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ABSTRACT

Predictors of novice learning in simulation environments were investigated in the domain of statistics. The first objective was to clarify the relation between intellectual ability and working method (e.g., orientation and systematical orderliness), and to determine the effects on learning of working method, independently of intellectual ability. A second objective was to determine whether instructional aid by presenting students with a well-structured task, instead of unguided learning by discovery, might compensate for lack of ability or a poor working method. Twenty-seven first-year university students of relatively high intelligence (n=14) or low intelligence (n=13) worked in either a structured or an unstructured learning environment. Thinking-aloud protocols were analyzed in terms of the quality of working method. Results indicate that the working method of high-intelligence subjects was significantly better than that of subjects of low intelligence; working method was also a strong predictor of learning, independent of intellectual ability. No learning effects due to the level of structure of the learning environment could be detected. Five data tables and a 28-item list of references are included. An appendix contains three definitions from the study. (Author/SLD)

Intellectual Ability and Working Method as Predictors of Novice Learning.

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ABSTRACT

Predictors of novice learning in simulation environments were investigated in the domain of statistics. The first objective was to clarify the relation between intellectual ability and working method (e g. orientation and systematical orderliness), and to determine the effect on learning of working method, independent of intellectual ability. A second objective was to determine whether instructional aid by presenting students with a well-structured task, instead of unguided learning by discovery, might compensate for lack of ability or a poor working method. Twenty-seven relatively high or low intelligent first year university students worked in either a structured or an unstructured learning environment. Thinking-aloud protocols were analysed on the quality of working method. The results indicated that the working method of high intelligent subjects was significantly better than that of low intelligent subjects, but that working method also is a strong predictor of learning, independent of intellectual ability. No learning effects due to structuredness of learning environment could be detected.

The novice-expert paradigm has yielded a vast amount of research on differences between novice and expert problem solving (Larkin, McDermott, Simon & Simon, 1980; Chi, Feltovich & Glaser, 1981; Schoenfeld & Herrmann, 1982; Anderson, 1985; Chi, Glaser & Farr, 1988; Thibodeau Hardiman, Dufresne & Mestre, 1989). Besides quantitative differences (e.g. number of errors and time on task), a number of qualitative differences have been found. Experts not only have more knowledge at their disposal, but their knowledge is also better organized (Chi, Glaser & Rees, 1982) and more of a procedural kind (Anderson, 1985; Jansweijer, Elshout & Wielinga, 1990). Before actually acting, experts pass through an elaborate qualitative analysis of the problem through which schemata of forward problem solving strategies are activated. Novices on the other hand, analyse a given problem in terms of superficial features (Chi et al., 1982) and are inclined to act immediately and unsystematically (Elshout, 1987; Jansweijer et al., 1990). This lack of metacognitive control results in a poor problem representation to which only weak problem solving strategies like means-ends analysis and working backwards can be applied (Glaser & Bassok, 1989; Glaser, 1990).

Not all novices are limited to equally poor problem solving behavior (Schoenfeld & Herrmann, 1982). Contrary to genuine novices, an 'expert-novice' tends to act more expert-like by orientating on a problem, working more systematically and more accurately, and by evaluating more during the problem solving process (Elshout, 1985). Furthermore, Chi et ai. (1989) demonstrated that better students elaborated more on the subject matter by generating self-explanations during the learning process. Deep orientation, systematical orderliness, evaluation and elaboration are the characteristics of a proficient working method. Such an effective working method is a metacognitive skill, or in terms of Glaser (1990) a self-regulatory ability, which is brought in by the student in order to structure the learning process (Veenman, Elshout & Bierman, 1989b). Metaphorically spoken, an effective working method might be regarded as a student's compass and skeleton-map on a voyage of discovery in a new domain. Without such an adequate outfit a novice expedition is likely to run ashore, especially for low intelligent students (Veenman, Elshout & Bierman, 1991).

There are three models for describing the relation between intellectual ability and working method. The first model regards an effective working method as a manifestation of intellectual ability. According to this model, working method cannot have a predictive value for learning, independent of intellectual ability. In a second, contrasting model working method and intellectual ability are independent predictors of learning. The last model thus is a mixed model, in which working method has a surplus value on top of intellectual ability, for the prediction of learning, while high intelligent novices tend to exhibit a better working method.

