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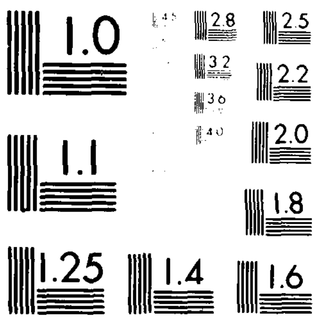

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A Partition of Group Performance Into
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in a Hypothesis Generation Task

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A technique is presented for partitioning group performance into two components: a component due to the increased information possessed by the group and a component representing the change in performance due to social interaction. The hypothesis-generation performance of individuals working alone was compared to the performance of interacting groups of four. The particular task employed permitted calculations of the veridical probabilities of generated sets of hypotheses. Analyses of results were based on a new method, obtained by pooling hypothesis sets from individual subjects to obtain "synthetic" groups.

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This method permits direct comparisons of interacting and synthetic groups hypothesis generation performance. Using this method, we found that groups of four subjects were equivalent to synthetic groups of 1.8 subjects.

A Partition of Group Performance Into Informational and Social Components in a Hypothesis Generation Task

A subject of long-standing interest has been the difference in decision-making abilities between individuals and interacting groups. The purpose of our study was twofold. The first was to compare group to individual decision-makers, focusing on one critical aspect of many real-world decision tasks, the generation of hypotheses. Hypothesis generation may be thought of as an aspect of predecisional behavior involving the generation of possible explanations to account for the data within a problem context (see Gettys and Fisher, 1979.)

Previous research examining hypothesis generation has demonstrated deficiencies in every context examined (Gettys, Mehle, Baca and Fisher, 1979; Mehle, Gettys, Manning, Baca and Fisher, 1979.) A possible remedy for such deficiencies would be to replace individual hypothesis generators with synthetic or interacting groups. Beyond the pooling of knowledge, the responses of one individual in an interacting group may serve as retrieval cues or prompts for others. Knowledge is pooled in a synthetic group, but social interaction usually is not present.

The second purpose of this study was to illustrate a new approach to investigations of group decision-making which may be of general interest. This technique is to partition group performance into meaningful components: a component which can be attributed to the increased information possessed by the group and another representing the change in performance due to social interaction. This new technique is discussed first.

A partition of group performance into meaningful components

In problem-solving tasks, a surprising result is that the old adage "two heads are better than one" is not always true. For example, Lorge, Fox, Davitz and Brenner (1958) surveyed a number of studies that contrasted group and individual performance and concluded that groups usually do as well as the best individual in the group. Campbell (1968) found that group responses were inferior to those of a single subject. Other studies (Hall, Mouton and Blake, 1967; Gustafson, Shukla, Delbecq and Walster, 1973; Klugman, 1947) have found that, in tasks requiring complex judgments, groups were superior to individuals.

Investigators have reported one rather robust result: a mathematical aggregate of the responses of individuals working along is superior to the responses of groups whose members were permitted to interact freely (Dunnette, Campbell and Jaastad, 1963; Gordon, 1923; Stroop, 1932; Taylor, Berry and Block, 1958; Van de Ven and Delbecq, 1971, 1974; Zajonc, 1962). Yet in some sense the adage should be true; two heads _should_ contain more information than one. However, this information is not always translated into superior group performance, primarily due to the social interactions that take place in a group situation.

In a problem-solving or decision-making task, if the relevant information of one individual is combined with that of another, we would expect this combined store to be superior to that possessed by either individual. However, it is possible for the sum of the two individual's information stores to be _less_ than that of the most knowledgeable individual if one or both individuals possess misinformation. It is also possible for the information possessed by one individual to be a proper subset of the information possessed by another. We will neglect these interesting, but somewhat pathological possibilities for the present.

Suppose then that individuals A and B are working on a problem-solving task. If P(a) is the probability that the information possessed by A contains a solution, and P(b) is similarly defined for B, then the probability that the pooled information possessed by A and B contains a solution is the familiar expression for the probability of the union:

$$P(a \cup b) = P(a) + P(b) - P(a \cap b). \tag{1}$$

It is in this sense that two heads should contain more information than one. This concept is illustrated by the Venn diagram analog of Equation 1 shown as Figure 1. The crosshatched area is A U B, representing the pooled information possessed by the two individuals jointly.

