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DECISION AUGMENTATION THEORY: TOWARD A MODEL OF ANOMALOUS MENTAL PHENOMENA

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ABSTRACT: Decision augmentation theory (DAT) holds that humans integrate information obtained by anomalous cognition into the usual decision process. The result is that, to a statistical degree, such decisions are biased toward volitional outcomes. We introduce our model and show that the domain over which it is applicable is within a few standard deviations from chance. We contrast the theory's experimental consequences with those of models that treat anomalous effects as due to a force. We derive mathematical expressions for DAT and force-like models using two distributions, normal and binomial. DAT is testable both retrospectively and prospectively, and we provide statistical power curves to assist in the experimental design of such tests. We show that the experimental consequences of our theory are different from those of force-like models except for one special case.

INTRODUCTION

We do not have positive definitions of the effects that generally fall under the heading of anomalous mental phenomena.[1] In the crassest of terms, anomalous mental phenomena are what happens when nothing else should, at least as nature is currently understood. In the domain of information acquisition, or anomalous cognition (AC), it is relatively

Since 1979, many individuals have contributed to the development of DAT. We would first like to thank David Saunders, without whose remark this work would not have been. Beverly Humphrey kept the philosophical integrity intact at times under extreme duress. We greatly appreciate the help of Zoltán Vassy, to whom we owe the *z* score formalism, and of George Hansen, Donald McCarthy, and Scott Hubbard, who gave constructive criticism and support.

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[1]The Cognitive Sciences Laboratory has adopted the term *anomalous mental phenomena* instead of the more widely known *psi.* Likewise, we use the terms *anomalous cognition* and *anomalous perturbation* for ESP and PK, respectively. We have done so because we believe that these terms are more naturally descriptive of the observables and are neutral with regard to mechanism. These new terms will be used throughout this paper.

straightforward to design an experimental protocol (Honorton et al., 1990, Hyman & Honorton, 1986) to ensure that no known sensory leakage of information can occur. In the domain of anomalous perturbation (AP), however, it is often very difficult.

We can divide anomalous perturbation into two categories based on the magnitude of the putative effect. Macro-AP includes phenomena that generally do not require sophisticated statistical analysis to tease out weak effects from the data. Examples include inelastic deformations in strain gauge experiments, the obvious bending of metal samples, and a host of possible "field phenomena" such as telekinesis, poltergeist, teleportation, and materialization. Conversely, micro-AP covers experimental data from noisy diodes, radioactive decay, and other random sources. These data show small differences from chance expectation and require statistical analysis.

One of the consequences of the negative definitions of anomalies is that experimenters must ensure that the observables are not due to "known" effects. Traditionally, two techniques have been employed to guard against such interactions:

1. Complete physical isolation of the target system.
2. Counterbalanced control and effort periods.

Isolating physical systems from potential "environmental" effects is difficult, even for engineering specialists. It becomes increasingly problematic, the more sensitive the AP device. For example Hubbard, Bentley, Pasturel, and Isaacs (1987) monitored a large number of sensors of environmental variables that could mimic perturbational effects in an extremely isolated piezoelectric strain gauge. Among these sensors were three-axis accelerometers, calibrated microphones, and electromagnetic and nuclear radiation monitors. In addition, the strain gauges were mounted in a government-approved enclosure to ensure no leak-age (in or out) of electromagnetic radiation above a given frequency, and the enclosure itself was levitated on an air suspension table. Finally, the entire setup was locked in a controlled access room which was monitored by motion detectors. The system was so sensitive, for example, that it was possible to identify the source of a perturbation of the strain gauge that was due to innocent, gentle knocking on the door of the closed room. The financial and engineering resources to isolate such systems rapidly become prohibitive.

