$).

Solution Time for Set Problems Preceding and Succeeding a Test Problem

As can be seen from Table 3, solving a test problem disrupted the solving of set problems. Problem solvers needed more time for solving set problems succeeding a test problem than for set problems preceding a test problem. This was confirmed by a paired samples t-test, $t(35) = 3.90$, $p < .001$.

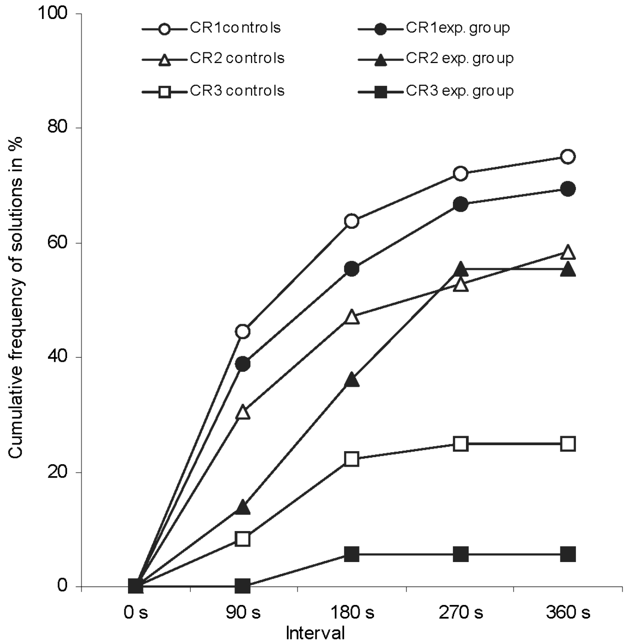

Figure 2. Cumulative frequency of solutions in Experiment 2 for the test problems CR1, CR2, CR3 across 90 s intervals.

Discussion

The main finding of Experiment 2 is the discovery of mental set effects. In the experimental group the solution of both CR2 and CR3 problem types were impaired in comparison with the controls. Furthermore, and again supporting the RCT, the hierarchy of problem difficulty remained intact (CR3 > CR2 > CR1). In addition, supporting the results from Experiment 1, problem solvers were quicker to solve subsequent set problems.

The solution of set problems that require a chunk decomposition representational change inhibits the solution of problems that require a constraint relaxation representational change. The results clearly indicate an interaction between the set problems and the problem difficulty of the test problems. There were no mental set effects for the CR1 problem, although as Figure 2 shows, solution rates are consistently below the controls. This could indicate that even for the CR1 problem, there may have been small mental set effects that could not be revealed by the coarse solution rate measure. Solution of the CR2 problem was clearly temporarily inhibited by the set problems, with the experimental group remaining stuck in impasse for a longer period than the controls. The strongest impact of the set

[2] Log transforming the data prior to analyses revealed a highly significant effect ($F(1, 140) = 17.44$, $p < .001$).

problems was on the solution rates of the CR3 problem. Here, only 2 of 36 participants of the experimental group were able to solve the problem compared with 9 out of 36 for the controls. The experimental group found it very difficult to break the impasse. Taken together, this pattern of results suggest that the more difficult the constraint to relax, the stronger the impact of the chunk decomposition set problems.

Another important finding was that the hierarchy of problem difficulty remains intact even under these conditions. The test problem CR3 remained more difficult than the test problem CR2, and CR2 was more difficult than CR1. That is, the change to the problem situation induced by the set problems did not affect the hierarchy of difficulty of the CR problems. This result provides further evidence that chunk decomposition and constraint relaxation are independent processes (see also Knoblich et al., 1999, Experiment 3).

Experiment 3

Experiment 3 examines the extent to which the repeated solution of constraint relaxation problems affects the solution of problems that involve either constraint relaxation, chunk decomposition, or neither of these (standard type problems). As with Experiment 1, different compositions of set problems were used to examine the relative effects of the set containing the same procedure (Same-Procedure Group, SPG) versus the set containing different procedures (Different-Procedure Group, DPG).