Insert Figure 1 about here

The additional information contributed by individual B increases the probability of the collection of hypotheses by the amount $P(b) - P(a \cap b)$. This is the probability of the unique component which B contributed to the common information store. It is the probability of the total relevant information possessed by B, P(b), less the probability of the information possessed by B which is redundant with the information possessed by A, $P(a \cap b)$. As knowledge is added to the common store, the amount of new information contributed by each new individual decreases.

A real, interacting group provides the opportunity for social interaction, an interaction which may enhance or impare performance. Whereas there is only an informational component of a synthetic group, there are two components to the performance of an interacting group--the information component and a social component. Social factors may facilitate or impare the pooling of information. In this

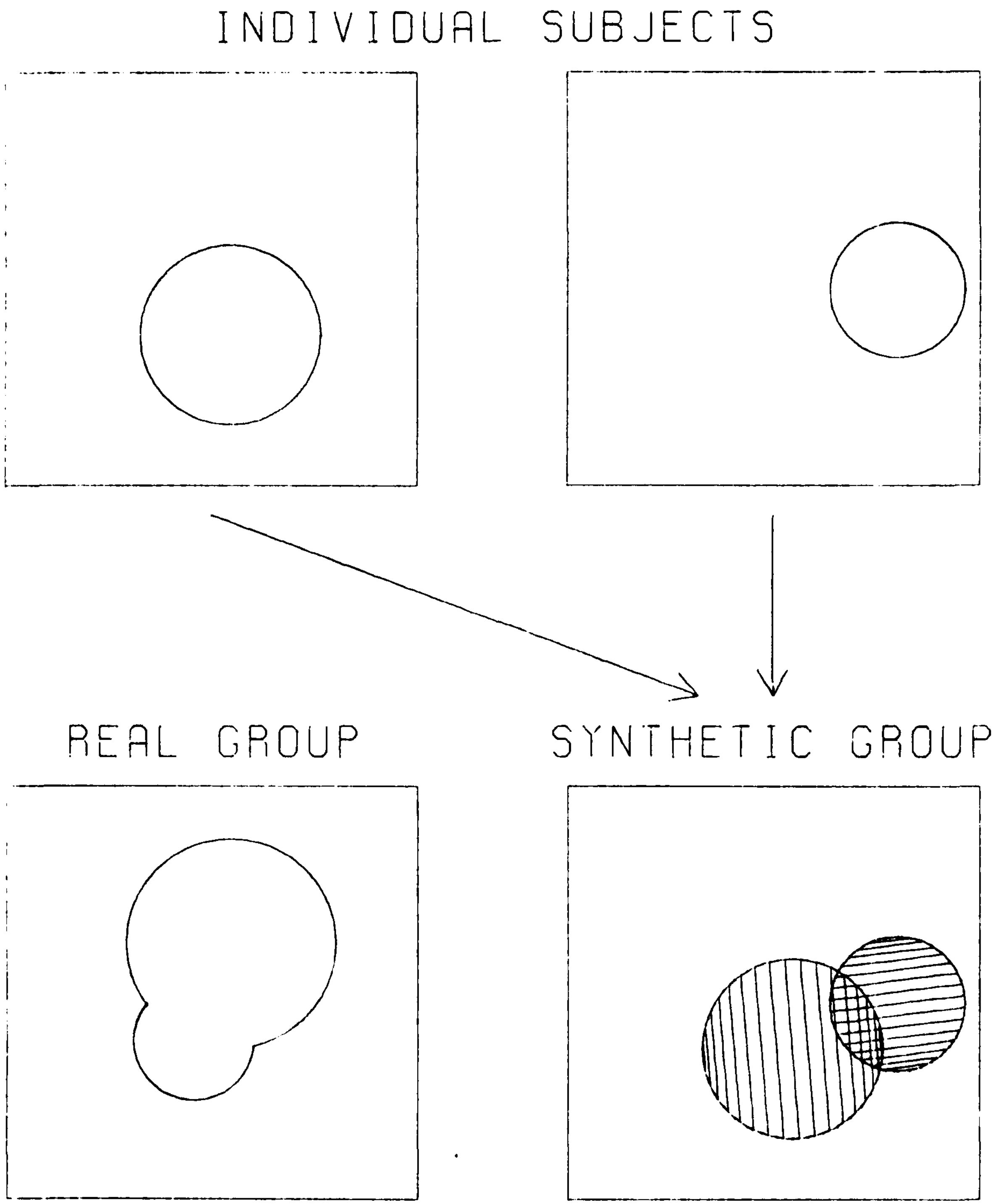

Figure 1. At the top are Venn diagrams representing the information possessed by two individual subjects given a set of data. Lower right is a diagram of the information obtained by pooling the two individuals to obtain a synthetic group. Lower left is a representation of the information that might be obtained if the individuals formed an interacting group.

