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Final Report--Objective E, Tasks 3 and 4

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INTUITIVE DATA SORTING: AN INFORMATIONAL MODEL OF PSYCHOENERGETIC FUNCTIONING

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SRI International

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Covering the Period 1 October 1985 to 30 September 1986

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SRI Project 1291

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ABSTRACT

We develop a comprehensive model of psychoenergetic functioning called Intuitive Data Sorting (IDS). Extending purely philosophical arguments, we derive specific mathematical predictions for the interpretation of random number generator experiments. Two experiments are analyzed: (1) a pseudorandom number generator (PRNG) experiment conducted at SRI International, and (2) a random number generator experiment conducted at the Princeton Engineering Anomalies Research laboratory at Princeton University. Preliminary results from the PRNG experiment are in statistical agreement with the IDS model. We show, however, that the Princeton University RNG data were collected under unfavorable conditions to serve as a test of the IDS model; we recommend an RNG experiment protocol that will allow a more favorable test.

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I INTRODUCTION

Since 1979, SRI International has been constructing a model of psychoenergetic functioning that may provide an explanation for a broad range of experimental data.* The idea first occurred to us as part of an interpretation of an experiment we conducted that year.[1]† In that experiment, it appeared that individuals were able to make decisions (psychoenergetically) based upon information propagating backward in time. This unorthodox concept, in its generalized form, is shown schematically in Figure 1 as one of the inputs to a decision process.

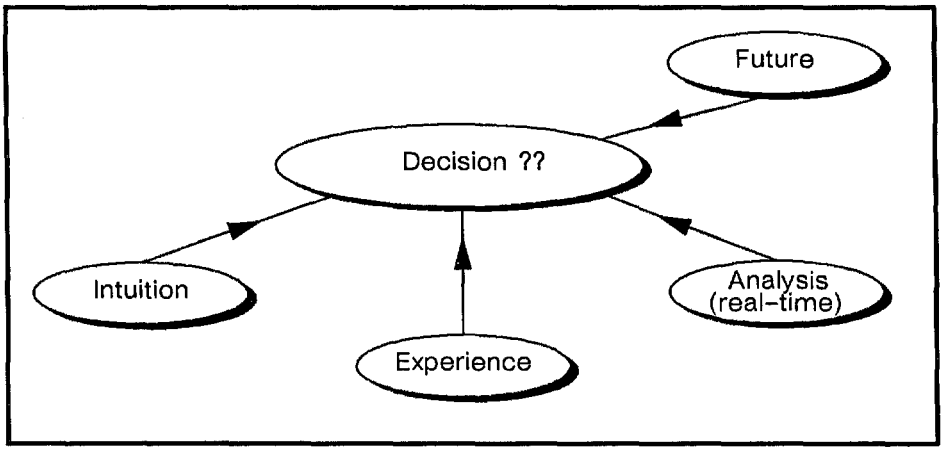

FIGURE 1 GENERALIZED DECISION PROCESS

For example, suppose that you had to decide if it were safe to cross a highway. Clearly, one input to that decision is real-time analysis: There is a continuous stream of traffic; don't cross the road. Suppose that there was only one car on the road, but it was at some distance away. Experience might suggest that you are unable to run fast enough to avoid being hit; don't cross. Without defining intuition, it might tell you *not* to cross the highway even though

* This report constitutes deliverable "a"--final report on RA perturbation of device-driven random sequences--for Objective E, Task 4, Conduct a retrospective test and analysis of the Intuitive Data Sorting (IDS) model, and the deliverable--final report on RA activity upon pseudorandom number generators--Objective E, Task 3, Investigate RA activity by examining statistical changes of state of pseudorandom number generators.

† References are listed at the end of this report.

all other indicators suggest that it is safe. We recognize that all these processes are intermixed, and that there may be others that we have not yet considered.

Our model proposes that there is one other source of input to the decision process that has not yet been considered--information propagating backward in time from the future. You have an impression (maybe a visual experience) that indicates that you are dead on the highway; don't cross the road.

While there are specific examples of information propagating backward in time in physics (e.g., the Dirac equation--a positron traveling *forward* in time is mathematically identical to an electron traveling *backward* in time), the idea that it is possible at the macroscopic level is *not* generally accepted. It is beyond the scope of this report to discuss the profound implications for physics and philosophy if it were true.

Since the late 1930s, however, the parapsychological research journals have been reporting evidence that information from the future *is* available in the present--at least statistically. We are not able, at this time, to provide a complete analysis of this literature, which claims evidence for precognition--the parapsychological term for accessing information from the future. Rather, we provide a brief discussion of two of the pertinent reports.

In 1983, C. T. Tart reviewed the precognition "forced choice" literature as part of an investigation to determine information rates for both real-time and precognition experiments[2] In this context, "forced choice" implies that the subject was aware of the limited number of possible targets, but was blind to the actual target chosen for any single trial. Tart found 32 studies, of this type, that claimed statistically significant evidence for precognition.

In 1986, Nelson *et al.* reported the results of over 400 "free-response" precognition trials demonstrating strong statistical evidence for information flow from the future.[3,4] "Free-response" experiments differ from "forced-choice" in that the target material is relatively unbounded (i.e., while the general nature of the target material might be known by the subject, the range of target possibilities is very large and is unknown to the subject).

Because these reports provide strongly suggestive evidence for macroscopic information flow from the future, we proceed with the development of the model.

A. A Conceptual Thought Experiment

Consider an arbitrarily complex experiment as shown in Figure 2. Further, suppose that this experiment has *one* result and that there is a single decision required *before* the experiment is conducted. (We recognize that complex experiments produce more than

one result and require many decisions for their design; therefore, we are considering only the primary result and decision, and are including the lesser results and decisions as part of the complexity of the experiment.) There are no limitations placed upon the complex experiment. In principle, it might be conducted by many researchers at different laboratories for many years.

To be specific, let us assume that the single decision involves turning a knob to one of five settings, 1 through 5. Also consider that the single result is a meter reading in which we assume a high reading is "good." Our model proposes that the following internal dialogue by the decision maker is possible:

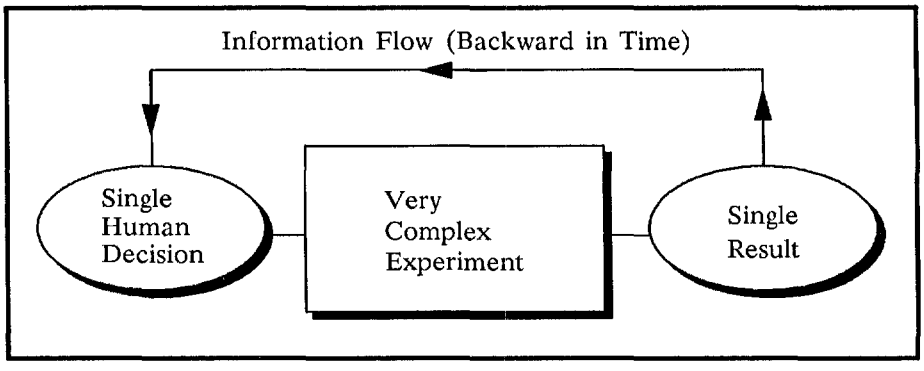

FIGURE 2 A CONCEPTUAL THOUGHT EXPERIMENT

If I were to conduct this experiment with the knob set at 2, let me "peek" into the future and examine the result. I perceive the meter showing a low reading and thus I reject that option. Suppose I were to conduct this experiment with the knob set at 4. I perceive the meter showing a very high reading. Because I like that result, I will set the knob at 4, and conduct the experiment!