Empirical studies do not consistently support one of these models. Veenman and Elshout (Veenman et al., 1989b; Elshout & Veenman, 1990) reported the results of an experiment in the domain of heat theory, that corroborated the first model. They had high and low intelligent subjects working for about an hour in a computer simulated Heat Lab while thinking aloud. Tape-recorded thinking-aloud protocols were analysed on the quality of working method. High intelligent subjects showed both a more proficient working method and a significantly better learning performance than low intelligent subjects. Working method correlated significantly with learning measures, but when intelligence was partialed out these correlations approximated zero. Some support for the second or the third model was gathered by Swanson (1990), though the research was primarily concerned with problem solving instead of learning. Children, who were selected on high or low aptitude (as measured by a cognitive abilities test) and on high or low metacognitive knowledge (by means of a questionnaire), had to perform two Piagetian tasks. Swanson's results showed that high-metacognitive individuals outperformed low-metacognitive individuals regardless of their aptitude level, indicating that metacognitive skills can compensate for cognitive ability. Swanson's experimental design, which forces intelligence and metacognitive knowledge to be orthogonal, does not permit to decide whether the second or the third of the three models is favored by these results. Recent research in the domain of electricity (Veenman & Elshout, 1990) however, provided support for the mixed model. High and low intelligent subjects worked for several hours in a simulated Electricity Lab, learning the principles of Ohm's law. The results indicated that, while working method and intellectual ability correlated moderately, working method contributed significantly to the learning process, independent of intellectual ability. Clearly, the relation of working method with intellectual ability is an intricate one that remains to be clarified.

Realistic learning environments involve learning to solve complex and knowledge-rich problems which are representative for everyday problem solving. Simulations, used as an instructional tool, allow for learning by doing and learning by discovery under restricted realistic conditions. They are said to enable students to bridge the gap between reality and abstract knowledge, to improve motivation and enhance learning by an active student interaction, and in general to provide students with an appropriate cognitive and affective context for learning (de Jong, 1991). Essential for simulation as instructional tool is the continuous presence of learner activities. Students need to engage in exploring a domain thoroughly by generating hypotheses and testing these hypotheses by actively designing and performing experiments in the simulation environment (Reimann, 1989; Goodyear, Njoo, Hijne & van Berkum, 1990). Because of its explorative nature, learning with simulations involves complex problem solving, inductive reasoning and discovery learning, which puts a high cognitive demand on the student (Goodyear et al., 1990; de Jong, 1991). A large number of alternative actions might overwhelm students and result in a trial-and-error mode of behavior (van Berkum & de Jong, 1990). On the other hand, students might also adopt a waiting attitude, not using the opportunities for learning that the simulation environment offers (Njoo & de Jong, 1989) or not being able to use them properly due to limited intellectual resources or a poor working method (Veenman et al., 1991). It is generally conceived that a completely learner controlled situation is problematic, especially for the weaker students (Goodyear et al., 1990). As a consequence, de Jong and others (van Berkum & de Jong, 1990; de Jong, 1991) take the position that learning in simulation environments should be accompanied with at least some instructional guidance.

Instructional aid by presenting students with a well-structured simulation environment, might compensate for lack of ability or a poor working method. The conceptual difficulties of low intelligent students, due to the complexity of the subject matter, could be relieved by prestructuring the information that is to be processed. By providing them with pre-set experiments that elaborate on essentials of the domain, students should be urged to formulate and evaluate hypotheses, to vary the values of variables systematically, and to reconsider possible misunderstandings (Collins & Stevens, 1983). Instructional aid though, should not be limited to non-specific interventions (e.g. passively providing students with pre-set experiments or simply structuring the subject matter without specific feedback), since in several studies these interventions did not improve learning (Veenman et al., 1989b; Elshout & Veenman, 1990; Veenman & Elshout, 1990). Even when guided by instruction, the learning activities of low intelligent students invariably needed explicit corrections (Veenman et al., 1991). Consequently, low intelligent students, who might also suffer from a poor working method, are expected to profit more from a structured learning environment in which explicit feedback is included.

In a new experiment, which was designed in another domain to avoid domain specific effects, the concept of correlation was focussed on as an appropriate study-theme for our subjects. The correlation between two dichotomic variables is a topic with sufficient complexity to bring forth an elaborate learning process, but still relates easily to everyday experiences (Inhelder & Piaget, 1958). In discovering principles of correlation by experimenting with data-sets, intellectual ability and working method are likely to play an important role. Furthermore, instructional guidance combined with extensive domain-specific feedback is expected to steer the learning process, which might be profitable to particularly low intelligent students.