sense, interacting group performance is the result of the combination of the informational and the social components. A comparison between the group performance of a synthetic and an interacting group using Equation 2 is of interest, because it allows us to estimate the social component of performance. By using Equation 1, we can write two equivalent expressions for a social interaction factor as follows:

$$\text{Social interaction} = P_i(a \cup b) - P_s(a \cup b) = P_s(a \cap b) - P_i(a \cap b), \qquad (2)$$

where the subscripts _s_ and _i_ denote synthetic and interactive groups, respectively. Notice that the P(a) and P(b) terms cancelled. These are informational terms rather than social factors. If the social interaction is facilitory, then the social interaction term will be positive. A negative social interaction term indicates that social interaction impared performance.

Insert Figure 2 about here

Figure 2 illustrates an extension of these ideas to the case of synthetic and interacting groups of four subjects. (The appropriate equations are generalizations of the above equations and are given by most elementary probability texts.) There are three points on the graph which can be empirically determined: the performance of a single individual (A), interacting group performance (B), and synthetic group performance (C).

The difference between points A and C is the improvement in task-relevant information that working in a group provides. The difference between B and C is the social interaction factor, which is shown here as negative. The difference between A and B is the actual gain in performance of an interacting group over an individual.

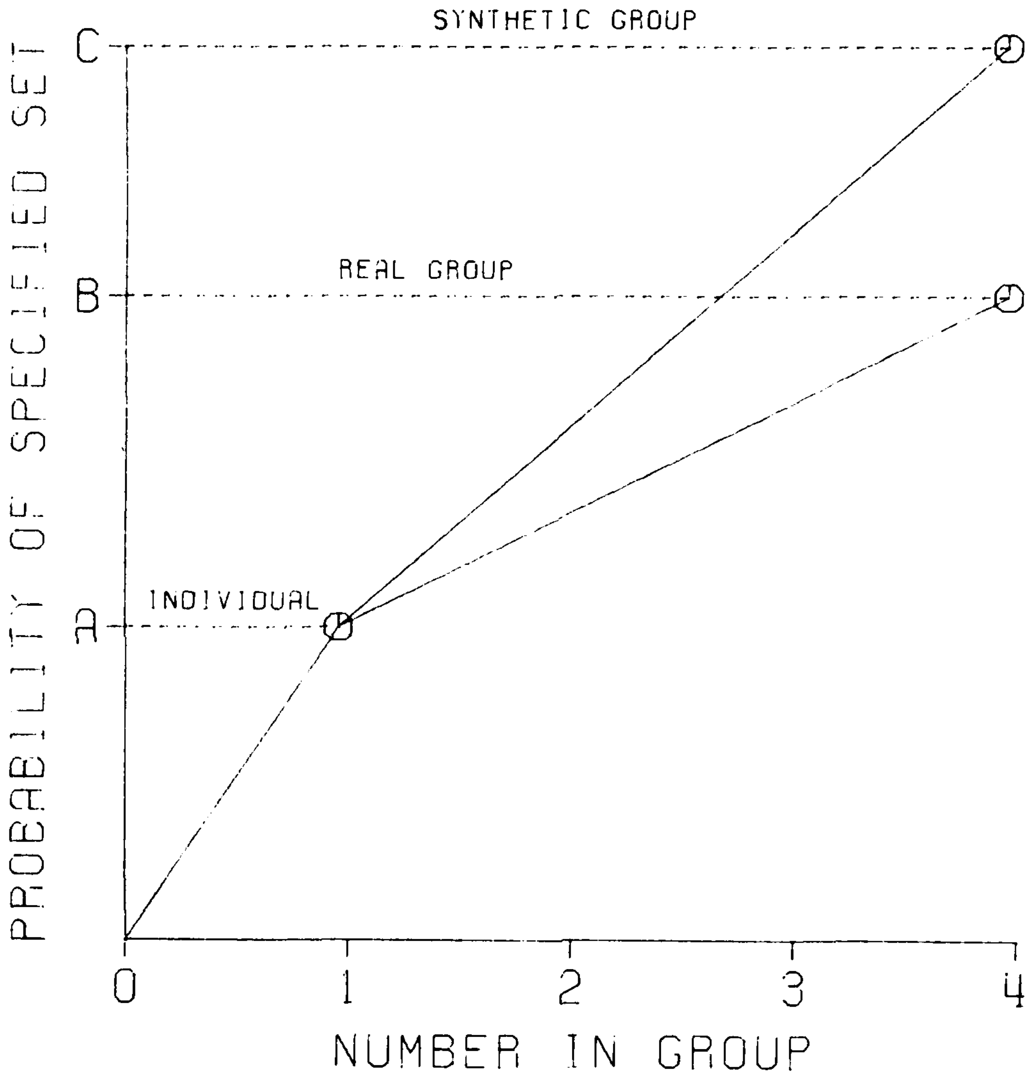

Figure 2. Comparison of the performance of individual subjects, point A; interacting groups, point B; and synthetic groups, point C. The significance of these points is explained in the text.

Figure 2 makes explicit those ideas that were more or less implicit in previous group research. We see that interacting groups will or will not exceed individual performance depending on the subtractive combination of two factors--information gained by pooling group information and social interaction. Perhaps these ideas will aid in reconciling the rather contradictory results in group problem-solving research.

Extending the approach

We believe that this partition could be useful in a variety of problem-solving and decision making tasks which involve both convergent and divergent thinking. In a convergent task, the object is to find a solution to a problem, or to make a correct decision. The development that we have discussed is appropriate for these tasks. Convergent tasks have the property that there is only one (or several) solution to the problem. The problem solver or decision maker must choose the one possible or optimal solution from many.

A divergent task, as we have shown, may also be partitioned into informational and social components. Hypothesis generation is an example of a divergent task because the object of the hypothesis task is to generate as many explanations as possible for a given set of data. The explanations should meet a minimum criterion for plausibility; that is, they should be consistent with the data of the problem and be likely enough to be useful as potential explanations for the data. Therefore, hypothesis generators generate many hypotheses in response to a given set of data, satisfying the definition of a divergent task.