The second method, which is commonly in use, is to isolate the target system within the constraints of the available resources and then construct protocols that include control and effort periods. Thus, we trade complete isolation for a statistical analysis of the difference between the control and effort periods. The assumption implicit in this approach is that environmental influences of the target device will be random and uniformly distributed in both the control and effort conditions, while anomalous effects will tend to occur in the effort periods. Experiments with micro-AP devices such as random number generators are examples of this method. The generators should be isolated as much as possible, but environmentally induced interactions are averaged out across effort and control conditions. Our arguments in favor of an anomaly, then, are based on statistical inference, and we must consider, in detail, the consequences of such analyses.

BACKGROUND

As the evidence for anomalous mental phenomena becomes more widely accepted (Bern & Honorton, 1994; Radin & Nelson, 1989; Utts, 1991), it is imperative to determine their underlying mechanisms. Clearly, we are not the first to begin thinking of potential models. In the process of amassing incontrovertible evidence of an anomaly, many theoretical approaches have been examined; in this section we outline a few of them. It is beyond the scope of this paper, however, to provide an exhaustive review of the theoretical models; a good reference to an up-to-date and detailed presentation is Stokes (1987).

Brief Review of Models

Two fundamentally different types of models of anomalous mental phenomena have been developed: those that attempt to order and structure the raw observations in experiments (i.e., phenomenological models) and those that attempt to explain these phenomena in terms of modifications to existing physical theories (i.e., fundamental models). In the history of the physical sciences, phenomenological models, such as Snell's law of refraction or Ampere's law for the magnetic field due to a current, have nearly always preceded fundamental models, such as quantum electrodynamics and Maxwell's theory. In producing useful models of anomalies, it may well be advantageous to start with phenomenological models, of which DAT is an example.

Psychologists have contributed interesting phenomenological approaches. Stanford (1974a, 1974b) proposed psi-mediated instrumental response (PMIR). PMIR states that an organism uses anomalous mental phenomena to optimize its environment. For example, in one of Stan-ford's classic experiments (Stanford, Zenhausern, Taylor, & Dwyer, 1975) subjects were offered a covert opportunity to stop a boring task prematurely if they exhibited unconscious anomalous perturbation by perturbing a hidden random number generator. Overall, the experiment was significant in the unconscious tasks; it was as if the participants were unconsciously scanning the extended environment for any way to provide a more optimal situation than participating in a boring psycho-logical task!

As an example of a fundamental model, Walker (1984) proposed a literal interpretation of quantum mechanics and posited that since superposition of eigenstates holds, even for macrosystems, anomalous mental phenomena might be due to macroscopic examples of quantum effects. These ideas spawned a class of theories, the so-called observation theories, that were based upon quantum formalism either conceptually or directly (Stokes, 1987). Jahn and Dunne (1986) have offered a "quantum metaphor" which illustrates many parallels between these anomalies and known quantum effects. Unfortunately, these models either have free parameters with unknown values or are merely metaphors. Some of these models propose questionable extensions to existing theories. For example, even though Walker's interpretation of quantum mechanical formalism might suggest wavelike properties of macrosystems, the physics data to date not only show no indication of such phenomena at room temperature but provide considerable evidence to suggest that macrosystems lose their quantum coherence above 0.5 Kelvins (Wash-burn & Webb, 1986) and no longer exhibit quantum wavelike behavior.

This is not to say that a comprehensive model of anomalous mental phenomena may not eventually require quantum mechanics as part of its explanation, but it is currently premature to consider such models as more than interesting speculation. The burden of proof is on the theorist to show why systems that are normally considered classical (e.g., a human brain) are indeed quantum mechanical; that is, what are the experimental consequences of a quantum mechanical system over a classical one?

Our decision augmentation theory (DAT) is phenomenological and is a logical and formal extension of Stanford's elegant PMIR model. In the same manner as early models of the behavior of gases, acoustics, or optics, DAT tries to subsume a large range of experimental measurements into a coherent lawful scheme. We hope that this process will lead the way to the uncovering of deeper mechanisms. In fact, DAT leads to the idea that there may be only one underlying mechanism of all anomalous mental phenomena, namely, a transfer of information from future to past.