METHOD

Subjects.

Some months prior to the experiment intellectual ability was assessed by a series of ability tests, representing several components of the Structure-of-Intellect model (Guilford, 1967). Those first-year psychology students whose composite scores deviated at least one standard deviation from the mean (M= 17.47, sd= 3.88, N= 459), were denominated as either high or low intelligent. Fourteen high and thirteen low intelligent students who recently had followed a introductory statistics course, participated in the experiment. Though all of them were familiar with some general principles of correlation, they were ignorant of the phi-coefficient.

Learning conditions.

A statistics environment was implemented in Course of Action, an authoring language for Macintosh computers (Veenman, Balk & Bierman, 1989a). Data-sets, derived from everyday examples, could be altered by the student and the correlation could be calculated by the program on request. By estimating correlations, students first had to determine which values contributed positively to the correlation and which values contributed negatively. Next, they had to discover a simple method for inclusion of both positive and negative values into a correlational measure: the Piaget formula (adapted from Inhelder & Piaget, 1958). This formula, based on a simple additive model, disregards the skewness of distributions. Finally, students had the opportunity to experience the effects of distributional skewness by determining the constraints for application of the Piaget formula. They were presented subsequently with a general formula, the phi-coefficient which is based on a more complex, multiplicative model.

Simulation environments were implemented separately for a structured learning condition with instructional guidance and for an unstructured condition that allowed for unguided discovery learning. The data-sets in the structured simulation environment were presented in two by two diagrams throughout the course, while students in the unstructured environment had to reorganize the data by themselves. Furthermore, a computer assisted instruction shell overlaid the structured simulation environment. This CAI shell served as a tutor for teaching and explaining parts of the subject matter, provided students with guidance during experimentation, and offered students the opportunity to jump backwards for consulting previously given information. Accordingly, the construction and interpretation of two by two diagrams was explicitly taught in the structured environment, while students in the unstructured condition only received a short explanation about the series of data displayed. During estimation of correlations, students in the structured environment received specific feedback if their estimation was not proximate. This feedback included a second diagram constructed from the estimated correlation, that was to be compared with the original diagram and its true correlation. During experimentation, students in the structured condition were required to generate a hypothetical formula and to enter a value calculated by that formula, before the true correlation for a certain diagram was revealed to them. General feedback was given about the extent the calculated correlation deviated from the true correlation. However, the entered values were also matched by the program to some singular respons patterns (for instance the tendency to neglect the data that contribute to the correlation negatively) and specific feedback was added to these responses. Furthermore, students in the structured condition received explicit instructions about how to perform a number of 'telling' experiments. An example of such an instruction was to make one cell of the diagram zero and then, step by step, raise the value of that cell with one point whilst lowering the other one on the diagonal of the diagram (thus keeping the value of Piaget's formula constant and changing the phi-coefficient systematically; see the appendix). Students in the unstructured condition on the other hand, had to design their own experiments and received no feedback. While formulas in the unstructured condition were presented without further comment, they were explained thoroughly in the structured condition with questions addressing students on their understanding of the subject matter. Actually, the structured condition provided students with extensive support during the learning process in the simulated environment.

Procedure.

The subjects were assigned randomly to either the structured or the unstructured learning condition. The unstructured condition contained 6 low and 7 high intelligent subjects, while 7 low and 7 high intelligent subjects were engaged in the structured condition. Before entering one of the learning environments, all subjects received a short instruction about operating the Macintosh computer and a general refreshment course in basic statistics. During their work in the simulation environment, which took about 2 to 3 hours, thinking-aloud protocols of all subjects were tape-recorded. Time on task was not controlled, but was included in the study as a concomitant variable. Student notes, if any, were preserved in order to be analysed in relation to the protocols. The protocols were scored for quality of working method (the five scales being Orientation Activities, Systematical Orderliness, Accuracy, Elaboration and Evaluation Activities) and the level of learning reached. The analyses were conducted by two judges who received no prior information about the student's intelligence-test scores. They performed the analyses together, arguing until agreement was reached.

Aspects of the Working Method were scored separately from the protocol segments corresponding to three subdivisions in the learning program: learning to estimate correlations, discovering principles of the Piaget formula and exploring constraints for using the Piaget formula. These protocol segments appeared to have the substantial length which is required for protocol analysis. Quality of Orientation Activities was judged on indications of analysing a problem, building a mental model of the task and generating predictions. Judgements of Systematical Orderliness were based on the quality of planning and systematical execution of those plans. Criteria for Accuracy were precision of calculation, correct usage of quantities and the avoidance of negligent mistakes. Evaluation Activities were judged on monitoring and checking, while judgements of Elaboration were concerned with generating explanations, relating the subject matter and recapitulating. All aspects were rated on a ten-point scale and average scores on the five sub-scales were computed for each subject.