It is necessary to have a criterion of performance to calculate the partition for hypothesis generation tasks. The criterion we employed was the veridical posterior probabilities. This criterion is not always an option. An alternative criterion is a simple count of the number of hypotheses generated; this criterion may prove to be perfectly adequate in some contexts. Providing a criterion of performance for many convergent tasks poses less of a problem, because a subject (or group) is either right or wrong.

The second necessary condition for the partition is that the algorithm for developing a synthetic group be well understood. In another context, Einhorn, Hogarth and Klempner (1977) have discussed algorithms for calculating group point estimates. If the performance of the synthetic group is to be used to estimate the gain in information resulting from pooling information, then the algorithm used should have the property of accurately reflecting the information that the group possesses. Clearly, much ingenuity will be needed to develop an algorithm in some tasks.

We also see possibilities for extending or elaborating this partition. It may be possible to further partition both the informational and the social components of performance in useful ways. For example, the informational partition could be elaborated by making a distinction between recall and recognition. An individual working on a problem solving task must recall from memory the information necessary to solve the task. In interacting groups, however, only one member of a group necessarily must recall a particular fact or idea; other members of the group may be able to add other information to this idea or attest to its excellence using recognition memory. Therefore, it might be possible to measure <u>both</u> the recall and recognition performance of individuals, and by so doing partition the informational component further. In this case the algorithm for the synthetic group might include the assumption that an idea must be recalled by at least one member, and recognized by all. A further partition of the social component could be made by varying the type of social interaction allowed.

The hypothesis generation task

The hypothesis generation task used in this study is somewhat novel, and for that reason needs some justification and explanation. It is by nature a divergent task; subjects were given a course that a student at the University of Oklahoma had taken, and were asked to list as many plausible majors for this student as possible. To discourage subjects from making a "memory dump" of all possible majors, we defined a "plausible major" as any major that includes at least two percent of the students who had taken that course. The concept of plausibility is desirable in this context because it prevented subjects from making the specious argument that any major is possible and should, therefore, be a valid response. (In fact, not all majors take all courses.)