For the above dialogue to be sensible, we must be able to "sample" the future--reject the unwanted ones, and "select" a preferred one. When the model is formulated mathematically and applied to a specific set of experiments, it will provide compelling evidence (see below) that this unorthodox idea *is* possible.

B. A Practical Thought Experiment

By describing a practical thought experiment, we will illustrate an important consequence of the model. If we are allowed to "sample" the future, then what was previously thought of as a cause-and-effect relationship might be confused with an informational relationship involving no causality at all.

Suppose that we wanted to demonstrate that cyclamates *cause* cancer in laboratory rats. Further, assume that normal double blind protocols are in effect. A laboratory assistant is asked to administer injections to two separate groups of rats--one a control group, the other a target group. By double blind, we mean that the assistant does not know which is the control group, nor which injections will be cyclamates rather than biologically neutral cyclamate placebos.

Let us assume that the experiment produces a statistically significant (e.g., $p < 0.01$) separation between the control and target groups (i.e., the probability of a target rat contracting cancer is significantly larger than for a control rat). This result is shown schematically in the lower half of Figure 3. The conclusion that is drawn from this experiment is that whatever was in the syringe *caused* cancer in the rats.

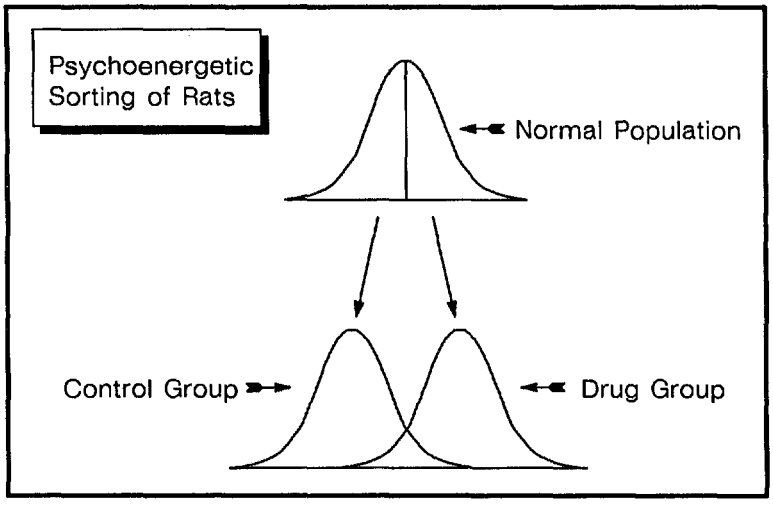

FIGURE 3 A PRACTICAL THOUGHT EXPERIMENT

To illustrate an informational explanation of this same result, we describe a totally *fraudulent* way in which this experiment might be conducted. Suppose that the researcher is motivated to cheat, and in doing so is able to select from a normal population of rats those that are predisposed toward cancer. (Because this is a thought experiment, we can invent a mechanism by which he/she could do this.) We assume that this researcher is sophisticated in statistical matters and sorts the selected rats into target and control groups in such a way (by cross mixing them) to produce the identical results described above. Furthermore, to preclude any possible confounding of the fraudulent outcome, the researcher replaces the contents of the syringes with distilled water. Then he/she lets the experiment proceed as above.

The statistically significant result ($p < 0.01$) would still be interpreted as before. Whatever was in the syringe *caused* cancer in the rats--in this case distilled water! Thus, a purely informational process (knowledge of the individual rats' predisposition toward cancer) is mistaken as a causal one (distilled water causes cancer in rats).

The researcher, in the above example, need *not* be fraudulent to produce the *identical* result. We propose that by statistically "peeking" into the future he/she is able select the predisposed rats. For example, having picked a rat, he could sample the future to determine if that rat is likely to contract cancer. If so, he would add it to the target group; if not, it would be included in the control group. Thus, this researcher has "simply" psychoenergetically sorted rats (see Figure 1). We call this putative ability Intuitive Data Sorting (IDS).

Because large bodies of research have concluded some form of cause–and–effect relationship based upon statistical hypothesis testing, it is important to determine if our model has any scientific basis. What follows is the application of our model to a large body of psychoenergetic experimental data.

II BACKGROUND

In 1969, Schmidt[5] introduced a type of psychoenergetic experiment in which individuals were asked to "modify" the statistics of "true" random number generators (RNG), i.e., devices that generate sequences of numbers based on some fundamental random process such as radioactive decay or thermal noise. Since publication of that important initial paper, we have been able to locate (through 1984) 56 pertinent references in English language journals and reports describing a total of 332 individual binary RNG experiments. We simulated an additional 95 nonsignificant experiments to account for a "filedrawer" problem (i.e., experiments that were conducted and not published because they were not significant).[6] By including these simulated studies in the data base, we refrain from using an artificially inflated data base because of selected reporting of "successful" studies. In the preliminary analysis of these data, we calculated that the probability that the observed deviations occurred by normal statistical fluctuations alone was $p \leq 3.9 \times 10^{-18}$ during experimental conditions, and $p \leq 0.78$ under control conditions. Clearly, there is a statistical anomaly within these data.

Since 1969, there has been considerable discussion about mechanisms that can explain these RNG results.[5,7,8] (For the purpose of this report, we assume that artifact and incorrect statistics have been accounted for. Radin has shown that this assumption is true to first order;[6] a detailed meta-analysis is now in progress to determine the overall validity of the RNG data base.) The most frequently proposed explanations are remote action (RA) and precognition. Under an RA hypothesis, by definition, a participant "forces" a physical modification in a source of random signals so as to produce a change in the output statistics. Alternatively, under the IDS hypothesis, we propose that humans can make decisions (by psychoenergetic means) to take advantage of the natural and unperturbed fluctuations of a system. In the context of an RNG experiment, it appears that individuals can anticipate locally deviant subsequences from within larger and unperturbed sequences and make decisions based upon that knowledge. Suppose that an individual is asked to "make" the RNG produce more binary ones (1s) than zeros (0s). Rather than "causing" the device to produce binary ones, we suggest that the participant has simply initiated the run by anticipating when the RNG was going to produce a series of ones as part of its natural

binomial fluctuation. Thus, the participant has capitalized upon natural events, rather than "causing" anything to occur.