The level of learning reached, was scored from the thinking-aloud protocols by subdividing the learning program in coherent parts and rating the corresponding protocol segments on a ten-point scale. Five parts were discriminated and scored on mastery of the specific subject matter: construction of a diagram or table, estimation of correlations, learning the principles of the Piaget formula, learning the distributional effects on the Piaget formula and calculation of the correlation coefficient. For each subject an average score was calculated.

Problems.

In a pretest-posttest design subjects were presented with a series of problems prior to and shortly after the experimental course. After a delay of three weeks the subjects were offered another series of problems as a retention test. The problems dealt explicitly or implicitly with the correlation between two dichotomous variables in everyday situations. Explicit problems actually asked subjects to calculate the correlation before drawing a conclusion. Implicit problems on the other hand, did not ask for a calculation but requested a justified conclusion. Hence, the explicit problems measured the acquired knowledge and competency in correlational calculation, while the implicit problems additionally measured transfer of learning. Solving the problems of both types required a fair amount of qualitative as well as quantitative reasoning about correlation. An implicit problem was for instance:

> In research of the relation between job-responsibility and stress-experience sixty subjects are included, of which 30 percent is having a responsible job. A stress-questionnaire shows that 60 percent of all subjects are experiencing job-related stress, while eight subjects with a responsible job are experiencing stress. What is your conclusion about the relation between job-responsibility and stress-experience? Explain your answer.

The pretest consisted of only 4 implicit problems. Both the posttest as well as the retention test were composed of 4 implicit and 5 explicit problems, which were presented in a jumbled sequence. The 4 implicit problems corresponding to the pretest items, will be denominated as respectively posttest 1 and retention test 1. The 5 problems with explicit instruction will be referred to as posttest 2 and retention test 2.

Thinking-aloud protocols of the pretest, posttest and retention test problems were analysed prior to the course-protocols by the two 'blind' judges. The problems were scored one at the time for all subjects. Each problem was rated as a school mark on a ten-point scale, as is usual in Dutch education (with 5 being the highest fail-score and 6 being the lowest pass-score). The judgements were based on three criteria for solving the problem correctly: converting the problem statement to a correct diagram or table, (partial) calculation of the correlation coefficient and drawing a justified conclusion. A small miscalculation was not severely penalized. For each subject an average score on the pretest, posttest 1, posttest 2, retention test 1 and retention test 2 was calculated.

RESULTS

Problems.

The internal consistency of the pretest was rather low (alpha was .39), presumably indicating that the subjects have only slight initial knowledge of two by two contingency relations. Though, in accordance with this interpretation, the general level of pretest scores was poor, an Anova showed a significant effect of intellectual ability with $F(1,23)=8.00$ ($p<.01$), indicating that high intelligent subjects possessed slightly more knowledge about correlations to start with. The correlation between intelligence and pretest scores was .50 (.36 after correction for extreme groups of intellectual ability, following the procedures of Gulliksen (1961)).

The reliabilities of the posttest were .84 and .83 for respectively posttest 1 and posttest 2. Anova's on both posttests showed robust intelligence effects (see Table 1) with high intelligent subjects performing better than low intelligent subjects. No effects due to learning condition or interaction were obtained.

The reliabilities of retention test 1 and 2 were respectively .86 and .87. Strong intelligence effects were established with Anova's on both retention tests (see Table 1). Again, no learning condition effects were obtained for both tests, but the interaction effect was significant for retention test 2 (see Table 1). However, this interaction effect certainly did not confirm the hypothesis that low intelligent subjects would profit more from the structured learning environment compared to high intelligent subjects. The scores of low intelligent subjects in the unstructured condition actually surpassed those of low intelligent subjects in the structured condition (see Table 3).

Table 1. Results of Anova's on the learning measures.

Learning measures.	IQ	Learning condition	Interaction
Posttest 1	22.52 ($p<.0001$)	0.01	0.00
Posttest 2	25.36 ($p<.0001$)	0.53	0.05
Ret. test 1 #	12.60 ($p=.0018$)	0.09	0.31
Ret. test 2 #	47.51 ($p<.0001$)	0.29	6.56 ($p<.02$)
Level of learning	17.06 ($p=.0004$)	1.35	1.35

Except for # with $F(1,22)$, elsewhere $F(1,23)$ is applicable.