Method

Participants

108 paid participants (38 male, age range: 17–58), were recruited by advertising at the University of Munich campus and in local newspapers and received €7. Participants were screened beforehand for familiarity with Roman numerals. Each participant was randomly assigned to one of the two experimental conditions or to the control group.

Material and Apparatus

The apparatus was the same as in Experiment 1. However, the participants worked on only three test problems. Participants in the experimental groups solved 22 set problems (block lengths of 6, 7, and 8 set problems, and one set problem after the final test problem). The controls solved anagrams for 16 minutes divided into three blocks (two blocks of 5 min and one block 6 min).

The SPG problems included only CR2 type problems (see Table 1). The procedure for the solution of these problems was always to move one matchstick across the equal operator and the minus operator. The DPG problems included both CR2 and CR3 problems (as seen in Table 1) plus a further type of CR3 problem, R-CR3. R-CR3 problems have not been introduced thus far, but require the transformation of a second equals sign into a plus (the reverse of the action that is required for CR3 problems). For example, III = II = V would produce III + II = V. Each block of set problems had one of the three test problems (ST, CD, or CR1) added onto the end.

Procedure and Design

The procedure is identical to that of Experiment 1, except participants had 180 s rather than 120 s to solve the set problems. The upper time limit was increased because it is expected that at the beginning of the experiment it might be quite hard to solve the set problems.

Results

Solution Frequencies for Test Problems

Figure 3 displays the cumulative solution rates for different groups and test problems. There was a hierarchy of problem difficulty between test problems ST and CD (see panel a). McNemar tests (with significance values reduced to cater for familywise error rates) confirmed that the CD problem was solved with less frequency than the ST problem (χ^2 (1, N = 108) = 30.19, p < .001). However, as can be seen in Figure 3, there was no difference between the ST and CR1 problems, because the DPG showed an extraordinarily high solution rate for the CR1 problem (χ^2 (1, N = 108) = .72, p .05).

Controls were more successful in solving the ST problem than participants in the SPG and DPG conditions. An analysis of final solution rates showed that there were significant differences between the control and SPG groups (χ^2 (1, N = 36) = 23.27, p < .001), and the control and DPG groups (χ^2 (1, N = 36) = 13.09, p < .001). There was no difference across the two experimental groups (χ^2 (1, N = 36) = .28, p > .05). Although Figure 3a suggests a difference between the two experimental groups at earlier time intervals, tests at these intervals were not significant (all p > .05).

Participants in the control group also solved more CD problems. Comparisons on final solution rates reveal significantly more solvers in the control group than the SPG group (χ^2(1, N = 36) = 12.04, p < .001), and significantly more solvers in the control group than the DPG group (χ^2(1, N = 36) = 9.75, p < .01). There was no difference between the experimental groups (p > .05).

The pattern for the CR1 problem was quite different. Final solution rates showed no difference between the control group and the SPG group (p > .05). However, partici-