In our final report to a client in FY 1984, we applied the IDS formalism to the data base of RNG experiments described above.[9] We found that the data were described by the IDS model rather than the RA hypothesis. There were problems, however, with the comparison of the IDS model to the previously published RNG data base. The IDS formalism is derived from the assumption that the sequence length, [n], results from a *single* press of a button. *None* of the experiments in the data base were reported in that way. All of the data were aggregates over many button presses. While we were able to draw conclusions based upon averaged data, (e.g., on the average, IDS appears to account for the results in the historical data base), the ideal test of IDS must be conducted using data resulting from single button presses.

There are two questions that should be addressed when conducting single button press experiments:

- Is IDS possible under conditions that preclude any RA? If so, are there any sequence length dependencies in the ability?
- Can IDS provide an interpretation of RNG data?

We have addressed both issues as separate tasks for FY 1986. The first task was to examine the IDS model, at SRI under a condition that precludes RA--using pseudorandom number generators. To know if IDS is possible, in principle, we must conduct experiments that have as few confounding factors as possible. The second was to examine the IDS model using "true" RNGs. The only data of this type that was available was collected by the Princeton Engineering Anomalies Research (PEAR) Laboratory, in the school of Engineering at Princeton University.[10] We therefore let a subcontract to this laboratory to provide us with their single button press RNG data.

III METHOD OF APPROACH

Our method of approaching the data generated at SRI and Princeton proceeds in three phases:

- Theoretical considerations--a derivation of mean chance expectation for the various models under study.
- The SRI data--details of the pseudorandom data collection and display.
- The PEAR data--details of the Princeton "true" RNG data collection.

A. Theoretical Considerations

The data analysis proceeds in three steps, data reduction, definition of mean chance expectation, and analysis and hypothesis testing.

1. RA Data Reduction

For each button press, the raw data consist of a sequence length [n] and the number of "hits" [h] (e.g., binary 1s). We transform these data into logarithmic form for analysis by computing the following quantities for each data point:

$$p = \frac{h}{n} \ ,$$

$$\ln|\Delta p| = \ln\left|\left(\frac{h}{n} - 0.5\right)\right| \ ,$$

$$\ln(n) \ ,$$

and

$$z = \frac{p - 0.5}{\frac{1}{2}\sqrt{\frac{1}{n}}} \ .$$

If the linear correlation coefficient for all pairs of data points, ln(n) and $\ln|\Delta p|$, is significant, then a straight line may be fit to the data, and thus, the raw data are reduced to two coefficients--the slope and the intercept.

2. Mean Chance Expectation

In the absence of *all* forms of psychoenergetic functioning, we must determine, theoretically, the mean chance expectation (MCE) for the type of data described above.

a. Theoretical Considerations for Overall Mean Chance Expectation

We define the sequence length, [n], as the number of samples collected from an RNG as a result of a single button press. If we consider all possible values of sequence lengths, it is convenient to use the binomial statistic in its exact form for $n < 200$, and use the normal approximation for larger sequence lengths. We use the observed fractional hit rate, p (hits/trials), minus the expected fractional hit rate, p_0 (equal to 0.5 for binary RNGs), as the dependent variable, $\Delta p = p - p_0$, and [n] as the independent variable.

For the "continuous" region where $n > 200$, Δp is normally distributed about a mean of zero with a standard deviation of σ_0 given by

$$\sigma_0 = \sqrt{\frac{p_0\, q_0}{n}} \quad ,$$

where $q_0 = (1 - p_0)$. For convenience, we shall examine the statistical properties of [n] and Δp in logarithmic form--ln(n) and ln(Δp), respectively, and, without loss of generality, consider only the absolute value of Δp, $|\Delta p|$. The expected value of $\ln|\Delta p|$ is given by

$$\overline{\ln |\Delta p|} = \frac{\int_{\sim 0}^{\infty} \ln |\Delta p|\; e^{-0.5 \left(\frac{\Delta p}{\sigma_0}\right)^2} d\,(\Delta p)}{\int_{\sim 0}^{\infty} e^{-0.5 \left(\frac{\Delta p}{\sigma_0}\right)^2} d\,(\Delta p)} \quad . \qquad (1)$$

Following the usual definition of a z-score, let

$$|z| = \frac{|\Delta p|}{\sigma_0} \quad .$$

Substituting into Equation (1), we find that

$$\overline{\ln |\Delta p|} = \ln \sigma_0 + \overline{\ln |z|} \quad .$$

And because

$$\sigma_0 = \sqrt{\frac{p_0 q_0}{n}} \quad ,$$

$$\overline{\ln |\Delta p|} = 0.5 \ln p_0 q_0 + \overline{\ln |z|} - 0.5 \ln n \quad . \qquad (2)$$

Equation (2) is a simple way to express the null hypothesis of no psychoenergetic functioning for the RNG data. If many RNG runs of varying sequence lengths are conducted in the absence of all psychoenergetic phenomena, the natural logarithm of the sequence lengths and their associated logs of $|\Delta p|$'s are *linearly related*--having a slope of -0.5, and an intercept determined by p_0, q_0 and the average value of $\ln|z|$--a known constant.

Given the "unboundedness" of $|z|$ (i.e., $0 < |z| \leq \infty$), it may surprise some readers that there is a linear relationship between the expected value of $\ln|\Delta p|$ and $\ln(n)$. To demonstrate this linear relationship from a different perspective, we calculate the expected linear correlation coefficient, r, under the null hypothesis:[9*]

$$r = \frac{-0.5774 \times (S_X - S_M)}{\sqrt{19.7392 + \frac{(S_X - S_M)^2}{3}}} \quad . \qquad (3)$$

S_X and S_M are the logarithms of the maximum and minimum sequence lengths, respectively.

Equations (2) and (3) form the basic set of relationships that describe, in detail, the expected results under the null hypothesis.

A significant note must be added at this point. Equation (2) represents the MCE under a normal approximation. As we will show, for any actual experimental case, the

* The authors wish to acknowledge and thank Dr. J. Utts for deriving this relationship.

difference between normality and the exact binomial calculation becomes important in determining the expected slope of the MCE line. Table 1 shows a comparison between the normal approximation and the exact binomial calculation for the expected value of $\ln|\Delta p|$ as a function of selected sequence lengths.