The "majors from courses" task is advantageous because it allows the methods of analysis described earlier. It is possible to interrogate the master files of student enrollments to determine the veridical probabilistic relationships between courses and majors. This task allows a more sophisticated comparison between synthetic and interacting groups than has been possible using other tasks.

Some of the difficulties in comparing synthetic to interacting groups in other paradigms are illustrated in the Taylor, Berry and Block (1958) study. The basic result was that interacting groups were significantly inferior in producing ideas. A typical stimulus in this study was: "What steps can you suggest that would get more Europeans to come to this country?" Since there was no way to determine objectively whether one response was better than another, evaluation of responses was subjective. The determination of whether two responses were dissimilar was also subjective.

In the analyses reported in the Taylor et al. study, the responses made by the subjects who worked alone were pooled to simulate only one size synthetic group. A significant difference was found between synthetic and interacting groups of 12. However, the size of synthetic groups necessary to produce a set of responses equivalent to the set produced by the interacting groups could not be determined.

Another potential problem with this type of research is that since the synthetic groups were constructed by randomly assigning subjects to groups after data collection, results may be quite sensitive to the particular random ordering used. The strategy employed in the present study to avoid this potential problem was to examine the performance averaged over all possible orderings of subjects.

In contrast, the hypothesis generation task employed in this study had an objective criterion of performance. The posterior probabilities of each of the plausible hypotheses in the set generated by an individual or interacting group were added together. This expression is:

$$P(\text{Correct}) = \sum P(M|C) > .02, \qquad (4)$$

where P(Correct) is the probability that the set of hypotheses contains the correct hypothesis and $P(M|C)$ is the probability of a major given a particular class. These veridical (population) probabilities of each possible major were obtained by analyzing the student master record file computer tapes. An analysis of this type was done for each of the classes presented as data to subjects. The task permitted calculation of the veridical probability that the true state of the world would be included in a particular set of majors.

Our approach to comparing synthetic to interacting groups was to take the union of the sets of hypotheses generated by individuals to create synthetic hypothesis sets for groups of various sizes. Then P(Correct) was calculated for the hypotheses in the synthetic set using Equation 4. Thus we were able to construct a function relating synthetic group size to hypothesis set probability.

For example, the value of this function at four, corresponding to synthetic group size of four, would be the mean probability of hypothesis sets generated by all possible synthetic groups of size four.

Values in the domain of this function would consist of consecutive integers from one to the number of subjects participating in the study as individuals (16 in the present study.) Values in the range of this function could only be calculated by making extensive use of a computer. For example, to examine the synthetic group of size four, all possible combinations of 16 taken four at a time (1,820) distinct synthetic groups would need to be constructed. The mean probability of the aggregate hypothesis sets over these 1,820 synthetic groups would be caluclated as the value of the function at four.

As defined, this function would be continuous and monotone, and thus have an inverse. The inverse function could be interpreted as a metric relating interacting groups to synthetic groups having equivalent performance. This metric could be used to address the question of whether synthetic groups are superior or inferior to interacting groups of equal size and would provide an easily interpretable measure of the difference. For example, interacting groups of four could be found to be equivalent to synthetic groups of size three or size five. The weight of published results suggests that equivalent synthetic groups would be <u>smaller</u>. This metric could also be used to create the partition described earlier.

Method

Subjects

The subjects were 80 female students enrolled in an introductory psychology course at the University of Oklahoma. Sixteen of the subjects worked individually; the remaining 64 worked in groups of four.

Procedure

The stimuli were eight written problems to which the subjects made written responses. For each problem, subjects were given a brief description of a course offered by the University of Oklahoma and the associated course number. Courses having large enrollments were chosen for use as problems. See Mehle, Gettys, Manning, Baca, and Fisher (1979) for further discussion of this paradigm.

The principle manipulation was a comparison of subjects working alone to subjects working in groups of four. In the "individual" condition, each of 16 subjects was given the set of eight problems. These subjects were instructed not to discuss the problems with each other. In the other condition, 16 groups of four subjects each were run separately. The members of each group were instructed to work together to generate hypotheses for each problem. One group member was chosen to make a written list of all responses made by the group. The individuals and groups were given the same problems.