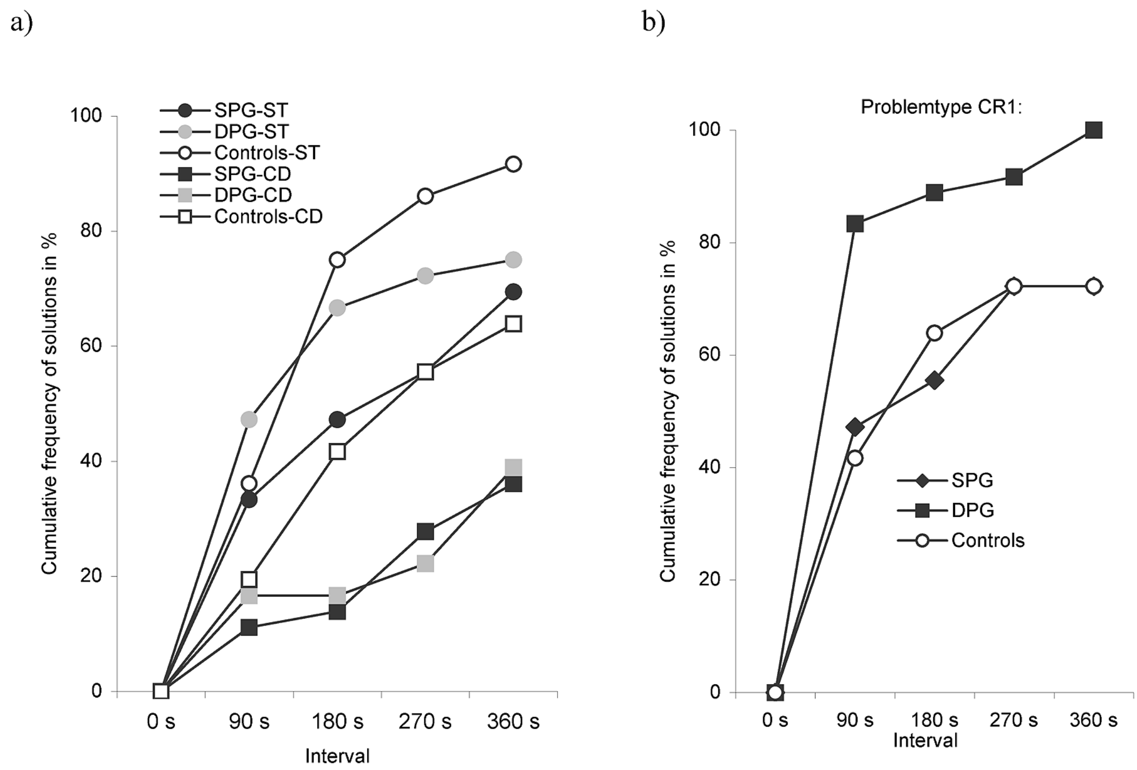

Figure 3. Cumulative frequency of solutions in Experiment 3 for the test problems ST, CD, and CR1 across 90 s intervals. The figure displays the test problems with standard goal representation on the left (panel a) and the constraint relaxation test problem on the right (panel b).

pants in the DPG group solved significantly more CR1 problems than controls (χ^2 (1, N = 36) = 13.85, $p < .001$), and solved significantly more CR1 problems than the SPG group (χ^2 (1, N = 36) = 11.61, $p < .001$). The application of different procedures that manipulate the operators of the equations produces a strong facilitative effect on the performance of the CR1 problem.

Solution Time for Set Problems

Again, the set problems were not too easy for participants, with 11.2% of the presented set problems not being solved. 12 out of 72 participants were able to solve all set problems (average = 2.7 unsolved set problems; range = 0–10; median = 2). A mixed ANOVA with the between factor Group and the within factor serial position revealed no significant main effect for Group ($F(1, 70) = .57$; $p > .05$), but a significant main effect for serial position ($F(5, 350) = 33.52$, $p < .001$) and a significant interaction between Group and serial position, $F(5, 350) = 3.60$, $p < .01$[3]. Posthoc tests showed the first problem to have been solved significantly more slowly than the sixth problem for both experimental groups ($p < .001$), see Table 2.

Solution Time for Set Problems Preceding and Succeeding a Test Problem

As can be seen from Table 3, problem solvers needed more time for solving set problems that succeeded a test problem than they did for set problems that preceded a test problem. This observation is confirmed by a 2 × 2 mixed ANOVA with the between factor Group and the within factor Position. There was a highly significant main effect for the factor Position, $F(1, 70) = 14.93$; $p < .001$, and a significant interaction between the factor Group and Position, $F(1, 70) = 7.01$; $p < .01$. The interaction shows that the SPG was more affected by having an intervening test problem between two set problems, resulting in an increase in solution time for the set problem after the test problem. For the DPG group, no increase was found.