Table 1

EXACT AND APPROXIMATE VALUES OF $\ln|\Delta p|$

Sequence Length	Exact Binomial	Normal Approx.	Percent Error
200	-3.7880	-3.9774	4.76
2000	-5.0504	-5.1288	1.53
10000	-5.8922	-5.9335	0.70
100000	-7.0689	-7.0848	0.24

For any given experiment, the MCE line should be computed in the following way:

- Compute the exact value for $\ln|\Delta p|$ for each sequence used in the experiment.
- Fit the above result with a *weighted* straight line. The weighting factor for each sequence length is the number of trials, for that sequence length, that were conducted in the experiment under study.
- Use the slope and intercept from the above for the MCE values.

b. Theoretical Considerations for an RA Interaction

Because in the most general case of RA a subject could "perturb" the RNG device in any way, the Gaussian in Equation (1) must be replaced by an arbitrary function, $f(\Delta p,n)$. Or,

$$\overline{\ln|\Delta p|} = \frac{\int_{\sim 0}^{\infty} \ln|\Delta p|\, f(\Delta p,n)\, d(\Delta p)}{\int_{\sim 0}^{\infty} f(\Delta p,n)\, d(\Delta p)} .$$

To evaluate this general relationship, we must assume some specific form for $f(\Delta p,n)$. From this point on in the development of the model, we will assume that RA induces a *minor* perturbation in the physical system. Thus, we assume that $f(\Delta p,n)$ remains Gaussian, but RA shifts its mean--slightly.

We consider a class of RA models in which RA perturbs (to a small degree) a binomial distribution by shifting its mean. The theoretical task is to evaluate the expected value for the $\ln|\Delta p|$ using Equation (1). Define

$$\Delta p = p - p_s$$
$$\Delta p_s = p_a - p_0$$
$$\Delta p_a = p - p_a = \Delta p - \Delta p_s \quad .$$

As before, p_0 is the mean of an unperturbed distribution, and now p_a is the mean of a shifted distribution. Δp_a is the difference between the observed fractional hitting rate, p, and the shifted mean, p_a, and Δp_s is the shift in the means of the two distributions. We have derived the expected value of $\ln|\Delta p|$ elsewhere,[9] but we present a simplified version of it here.

For this calculation, we assume that the RNG is binary (i.e., $p_0 = 0.5$). Under these conditions, the expected value of $\ln|\Delta p|$ is given by

$$\overline{\ln|\Delta p|} = 0.5\ln(0.25) + \overline{\ln[zf(\Delta p_s) + z_s]} - 0.5\ln(n) \quad , \qquad (4)$$

where

$$z_s = \frac{\Delta p_s}{\sigma_0} \quad ,$$

and

$$f(\Delta p_s) = \sqrt{1 - 4\Delta p_s^2} \quad .$$

This latter term arises because the variance of a binomial distribution depends upon the mean of that distribution. If the shift of the distribution is small (i.e., $\Delta p_s \approx 0$), then $f(\Delta p_s) \approx 1$. For any RA model under consideration, we must define how the mean of

the shifted distribution behaves as a function of the sequence length, [n], and knowing that [z] is distributed normally, the evaluation of Equation (4) reduces to the evaluation of the expectation of $\ln(zf(\Delta p_s) + z_s)$. Or,

$$\overline{\ln\,[\,z\,f(\Delta p_s) + z_s]} = \sqrt{\frac{2}{\pi}} \int_{\sim 0}^{\infty} \ln\,[\,z\,f(\Delta p_s) + z_s]\, e^{-0.5\,z^2}\, dz \quad . \qquad (5)$$

Let us now consider a general class of binary RNG models where the mean of a binomial distribution is shifted by an amount:

$$p_a = 0.5\,(1 + a) \quad ,$$

and

$$\Delta p_s = p_a - 0.5 = 0.5\,a \quad ,$$

where [a] is an RA strength parameter. That is to say, the properties of the RNG device are modified by RA such that the mean probability of producing a hit has been shifted from 0.5 to p_a. There are many other models that we might consider, but this particular one has been proposed by the PEAR group. They report that if n = 200, [a] is approximately 0.001.[10, 11]

In other words, this model implies that individuals cause the mean probability of producing a hit to be constant, regardless of the sequence length. (The logarithm term in Equation 4 *does* retain an n-dependency through the z_s term even though Δp_a does not.) RA perturbs the device on a bit-by-bit basis that is independent of the number of bits in the sequence. Figure 4 shows the result of evaluating Equation (4) for various values of [a] compared to the MCE line.

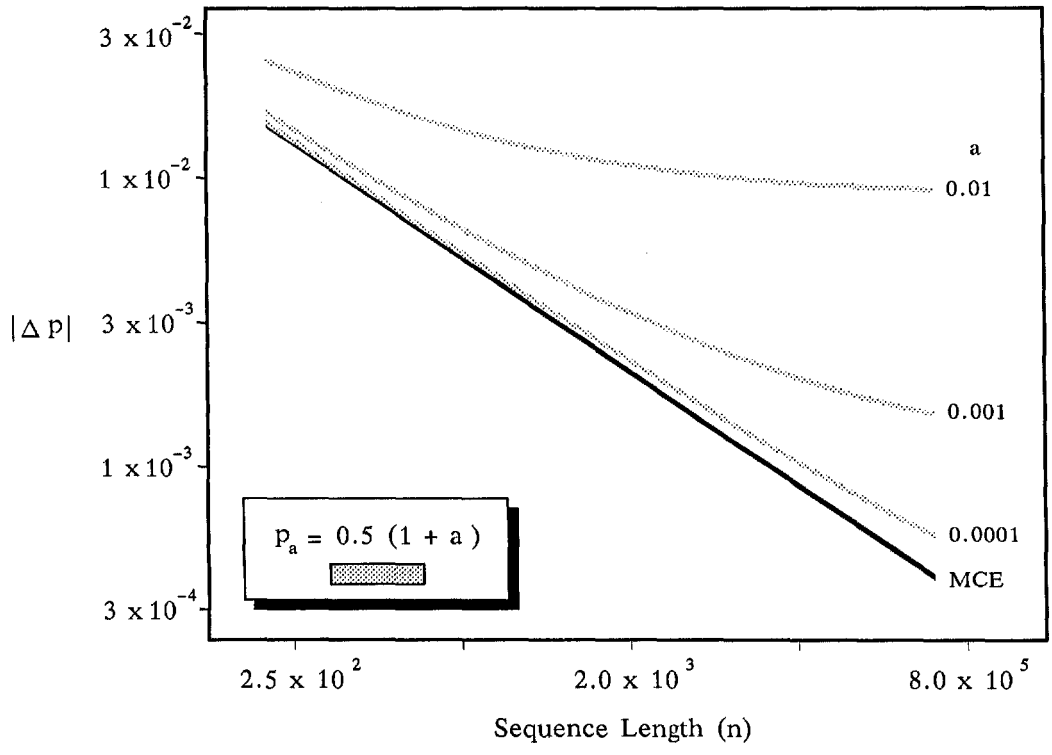

FIGURE 4 ONE RA MODEL COMPARED WITH MCE

c. Theoretical Considerations for the IDS Model

Equation (2) represents the MCE condition in which no psychoenergetic interaction is present. Because one premise of the IDS model is that *no* causal interactions occur, there is only one term in Equation (2) that can possibly account for a non-causal, but psychoenergetic effect. The $0.5 \ln(p_0 q_0)$ and the $-0.5 \ln(n)$ terms are consequences of the standard deviation for the *unperturbed* distribution of Δp; therefore, the only remaining term, the expected value for $\ln|z|$, must contain the IDS considerations.