For each problem, subjects or groups were given five minutes to list all majors of an "unknown student" who has taken the given course. Subjects were instructed to include a major only if two percent or more of the students who took the course had that major. Subjects were also told that they would not be penalized for giving responses that did not meet this criterion. (Only responses that satisfied the two percent criterion were included in the data analyses.)

Results

The purpose of an initial analysis was to compare responses of individuals and interacting groups. Data was obtained by analyzing a computer master record of the coursework taken by undergraduate students at the University of Oklahoma. For these analyses, the "population" was defined as the current student population at the University of Oklahoma. The computer file contained information on the courses taken over the previous four years by students currently enrolled at the University. The probabilistic relationships between classes and majors obtained by analyzing the computer file were regarded as population parameters, used as veridical probabilities. Using these probabilities of individual majors, it was possible to calculate the veridical probability of any set of hypotheses.

The dependent measure for this study was the probability that the major of a student who has taken the given course was contained in the set of hypotheses generated by an individual or group.

An advantage to using hypothesis set probability over other possible measures of the "goodness" of hypothesis sets, such as a simple count of the number of hypotheses, is the straight-forward interpretation possible. For example, if the probability of a set of hypotheses is 60 percent, then 40 percent of the time, the decision maker would fail to consider the true state of the world in subsequent decision analysis.

In accordance with the instructions given to subjects, majors with veridical probabilities of less than .02 for the course being considered were not included. In this initial analysis, the hypothesis set total probability was calculated for each individual subject and for each group, for each of the eight problems. As an example, the datum for one problem was: "Sociology 1113, Introduction to Sociology." One individual generated the hypothesis set: Art, Music, Mathematics,

Table 1

Comparison of Individual to Group

Hypothesis Set Probability

	Mean Percent Probability of Hypothesis Sets		
Problem Number	Individuals	Interacting Groups of Four	Synthetic Groups of Four
A	80.3	85.9	89.2
B	30.0	39.6	49.7
C	32.2	44.1	52.7
D	25.1	34.5	50.8
E	27.6	40.9	49.5
F	31.0	42.6	52.6
G	24.9	30.0	50.0
H	16.7	24.2	37.6
Average	33.5	42.7	54.0

Psychology, Sociology, History, Education, Drama and Nursing. The veridical probability that a student who had taken Sociology 1113 had a major that was an element of this set of hypotheses was calculated to be 22.14 percent.

Continuing with this example, an interacting group of four subjects generated the set: Sociology, Psychology, Social Work, Chemistry, Zoology, Political Science, Nursing, Journalism, Economics, Drama, Education and Engineering. The veridical probability of this set was calculated to be 34.45 percent. Problem means for this analysis are presented as the first two columns of Table 1.

Insert Table 1 about here

The third column of Table 1 was calculated by pooling the responses of individual subjects to obtain aggregate hypothesis sets for synthetic groups of size four. The column entries in the first two columns are means over 16 individuals and 16 groups, respectively. The third column means are over the 1,820 possible distinct synthetic groups of size four (all possible combinations of 16 taken four at a time.) Examining the problem means, interacting groups were superior to individuals for all eight problems. Synthetic groups were superior to interacting groups and to individuals on each of the eight problems.

An analysis of variance was performed on the data represented by the first two columns of Table 1, blocking on problems. The difference between the mean of 33.5 percent and 42.7 percent was significant, $F\ (1,30) = 7.26$, $p<.05$. The problem effect was significant, but the problem by individual versus interacting group factor interaction was not significant.

A problem arises in attempting to include the synthetic group data, the third column of Table 1, in an analysis of variance. The difficulty is the differing number of observations available for each problem: 16 for individuals and for