Discussion

Experiment 3 produced several enlightening results. The most important finding was that performance on both the ST problem and the CD problem is inhibited by the set problems. In contrast, CR1 problems benefited from the

[3] Log transforming the data prior to analyses revealed a highly significant main effect for serial position $F(1, 350) = 37.39$; $p < .001$) and a highly significant interaction between Group and serial position ($F(4, 350) = 4.04$, $p < .005$).

repeated solution of the same type of constraint relaxation problem. Furthermore, participants in the experimental groups became increasingly faster at solving set problems. Solving a set problem immediately after a test problem was more strongly impaired in the SPG than in the DPG condition. The more flexible procedures in the DPG set condition make it easier to change back to the set procedure after an interrupt occurs.

For the SPG, set effects were strong because participants in this group solved only one type of constraint relaxation problem. For the DPG, mental set effects were of medium strength because the set is spread over several procedures – problems in the set consisted of three types of constraint relaxation problem. In sum, the repetition of constraint relaxation problems that formed the set inhibits the solution procedures for all types of test problem except those that were consistent with the set – i.e., constraint relaxation problems.

General Discussion

In three experiments the interplay between mental set and insight was addressed. Experiment 1 showed that set problems that did not require a representational change (noninsight problems) had no negative effects on problems that required a representational change (insight problems). In contrast, Experiment 2 showed that the repeated solution of problems that required a chunk decomposition representational change inhibited the solution of problems that required a constraint relaxation representational change. Here the negative influence of the set interacted with the extent of the necessary representational change. Experiment 3 showed on the one hand that when the set contained constraint relaxation problems, the solution performance of both noninsight and chunk decomposition problems was inhibited, while on the other hand the solution performance of problems with other constraints to be relaxed was not affected (and was even facilitated in some cases).

In sum, the three experiments reveal an interesting asymmetry between the interplay of mental set and insight. Mental set effects were always found when the problems in the set required a different representational change to the test problems. In contrast, no mental set effects were found when the problems in the set required the application of prior knowledge in order to solve them. It seems plausible to argue that learning a new insight in the solution of a problem and successively reinforcing this new insight suppresses alternative processes that are necessary for other problem types. As a consequence, alternative processes have no opportunity to surpass the threshold to awareness.

These findings may give a refined interpretation for the Gestalt view of mental set and insight: mechanization does not necessarily make problem solvers "blind" to an insightful solution (Birch & Rabinowitz, 1951; Luchins, 1942). This only occurs, at least under our experimental conditions, when the set involves insight problems requiring a different representational change to the test insight problem. That is, productive thinking (Wertheimer, 1959) is particularly affected when people become focused on other insightful features of a problem. In accordance with the Gestalt view are the findings of the hierarchy of problem difficulty, because at least for the controls we always found that the extent to which prior knowledge had to be overcome determined the problem difficulty of the test problems.

The experiments in this paper have revealed a set of results that must now be explained from a theoretical stance. First, noninsight set problems do not affect insight test problems. Second, insight *set* problems involving one form of representational change inhibit the solution of insight *test* problems requiring a different form of representational change. Third, solution of the set problems becomes faster as more set problems are solved and after a test problem some time is needed to re-establish the set procedure. Fourth, there is a hierarchy of problem difficulty for insight problems that relates to the extent of the necessary representational change (and this holds even when there are mental set effects).

The RCT is able to explain some of these results. However, in order to reach an overarching explanation, the procedural view of problem solving must first be described. Procedures are stated as a collection of rules that specify conditions under which an action is carried out, with a procedure becoming stronger the more often it is used. From a set of procedures that meet a particular condition, the strongest available procedure is always selected. It can be assumed that factors such as prior knowledge make some procedures more likely for selection than others. Within this framework, mental set is an artifact resulting from selection processes (Anderson, 1982; Newell, 1990; Anderson & Lebiere, 1998; Lovett & Anderson, 1996). When the procedure that was used to solve the first problem is successful, it gains activation and as such is used to solve the second problem in the set, in turn gaining activation and so on. Activation is only reduced when the procedure fails – as it would be when suddenly the problem solver is confronted with an insight test problem after having noninsight problems in the set.