In general terms, the expected value for $\ln|z|$ is given by

$$\overline{\ln|z|} = \frac{\int_{\sim 0}^{\infty} \ln(z)\, g(z,n)\, dz}{\int_{\sim 0}^{\infty} g(z,n)\, dz} \quad . \tag{6}$$

The function g(z,n) is the distribution that reflects a subject's ability to select subsequences, leading to z-scores. For example, if a subject were *always* able to select subsequences (regardless of sequence length) leading to z = 2.15, then g(z,n) contains no n-dependence and is a Dirac delta function at z = 2.15. If g(z,n) is simply a Gaussian with a mean of zero and a standard deviation of one, then Equation (6) reduces back to the null hypothesis. To determine predictions under the IDS model, Equation (6) must be evaluated for different assumptions for the function g(z,n).

Consider the case in which g(z,n) is not a function of the sequence length. Then, $g(z,n) = \gamma(z)$. Equation (6) becomes a sequence length independent constant, which can only affect the intercept of a straight line, regardless of any details of $\gamma(z)$. Figure 5 shows the RA hypothesis from Figure 4 and an example of the IDS case described above.

Suppose, however, g(z,n) does contain some n-dependencies. Even under the IDS hypothesis, we might expect this to be the case. Recalling that IDS is a psychoenergetic decision algorithm, we can imagine that better "decisions" result when a lot of "information" is available, or the reverse: "decisions" are inaccurate if there is not enough "information." It is possible that inaccurate "decisions" are made in the presence of too much "information" as well.

Elementary information theory tells us that the amount of information in a sequence of length [n] is proportional to [n] if the bits in the sequence are independent. Therefore, we can equate "information" in the above paragraph with the sequence length.

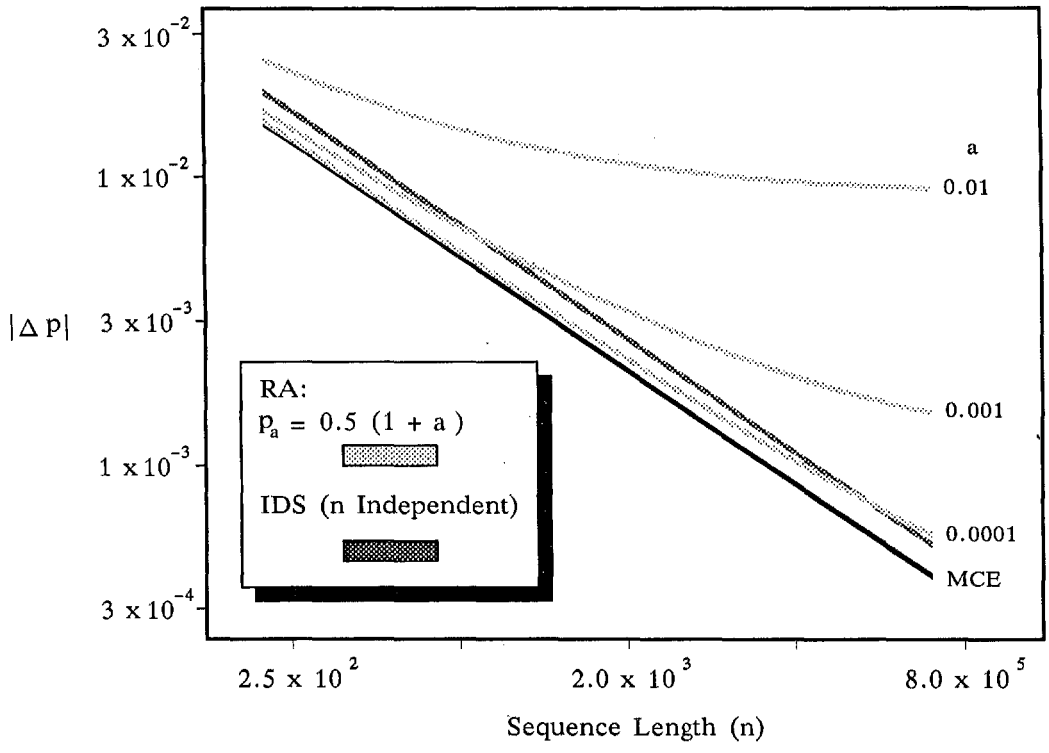

FIGURE 5 ONE IDS MODEL COMPARED TO MCE AND ONE RA HYPOTHESIS

We now examine the case in which g(z,n) retains a sequence length dependency. To define g(z,n), we transform the coordinates similar to what was done in the RA derivation. Let

$$\Delta z = z - z_0$$
$$\Delta z_s = z_a - z_0$$
$$\Delta z_a = z - z_a = \Delta z - \Delta z_s \quad ,$$

where z_a is the mean of a "shifted" Gaussian z-score distribution having a standard deviation of σ. Z_0 is the mean of the "unshifted" z-score distribution (i.e., $z_0 = 0.0$). Using this transformation, g(z,n) becomes

$$g(z,n) = e^{-0.5\left(\frac{\Delta z_a(n)}{\sigma(n)}\right)^2} .$$

Let zeta be given by

$$\zeta = \frac{\Delta z_a}{\sigma} .$$

Then Equation (6) becomes

$$\overline{\ln |z|} = \sqrt{\frac{2}{\pi}} \int_{\sim 0}^{\infty} \ln(\sigma\zeta + \zeta_s)\, e^{-0.5\zeta^2} d\zeta , \qquad (7)$$

where

$$\zeta_s' = \frac{\Delta z_s}{\sigma_0} , \quad (\sigma_0 = 1) .$$

We notice that Equation (7) is of the same form as Equation (5)--including their relative n-dependencies. Thus, depending upon the parameters involved in both equations, we would be generally unable to differentiate between RA and n-dependent IDS.

d. IDS vs. RA in Perspective

The IDS model appears to have the sensitivity to differentiate between some causal processes and some informational ones. In particular, the most obvious causal model (i.e., the "interaction" is, on the average, the same for each bit in the sequence) contains vastly different predictions than the most obvious IDS model (i.e., sequence length independent of the z-scores).

There is another class of RA models that have attracted attention:

$$p_a = 0.5\left(1 + \frac{a}{\sqrt{n}}\right) .$$

This particular form of $[p_a]$ leads directly to an n-independent $z_s = a$. $F(\Delta p_s)$ in Equation (5) becomes

$$f(\Delta p_s) = \left[1 - \frac{a^2}{n}\right]^{1/2} \approx 1 \quad .$$

This function is approximately equal to one for most actual cases (i.e., $a = 0.1$, $n > 200$). We note here, that it may be possible to separate even this RA model from IDS at small sequence lengths. Thus, Equation (5) reduces to a sequence length independent constant and is equivalent to the IDS case of $g(z,n) = \gamma(z)$ in Equation (6). Therefore, RA (of this form) and IDS are indistinguishable. All other forms of n-dependent RA contain a strong n-dependence in the z_s term.