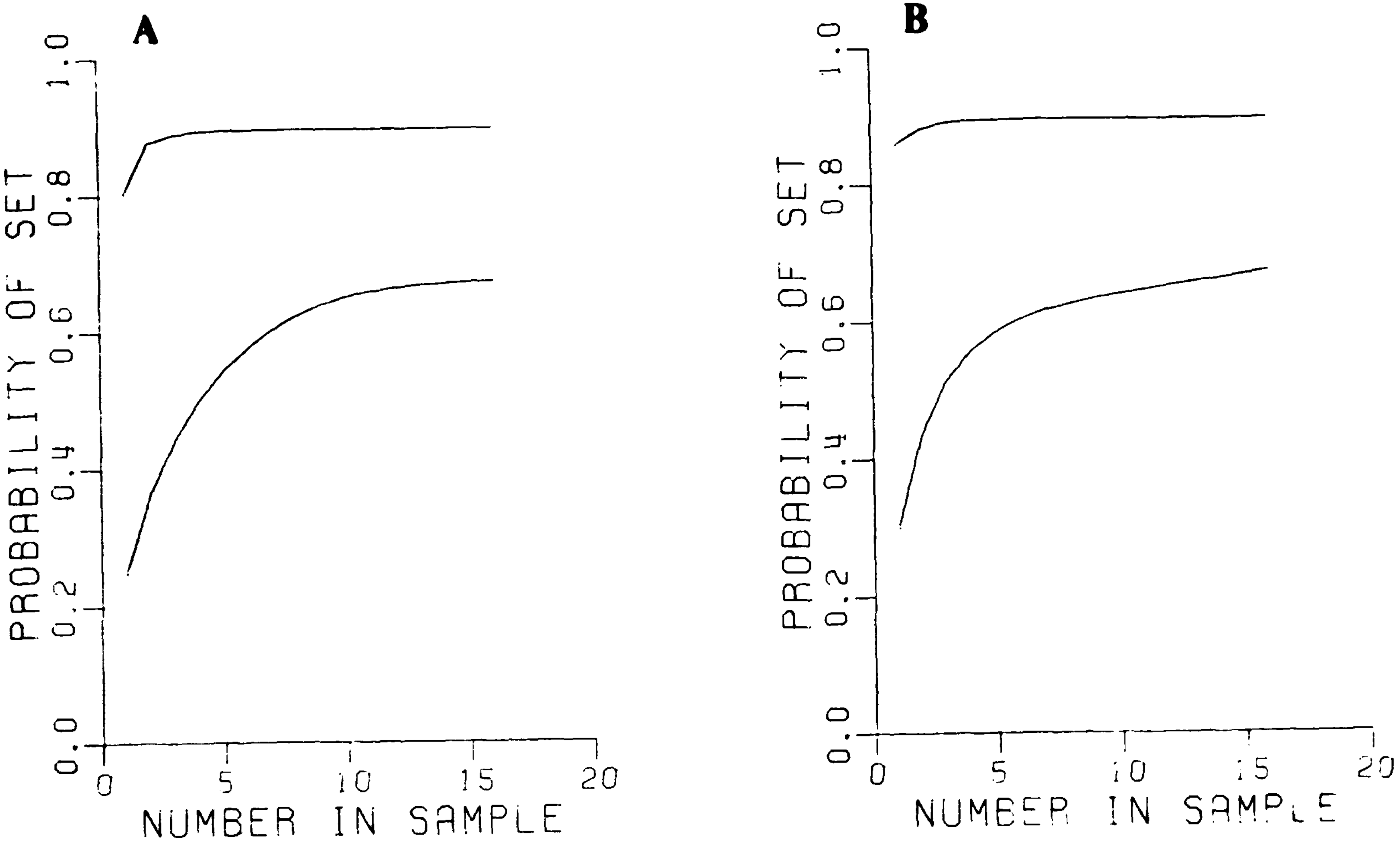

Figure 3. Mean synthetic hypothesis set probability as of function of the number of individuals (left panel) or interacting groups of four (right panel) whose responses were pooled. Shown in each group are the results for the two problems which showed the least or the most change in the ordinate. The results for the other six problems fall between these two extremes.

interacting groups versus 1,820 for synthetic groups. Instead, an independent *t* statistic was calculated on the problem means of Table 1, column 2 versus column 3. The difference between the mean of 36.9 and 54.0 was significant, $t(16) = 2.93$, $p<.01$.

In the next analysis, calculations were undertaken to determine the function relating size of synthetic groups to probability of hypothesis sets, as described previously. The function was determined for each of the eight problems. Figure 3a contains the graphs for the two extreme problems (those having the least and the most change in the ordinate.)

Insert Figure 3 about here

For the graphs in Figure 3a, the ordinate value of the function over an abscissa value of *n* is the mean probability of hypothesis sets over all possible synthetic groups of size *n*, where $n = 1,2,3,\ldots,16$. For any one of these synthetic groups, the aggregate hypothesis set was the union of the hypothesis sets generated by each of the *n* individuals comprising the synthetic group.

Using the graphs to determine the inverse function, it is possible to determine the size of the synthetic group equivalent in performance to the interacting groups. These numbers are presented as the first column of Table 2.