An Anova with repeated measures on the implicit problems (pretest, posttest 1 and retention test 1) with intellectual ability as the between-persons source of variance and time of testing as the within-persons factor, evidently showed a significant effect of intellectual ability with $F(1,24)=21.29$ ($p<.0001$). Furthermore, significant effects were obtained for time of testing ($F(2,48)=4.34$, $p<.02$) and the interaction of intellectual ability with time of testing ($F(2,48)=6.58$, $p=.003$). The mean scores in Table 2 clearly indicate that the high intelligent subjects learned more form the computerized course than low intelligent subjects, which difference persisted after the three weeks delay.

Table 2. Means and standard deviations (in parentheses) of the implicit problems.

	Pretest		Posttest 1		Retention test 1	
	LIQ	HIQ	LIQ	HIQ	LIQ	HIQ
Unstructured	4.13	4.79	3.71	5.96	4.35	5.96
condition.	(0.82)	(0.51)	(1.07)	(1.29)	(1.68)	(1.42)
Structured	4.00	4.82	3.75	6.01	3.89	6.11
condition.	(0.69)	(0.69)	(0.76)	(1.63)	(1.05)	(1.33)

Table 3. Means and standard deviations (in parentheses) of Posttest and Retention test with explicit calculation-instruction.

	Posttest 2		Retention test 2	
	LIQ	HIQ	LIQ	HIQ
Unstructured	4.73	6.97	4.88	6.23
condition.	(1.31)	(0.58)	(0.76)	(0.56)
Structured	4.51	6.57	3.91	6.86
condition.	(1.57)	(0.66)	(1.08)	(0.64)

Level of learning.

The internal consistency of the protocol-scored level of learning was satisfactory (alpha was .75). Correlations with other measures of learning ranged from .57 to .67. An Anova on the level of learning scores revealed a significant effect of intellectual ability (see Table 1) with the scores of high intelligent subjects exceeding those of low intelligent subjects. No effects of learning condition or interaction were established. Because the means in Table 4 might suggest an effect of learning conditions for low intelligent subjects in particular, an Anova was performed on their separated scores. However, the result of $F(1,11)=2.15$ ($p=.17$) confirmed the general conclusion that effects due to learning condition failed to appear.

Table 4. Means and standard deviations (in parentheses) of Level of learning scores.

	Level of learning	
	LIQ	HIQ
Unstructured condition.	4.87 (0.98)	6.60 (0.97)
Structured condition.	5.63 (0.89)	6.60 (0.48)

Working Method.

Alpha reliabilities for the five sub-scales of Working Method were .88, .85, .63, .81 and .88 for respectively Orientation Activity, Systematical Orderliness, Accuracy, Evaluation Activities and Elaboration. All subjects were real novices, that is to say, they showed rather poor Orientation activities. However, a significant effect of intellectual ability with $F(1,23)=27.56$ ($p<.0001$) indicated that high intelligent subjects orientated more than low intelligent subjects. As for Systematical Orderliness, subjects especially differed in the systematic implementation of a carefully designed sequence of data manipulations. High intelligent subjects were rated significantly higher on Systematical Orderliness than low intelligent subjects ($F(1,23)=21.34$, $p<.0001$). Though the intelligence effect on Accuracy was not significant ($F(1,23)=3.65$, $p<.07$), there is a minor suggestion for high intelligent subjects to work somewhat more accurately than low intelligent subjects. For Evaluation Activities also an intelligence effect in favour of high intelligent subjects was established ($F(1,23)= 15.76$, $p=.0006$). Elaboration, which often took the form of re-orientation after feedback was given, showed a similar effect of intellectual ability with $F(1,23)=19.10$ ($p=.0002$).

A general Working Method score was composed of all scores on the distinct measures together with two additional measures for completeness of diagrams drawn and tidiness of student-notes. The internal consistency of this composite score was high (alpha was .96). An Anova on Working Method scores showed a strong effect of intellectual ability with $F(1,23)=21.20$ ($p<.0001$). Working method correlated .68 with intellectual ability (.52 after correction for selection of extreme groups). The correlations of Working Method with the learning measures were high and, except for Posttest 1, these correlations remained high after intellectual ability was partialed out (see Table 5). Furthermore, after correcting for selection of extreme groups of intellectual ability, all of the partial correlations of Working Method with the learning measures were highly significant (see Table 5).