To separate RA from IDS in this case, requires a different approach altogether. Suppose that RNG experiments continue to produce significant results that appear to be independent of all known physical parameters (e.g., source type--β decay, noise, distance, shielding, etc.). Further, suppose that PRNG experiments continue to produce significant results. We would then argue that IDS is the preferred choice for a mechanism because:

- Precognition can be shown to be true by separate and fundamentally different experiments.
- IDS can be shown to be possible (PRNG results).
- Results of one of our RNG experiments[1] suggest that human-mediated RA must be able to switch on and off within 1 ms.
- There is no known force in nature that can interact equally with the weak nuclear and electromagnetic forces.

To us, it would seem more parsimonious to assume that humans are more able to anticipate the unperturbed natural fluctuations of an RNG, rather than generate "forces" that must conform to such a set of attributes.

3. Analysis and Hypothesis Testing

The first step, after data reduction, is to determine if we are justified in continuing with a linear analysis. To accomplish this, we calculate the linear correlation coefficient for all data points $[\ln(n), \ln|\Delta p|]$, and determine if there is a significant correlation (i.e., $[r]$ significantly different than 0.0) and, as a side interest, determine if the correlation is significantly different than expected [i.e., Equation (3)].

If the correlation is significantly different than 0.0, we fit the data with a straight line, where the intercept is determined at the average value of $\ln(n)$ for the data set. By

transforming the data about the average value of ln(n) slope and intercept hypotheses testing may be done separately. To determine if the observed line is significantly different from the MCE line, we use an ANOVA technique.[12] The F-ratios (from the ANOVA) for the two tests are given below.

Let $n_k = \ln(s_k)$, where s_k is the sequence length for the kth data point. Let $\overline{n}$ be the average value for the n_k over [m] data points, or

$$\overline{n} = \frac{1}{m} \sum_{k=1}^{m} n_k \quad .$$

The F-ratios are given by

$$F(\text{slope}) = \frac{m\,(b - b')^2 \times \left(\sum_{k=1}^{m} \frac{n_k^2}{m} - \overline{n}^2 \right)}{\Delta} \quad , \quad df1 = 1;\ df2 = (m - 2) \quad ,$$

and

$$F(\text{intercept}) = \frac{m\,(a - a')^2}{\Delta} \quad , \quad df1 = 1;\ df2 = (n - 2) \quad ,$$

where [a] and [b] are the intercept and slope for [m] data points, $(\ln(n), \ln|\Delta p|)$. [a'] and [b'] are the intercept (at $n_k = \overline{n}$) and slope for the MCE line. Δ is given by

$$\Delta = \frac{\sum_{k=1}^{m} M_k^2 + ma^2 + b^2 \sum_{k=1}^{m} n_k^2 + 2\,a\,b \sum_{k=1}^{m} n_k - 2\,a \sum_{k=1}^{m} M_k - 2\,b \sum_{k=1}^{m} n_k M_k}{m - 2} \quad .$$

M_k is the observed value of $\ln|\Delta p|$ for the kth data point.

If the F-ratio for the slope is not significant, then we can conclude that the z-scores do *not* have a sequence length dependency. Furthermore, if the F-ratio for the intercept is significant, then there is evidence in support of the IDS model. Deviations from this scenario will be discussed below.

B. The SRI Pseudorandom Data

In 1985, Radin and May described a protocol that could be used as the pseudorandom portion of a comprehensive test of the IDS model, and presented pilot data that appeared to support the IDS model.[13] We have modified and extended that original proposal to form the basis of our pseudorandom investigation.

1. Justification for a Pseudorandom Number Generator Experiment

We have proposed an elaborate model (IDS) that predicts significantly different results from those expected from an RA interaction. As part of a systematic investigation of the validity of the model, we must determine if an IDS "interaction" can be demonstrated, in principle, under conditions that preclude RA.

Because there has been *no* evidence to date to support the idea that computer hardware is susceptible to a putative RA interaction, we assume that a purely pseudorandom number generator (PRNG), which is seeded by a computer clock, constitutes an environment that precludes RA.

2. PRNG Experiment Description

The primary concept for this experiment is to study $|\Delta p|$ as a function of sequence length. To accomplish this, we design a PRNG experiment in which a single trial contains the following steps:

- Select a sequence length, [n], from a limited menu of lengths.
- Collect [n] bits from a PRNG that has been seeded from a computer system clock at the moment when the participant presses a button.
- Calculate $|\Delta p|$ and a z–score, and display the z–score to the participant.
- Store raw data for later analysis.

Since the data will be analyzed in logarithmic form, we chose the following 10 sequence lengths because they are relatively evenly spaced when they are expressed as logarithms, and they did not allow $\Delta p = 0.0$ (i.e., the $\ln|\Delta p|$ will remain finite): 101, 201, 501, 1001, 3501, 7001, 10001, 35001, 70001, and 100001. While we may have wanted to explore larger sequence lengths than 100001, we were limited by the speed of the Sun Microsystems Model 3/160–C computer, and by human factor considerations. The delay between a button press and the display of the result was approximately 1.5 seconds. This

delay was constant in spite of the actual sequence length chosen, in order for a given trial to maintain a double blind condition with respect to sequence length.

At the first trial of a series, the above sequences were placed in a random order and stored as part of a data file. The sequence length, for a given trial, was taken in order from this randomized list. Thus, the sequence length ordering was repeated every 10 trials.

The PRNG that was used (a Kendel shift register feedback algorithm) has been studied extensively theoretically by Lewis[14] and experimentally by May.[1] This algorithm meets the accepted tests for "randomness"[15] and was checked further in this particular experiment using control trials. The low order 15 bits from the system clock were used as seeds for the PRNG.

For each trial, the seed, sequence length, number of ones in the sequence, z-score, time (to the nearest second), and date of the trial were stored as part of a data file for later analysis.

C. The Princeton Engineering Anomalies Research Data*

In order not to "pre-select" data to support (or not) a given hypothesis, we obtained *all* of the data to date (September 1986) from one of PEAR's best RNG participants. A subset of these data has been reported previously, but we have a complete set as of this writing.[10]

A single trial was defined as a continuous collection of binary bits from a "true" RNG (i.e., the sequence was derived from the noise associated with a back-biased PN junction). For the data under study there were two trial lengths, 200 bits and 2000 bits. To avoid problems of a possible single dimensional "bias" in the hardware, a target bit was toggled at a rate such that each new bit from the generator was compared to the one's (1s) complement of the previous target bit. Data were collected in two fundamental modes, manual and automatic. In the manual mode, a single button press resulted in a single trial. During the automatic mode, a single button press resulted in 50 consecutive trials. In the IDS formalism, is the total number of bits (sequence length) resulting in a single button press is the independent variable. Thus, there are only 4 allowed values for this independent variable: 200, 2000,, 10000, and 100000.