Insert Table 2 about here

These numbers are interpretable as a measure of the performance of the interacting groups in terms of equivalent number of individuals, the metric described earlier. Clearly the effect of allowing individuals to interact during hypothesis generation is inhibitory. The pooled hypothesis sets of only 1.8 individuals were,

Table 2

Comparison of Interacting

To Synthetic Groups

Problem Number	Number of Individuals Needed in A Synthetic Group to Simulate An Interacting Group of Four	Number of Interacting Groups Needed to Simulate a Synthetic Group of Four
A	1.8	3.6
B	1.8	2.6
C	2.0	2.0
D	1.7	2.7
E	2.2	2.0
F	1.9	2.3
G	1.5	2.8
H	1.8	2.4
Average	1.8	2.5

on the average, as complete as the hypothesis sets generated by the interacting groups of four subjects.

A analogous analysis was carried out to examine the effect of pooling interacting groups hypothesis sets. The purpose of this analysis was to construct a metric relating the performance of synthetic groups of four to the equivalent number of pooled interactive groups of four. Functions calculated for two of the eight problems are plotted in Figure 3b.

The hypothesis sets pooled to produce Figure 3b are those of interacting groups of four subjects.

The metric resulting from this analysis is a measure of the number of interacting groups of size four which, if their hypothesis sets are pooled, would be equal in performance to a synthetic group of size four. The numbers, presented in the second column of Table 2, represent an alternate approach to comparing the performance of individuals to interacting groups. On the average, the hypothesis sets of 2.5 interacting groups of four would be as complete as the hypothesis sets of synthetic groups of size four.

It should be noted that either of the above metrics could be used to analyze other dependent measures of performance. For example, if veridical probabilities are not available, the metric could be computed in terms of number of distinct hypotheses generated by individuals and groups.

Discussion

The significant difference in the mean hypothesis set probability between subjects working individually and interacting groups suggests that a group of hypothesis generators is preferable to a single individual. That is, n hypothesis generators are better than one.

A more important matter, however, is: given n hypothesis generators, is it better to have them work alone or in interacting groups? This question was addressed by applying a metric to the performance of interacting groups. This metric provided a measure of the performance of interacting groups in terms of the equivalent number of individuals working alone. The conclusion, based on the data of the present study, is that it is preferable to have hypothesis generators work alone.

The performance partition represents another important way of looking at these results. The increased information possessed by the group, the C-A difference in figure 2, was estimated to be 20.5% from the means in Table 1. The social interaction factor (B-C) is negative, having a value of -11.3%. In this task, social interaction impares performance, although interacting groups were superior to an individual, as evidenced by the B-A performance difference of 9.2%.

As these results illustrate, partitioning performance into social and informational components gives new insights into group research issues. Had we used a task with a smaller informational component, interacting groups probably would have been inferior to individuals. Had social interaction facilitated performance, the extent of this facilitation would be unknown unless the information component had been estimated. This technique provides researchers with the necessary tool to factor information and social components, and thus to gain a greater understanding of the data.

The results reported do not rule out the operation of the postulated mechanism that subjects working in an interacting group may recall hypotheses using the responses of other members of the group as retrieval cues. However, if this mechanism was operating, its effect was apparently countered by the inhibitory effects of the group.

One possible extension to the previous discussion would be to consider the effects of misinformation on the pooling process. Suppose that one individual believes that the sun rises in the east, while another is equally convinced that the sun rises in the west. If the information stores of these two individuals are pooled, the resulting information store consists of two contradictory facts. A logical way to treat this inconsistency would be to conclude that the pooled information store has no reliable information on the direction of the rising sun. If these two individuals had differing degrees of belief, then a Bayesian combination of their subjective opinions might be appropriate. It would even be possible to weight the subjective opinions by the credibility of the individuals.

Should the possible existence of such misinformation be considered in calculating the pooled information store? The answer to this question seems to depend on the type of information that is being pooled and the task goals. For the case of factual information where the goal is simply to develop as much information as possible, misinformation should be dealt with by the pooling algorithms. Other situations are not as clear cut. In divergent tasks, where the goal is to develop possible problem solutions, an incorrect solution need not necessarily be costly. Convergent tasks are unaffected by incorrect solutions, unless those solutions are adopted by a decision-maker.

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