Table 5. Results of the correlational analyses.

Learning measures.	W.M.	IQ	W.M. part.cor.	IQ (corrected)	W.M. part.cor. (corrected)
Pretest	0.56 **	0.50 **		0.36 *	
Posttest 1	0.65 **	0.72 **	0.32	0.56 **	0.50 **
Posttest 2	0.76 **	0.71 **	0.55 **	0.56 **	0.67 **
Ret. test 1	0.74 **	0.66 **	0.54 **	0.50 **	0.65 **
Ret. test 2	0.81 **	0.82 **	0.62 **	0.69 **	0.74 **
Level of learn.	0.85 **	0.64 **	0.74 **	0.49 **	0.80 **

'W.M'. means working method; 'corrected' means corrected for selection of extreme groups of IQ;
* $p<.05$; ** $p<.01$.

Time on task.

The differences in time on task between both learning conditions were considerable ($F(1,23)=11.88$, $p<.003$). Subjects in the structured condition spent on the average 131 minutes working through the program, while it took subjects in the unstructured condition only 100 minutes on the average. However, correlations between time on task and learning measures were invariably low (ranging from -.23 to .11).

DISCUSSION

The results of this study confirmed once more that learning by doing is mediated by both intellectual ability and an effective working method. Furthermore, it was shown that high intelligent subjects exhibited an evidently better working method than low intelligent subjects. However, working method also proved to be a strong predictor of learning, apart from intellectual ability. These results clearly fit the mixed model, in which high intelligent novices tend to have a better working method but in which working method has a unique predictive value for learning too.

Extensive structuring of the learning environment did not improve learning, nor could an Aptitude-Treatment Interaction between intellectual ability and structuredness of learning environment be established. These results are in line with previous research of Veenman and Elshout (Veenman et al., 1989b; Elshout & Veenman, 1990; Veenman & Elshout, 1990). Though the instructional shell of the structured condition originated from a CAI tradition, some intelligent features made a considerable amount of branching possible as a consequence of student reactions. However, adding specific feedback to guided discovery learning did not compensate sufficiently for lack of ability or a poor working method. One possible reason for the absence of learning effects due to structuredness of learning environment emerged from the thinking-aloud protocols. By not reading an instruction thoroughly and as a consequence doing the wrong things, by not completing a sequence of tasks and by skipping the feedback, some students reduced the structured learning environment to an unstructured one. A poor working method may have prevented them from taking advantage of the structured learning environment. Very similar passive attitudes of students were observed by Njoo and de Jong (1989).

Clearly, most novices lack the prior knowledge, domain-specific knowledge as well as knowledge about how to perform an experiment, which is considered a prerequisite for successful learning in simulation environments by Goodyear et al. (1990). But for low intelligent novices it is the accumulation of knowledge deficiencies, limited intellectual resources and a poor working method that causes them to go astray during their Odyssey in a simulated environment. Even instructional guidance and feedback cannot provide sufficient help if the conceptual complexity of the task is making too high demands on the student.

Since working method appears to have a unique predictive value to learning, metacognitive mediation directed at raising the level of working method, might improve novice learning. This mediation is now being built into the electricity lab which was used by Veenman and Elshout (1990) and is expected to enhance learning through the improvement of working method.

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APPENDIX

Two by two contingency diagram:

a	b	a+b
c	d	c+d
a+c	b+d	

In this two by two contingency diagram the four observations a, b, c and d represent the possible combinations of two dichotomous variables: a is positive on both variable 1 and variable 2, b is positive on variable 1 and negative on variable 2, c is negative on variable 1 and positive on variable 2, and d is negative on both variable 1 and variable 2.

Piaget formula:

$$\frac{(a+d) - (b+c)}{n}$$

With n equals (a+b+c+d). This formula, adapted from Inhelder & Piaget (1958), is based on a simple additive model and disregards the skewness of distributions. Piaget's formula is only applicable if the marginal frequencies (a+b), (c+d), (a+c) and (b+d) are equal. Hence, a precondition for using Piaget's formula is a 50 percent distribution for both dichotomous variables.

Phi coefficient:

$$\frac{ad - bc}{\sqrt{(a+b)(c+d)(a+c)(b+d)}}$$

Calculation with the phi coefficient always results in the same correlational value as calculation by the product-moment correlation coefficient would, even if the marginal frequencies are unequal.