* We wish to express our appreciation to R. Jahn, R. Nelson and B. Dunne for providing access to their data and for their assistance in transferring it to our computer system.

For all sequence lengths, data were collected as a function of "aim"

- PK+ -- The participant attempts to force matches between the target bit and "response" bit from the generator.
- PK– -- The participant attempts to force mismatches between target bit and "response" bit from the generator.
- BL -- The participant makes no attempt to modify the bits from the generator. These data are referred to by PEAR as the baseline data.

The order of "aim" was determined in two modes: the volitional modes, in which the participant chooses the order of the triad, and the random mode, in which an RNG determines the order of the triad. Table 2 shows the data files that were used for the IDS analysis. A few of the button presses produced results in which the number of matches between target and response bits was *exactly* equal to one–half of the sequence length. Those special cases are ignored in our analysis to avoid computing logarithms of zero. The analysis will focus upon the specific aim regardless of volitional/random control of the aim.

Table 2

RAW DATA FOR OPERATOR 10--PRINCETON UNIVERSITY DATA

Data Set	Sequence Length	Button Presses	Number z=0
All PK ± (A_PK)	200	5918	332
	2000	15014	286
	10000	2065	13
	1000000	597	3
All PK + (PK+)	200	3088	162
	2000	7219	131
	10000	1028	9
	1000000	299	1
All PK - (PK-)	200	2830	170
	2000	7795	155
	10000	1037	4
	1000000	298	2
Volitional PK+ (V_PK+)	200	1471	79
	2000	4913	87
	10000	330	4
	1000000	105	0
Volitional PK- (V_PK-)	200	985	65
	2000	5203	97
	10000	328	1
	1000000	100	0
Random PK+ (R_PK+)	200	1617	83
	2000	2306	44
	10000	698	5
	1000000	194	1
Random PK- (R_PK-)	200	1845	105
	2000	2592	58
	10000	709	3
	1000000	198	2
All Baseline (BL)	200	0	0
	2000	2451	49
	10000	1170	12
	1000000	350	0

IV RESULTS AND DISCUSSION

The results of the SRI pseudorandom number generator experiment and the PEAR experiment will be discussed separately here and then compared in Chapter V, Conclusions and Recommendations.

A. The PRNG Experiment Results

In 1985, Radin and May reported pilot results for two participants (I.D. 105 and I.D. 531) who were selected on the basis of past successful performances in similar tasks.[1] For example, Participant 531 was the most significant contributor in our 1979 RNG experiment. In the 1985 pilot experiment, Participants 531 and 105 contributed 500 and 298 trials, respectively. The analysis showed that neither of the participants produced sequence length dependencies different from MCE (i.e., a slope of -0.5). However, the analysis revealed that both individuals showed independently significant evidence for IDS (i.e., the intercepts were significantly above MCE at the $p < 0.005$ level for each participant). Thus, our tentative conclusion from these data is that IDS appears possible, at least with these two participants.

During the FY 1986 program, we conducted the experiment in two phases: a screening and an experiment phase. For the pilot phases, we asked 20 individuals to contribute 100 trials each under the protocol described above. All but 4 of them completed this task. For availability reasons, the 4 participants contributed varying numbers of trials (less than 100). We had decided to select 7 individuals from within the pilot group to participate in a formal PRNG IDS experiment. The criterion for being included in the formal group was that the participant had to produce a significant increase above MCE of the variance of the z-score distribution over 100 trials (the MCE variance = 1.0).

Of the 16 participants who finished the 100 trial series, only one, 531, met the above requirement (variance = 1.37, $p < 0.008$). The second best performer, however, produced a variance = 1.21 ($p < 0.07$). Judging from the 1984 study, we would not expect to see a significant intercept with only 100 trials, and none were observed.

While it is particularly interesting that Participant 531 maintains his/her consistent performance, we felt that we should continue the pilot screening until we are able to select 7

significant participants. Thus, at this point, we do not have any results to report for the formal experiment.

B. The PEAR Results

1. Data Reduction and Analysis

Using the exact binomial procedure described in Chapter III, we have computed the MCE lines for the various data sets (see Table 3). These MCE lines were used as the basis for the IDS analysis that follows.

Table 3
MCE FOR EACH DATA SET

Variable	Data Set							
	A_PK	PK+	PK-	BL	V_PK+	V_PK-	R_PK+	R_PK-
Intercept (X=0)	-0.9514	-0.9502	-0.9525	-1.0923	-0.9379	-0.9498	-0.9575	-0.9545
Intercept (X-bar)	-4.8845	-4.8688	-4.8999	-5.4789	-4.8738	-4.9533	-4.8616	-4.8331
Slope	-0.5380	-0.5381	-0.5378	-0.5208	-0.5402	-0.5387	-0.5365	-0.5370
X-bar	7.263	7.233	7.293	8.420	7.242	7.397	7.219	7.164

We have analyzed the PEAR data from a "top down" perspective (i.e., beginning with the most combined data and ending with the most condition specific data). The first requirement from Chapter III is that we must determine if a linear analysis is appropriate for these data. For all data sets, the linear coefficient was strongly significant (i.e., $r \approx -0.6$ for all data sets) when compared to $r = 0$. Therefore, we are justified in continuing with the IDS analysis. Table 4 shows the results of this analysis (the data set abbreviations are taken from Table 2).

Table 4

RESULTS OF THE ANALYSIS OF THE PEAR RNG DATA

Variable	Data Set							
	A_PK	PK+	PK-	BL	V_PK+	V_PK-	R_PK+	R_PK-
Trials	23594	11634	11960	3971	6819	6616	4815	5344
Mean-Z	-0.0067	0.0180	-0.0308	-0.0097	0.0185	-0.010	0.018	-0.056
Z-Variance	1.018	1.016	1.019	1.035	1.002	1.025	1.036	1.012
p-of-Variance	0.024	0.110	0.070	0.062	0.454	0.083	0.038	0.274
Stouffer's Z	-1.031	1.946	-3.367	-0.613	1.516	-0.821	1.219	-4.124
p-of-Z	0.849	0.026	3.80(-4)	0.730	0.065	0.794	0.038	1.86(-5)
MCE								
X-bar	7.263	7.233	7.293	8.420	7.242	7.397	7.219	7.164
Intercept	-4.8606	-4.8420	-4.8754	-5.4778	-4.8502	-4.9349	-4.8305	-4.8017
Slope	-0.5380	-0.5381	-0.5379	-0.5208	-0.5402	-0.5387	-0.5365	-0.5370
DATA								
Intercept	-4.8606	-4.8469	-4.8737	-5.4580	-4.8574	-4.9338	-4.8319	-4.7989
Slope	-0.5317	-0.5471	-0.5157	-0.5276	-0.5449	-0.5167	-0.5486	-0.5144
F-Intercept	0.06	0.32	0.03	0.21	0.42	0.01	0.01	0.024
p-value	0.784	0.570	0.859	0.649	0.626	0.920	0.913	0.878
F-Slope	2.01	2.09	12.20	0.26	0.24	4.16	2.20	8.34
p-value	0.155	0.148	4.79(-4)	0.609	0.626	0.041	0.137	0.004
df-2	23592	11632	11958	3969	6817	6614	4813	5342

The meaning of MCE and data variables and their associated F-ratios have been discussed in Chapter III. The z-score variables are included here in order to make comparisons with the results published previously for part of these data.[10] The mean z-score is the average value of the z-scores for all the trials shown in each column; the MCE is zero. The variance for the z-score is calculated for the same data; the MCE is one. Note that both of these quantities were *not* calculated as absolute values. The Stouffer's z-score is the proper way of combining all the z-scores to test against the MCE hypothesis: no psychoenergetic functioning. The Stouffer's z-score is given by[16]

$$z_s = \frac{\sum_{k=1}^{n} z_k}{\sqrt{n}} \quad ,$$

where [n] is the number of trials.