The procedures required for solving insight problems therefore begin with a very low probability of selection. It is through the repeated failure of more high probability solution attempts (and thus a reduction in their probability of selection) that some time later an appropriate solution procedure is selected. Whilst the procedural view can explain basic mental set effects, it cannot explain the more subtle interplay between mental set and insight. Remember that noninsight set problems did not affect insight test problems. A two process model which bridges the RCT and proceduralization accounts is hence proposed to account for the data presented here.

The first process in the model involves representational change and the second process involves proceduralization.

Based on prior knowledge, the representational change process selects a procedure for the solution of the current problem. After a procedure has been selected, the second process, in accordance with the procedural approach, repeatedly reinforces the selected procedure after each repetition of its use (assuming it is successful). As a consequence the newly reinforced procedure becomes the most likely one for selection, under similar conditions.

When noninsight problems are used in the set, the first process can be skipped, and thus a purely procedural approach ensues. This results in the solution time of the set problems gradually decreasing. When then faced with an insight test problem, the representational change process is applied and hence the insight test problems are not affected by the prior solution of noninsight set problems.

When insight problems are used in the set, the representational change process can be used to help attain the relevant representational change process. The proceduralization process then reinforces this procedure such that the solution of test problems requiring a different form of representational change is inhibited. The hierarchy of difficulty seen in the solution of the test problems arises from the relative difficulty in selecting the appropriate procedure, in accordance with the RCT's concepts of tight and loose chunks, and the varying levels of constraint relaxation.

We think that our model is a mixture of a refined ACT-R model, according to the approach of Lovett and Anderson (1996) and the representational change theory of Ohlsson (1992). It should potentially enable us to bridge the gap between the Gestaltist's concept of restructuring (or representational change in cognitive terms) and ACT-R.

The process of proceduralization is basically the same as postulated in ACT-R. The repeated activation of a solution procedure prioritizes this procedure beyond other available procedures. This can be attained easily by increasing a weight assigned to each procedure. This mechanism provides a nice explanation of the Gestaltist's mental set findings (e.g., Luchins, 1942). We can further speculate what is necessary to extend the ACT-R model to implement the second process (representational change). The second process gives access to a "new" or weakly activated solution procedure. For example, in our experimental set up people need access to a solution procedure that changes operators. We have to consider two cases: first, the system "knows" the solution procedure but it is unable to access the procedure because its activation is too weak in comparison to the dominant procedure. This weakness could be overcome by a kind of incubation (stuck in an impasse). That is, the system decreases over time the activation of the dominant procedure. As a consequence other putative solution procedures get a chance to be selected. Here, the process of representational change can be described as linking a given problem to a known but unusual solution procedure. Second, and more sophisticated, the system has to generate new knowledge from the given problem and the existing prior knowledge. Yet, the system does not know that the manipulation of operators can solve an arithmetic problem. Again, the repeated failure of a solution procedure decreases the weight of the dominant procedure (negative feedback), but there appears to be no appropriate procedure that solves the problem. Now, only a fundamental change of the underlying concept of solving an arithmetic problem is necessary (constraint relaxation) – here, operators can also be considered as variable, hence changing operators is permitted. According to our findings the ACT-R model needs an additional function that prioritizes new and insightful knowledge in a special way, which perhaps could be explained by the fact that the new knowledge has to be newly established in the long term memory of the system.

This paper has shed light on the interplay between mental set and insight. It is clear that set effects are dependent on the kind of problems that are repeated and a subtle interplay between mental set and insight is seen. Mental set effects only cause problems for insight when the set actually contains insight problems. A simple two-process model between the RCT and proceduralization views of problem solving can be used to explain the findings presented.

Acknowledgments

This research was made possible by a grant from the German Research Foundation (DFG), KN-489/6–2.

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Received August 4, 2006
Revision received June 21, 2007
Accepted June 26, 2007

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