2. Discussion of the PEAR Results

We note that our analysis is consistent with PEAR's in that the difference between the PK+ data (the participant was tasked to force more matches than MCE regardless of the origin of the "aim" request--volitional or random) and PK- data as measured by the Stouffer's z-score ($z_{diff} = 3.75$, $p < 8.6 \times 10^{-5}$) is highly significant. While the magnitude of the effect is small, it is, nonetheless, persistent and statistically robust.

We are able to discuss the IDS analysis for all of the PEAR data by examining the most deviant (from MCE) data set. Figure 6 shows the best fit line for the PK- data compared to its MCE. We plot this particular data set because it produced the most significant deviation ($p < 4.79 \times 10^{-4}$) from the MCE slope.

While the slope of the data line is significantly more positive than the MCE slope, the intercept is not significantly different. In effect, the data line has rotated about its intercept point (i.e., sequence length = 1470). Yet, the Stouffer's z-score indicates strong evidence for some form of psychoenergetic functioning ($p < 3.8 \times 10^{-4}$) for this data set. The resolution of this apparent inconsistency involves understanding a fundamental, and unfortunate, problem with these PEAR data in general.

Their data were *not* collected to provide a specific test of our IDS model. Thus, the sequence lengths that were chosen and, more importantly, the number of trials collected at each sequence length, were not optimized for our test. In the extreme, if all the data were collected at a single sequence length, our IDS analysis is completely inappropriate (i.e., the IDS formalism requires testing as a function of sequence length). To first order, these PEAR data suffer from the same problem. Sixty-five percent of the total data shown in Figure 6 were collected at a single sequence length (i.e., 2000). When we examine these data at each sequence length, we find that the Stouffer's z-scores are -2.98, -0.80, -2.87, and -2.69 for sequence lengths of 200, 2000, 10000, and 100000, respectively. Thus, most of the data for this set are *not* significant, even though when they are combined across sequence lengths, they are highly significant.

The situation described above is similar for all data sets; none of the data sets produced significant intercepts. Because the data were not collected uniformly as a function of sequence length, it is difficult to interpret the results of analysis. We feel that it is premature to speculate upon forms of either RA or IDS models that can fit these data.

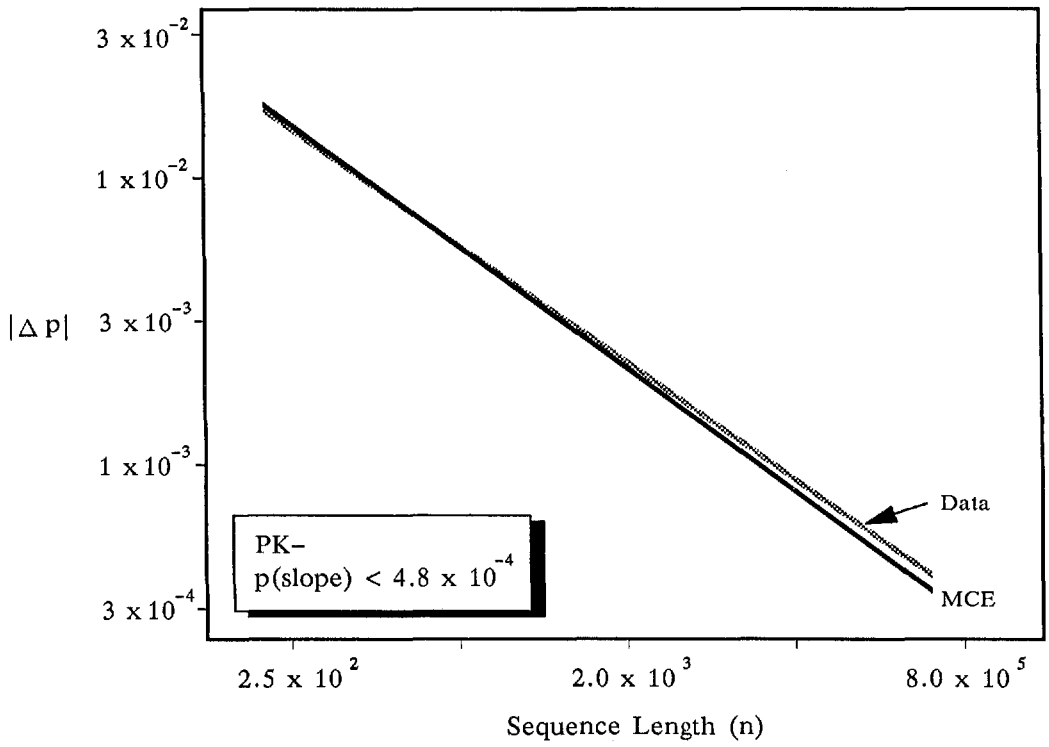

FIGURE 6 MCE AND PK- DATA

V CONCLUSIONS AND RECOMMENDATIONS

In this report, we have developed a detailed model (IDS) for psychoenergetic functioning. In particular, we have provided a mathematical formalism by which random number generator experiments may be used to test the concept.

Preliminary results using pseudorandom number generators (PRNG), indicate that an IDS ability appears possible. Many more data are required using PRNGs to confirm these preliminary results. It is anticipated that by 3rd quarter, FY 1987, we will be able to complete the PRNG experiment.

The PEAR data represent the largest amount of RNG data currently available. The PEAR group have reported strong statistical evidence of psychoenergetic functioning within this massive data base (i.e., 1.12×10^8 binary bits). It is unfortunate that the data were collected in such a way that an IDS analysis is inconclusive.

We strongly recommend that RNG data be collected with an equal number of trials as a function of sequence length. The protocol should be similar to the one in use in our PRNG experiment, in which a double-blind condition is maintained with respect to sequence length.

We conclude with some speculation. Suppose, after many experiments of different varieties, we could demonstrate that the philosophical concepts behind IDS *were* true. We would call into question *any* experimental results from *any* discipline that claim cause-and-effect relations based upon statistical inference.

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