Historical Evolution of Decision Augmentation

May, Humphrey, and Hubbard (1980) conducted a careful random number generator (RNG) experiment that was distinguished by the extreme engineering and methodological care taken to isolate any potentially known physical interactions with the source of randomness (Druckman & Swets, 1988, p. 189). It is beyond the scope of this paper to describe this experiment completely; however, those specific details that led to the idea of decision augmentation are important for the sake of historical completeness. The authors were satisfied that they had observed a genuine statistical anomaly, and additionally, because they had developed an accurate mathematical model of the random device, they were assured that the deviations were not due to any known physical interactions. They concluded in their report that some form of anomalous data selection had occurred, and they named it *psychoenergetic data selection.*

Following a suggestion by David R. Saunders of MARS Measurement and Associates, we noticed in 1986 that the effect size in binary RNG studies varied on the average as one over the square root of the number of bits in the sequence. This observation led to the development of the *intuitive data sorting model,* which appeared to describe the RNG data to that date (May, Radin, Hubbard, Humphrey, & Utts, 1985). The remainder of this paper describes die next step in the evolution of the theory, which is now named *decision augmentation theory.*

DECISION AUGMENTATION THEORY—A GENERAL DESCRIPTION

Since the case for AC-mediated information transfer is now well established (Bernm & Honorton, 1994), it would be exceptional if we did *not* integrate this form of information gathering into the decision process. For example, we routinely use real-time data gathering and historical information to assist in the decision process. Why then should we not include AC in the decision process? DAT holds that AC information is included along with the usual inputs that result in a final human decision that favors a "desired" outcome. In statistical parlance, DAT says that a slight, systematic bias is introduced into the decision process by AC.

This philosophical concept has the advantage of being quite general. To illustrate die point, we describe how the "cosmos" determines the outcome of a well-designed, hypothetical experiment. To determine die sequencing of conditions in an RNG experiment, suppose that the entry point into a table of random numbers will be chosen by the square root of the barometric pressure as stated in the weather report that will be published 7 days hence in the *New York Times.* Since humans are notoriously bad at predicting or controlling the weather, this entry point might seem independent of a human decision; but why did we "choose" 7 days in advance? Why not 6 or 8? Why the *New York Times* and not the *London Times?* DAT would suggest that the selection of 7 days, the *New York Times,* the barometric pressure, and square root function were better choices, either individually or collectively, and that other decisions would not have led to as significant an outcome. Other nontechnical decisions may also be biased by AC in accordance with DAT. When should we schedule a ganzfeld session? Who should be the experimenter in a series? How should we determine a specific order in a tri-polar protocol? DAT ex-plains anomalous mental phenomena as a process of judicious sampling from a world of events that are unperturbed. In contrast, force-like models hold that some kind of mentally mediated force perturbs the world. As we will show, these two types of models lead to quite different predictions.

It is important to understand the domain in which a model is applicable; for example, Newton's laws are sufficient to describe the dynamics of mechanical objects in the domain where the velocities are very much smaller than the speed of light and where the quantum wavelength of the object is very small compared to the physical extent of the object. If these conditions are violated, then different models must be invoked (e.g., relativity and quantum mechanics, respectively). The domain in which DAT is applicable is when experimental outcomes are in a statistical regime (i.e., a few standard deviations from chance). In other words, could the measured effect occur under the null hypothesis? This is not a sharp-edged requirement, but DAT becomes less apropos the more a single measurement deviates from mean chance expectation (MCE). We would not invoke DAT, for example, as an explanation of levitation if one found the authors hovering near the ceiling! The source of the statistical variation is unrestricted and may be of classical or quantum origin. A potential underlying mechanism for DAT is precognition. By this means, experiment participants become statistical opportunists.

DEVELOPMENT OF A FORMAL MODEL

While DAT may have implications for anomalous mental phenomena in general, we develop the model in the framework of understanding experimental results. In particular, we consider anomalous perturbation versus anomalous cognition in the form of decision augmentation in those experiments whose outcomes are in the few-sigma, statistical realm. We define four possible mechanisms for the results in such experiments:

1. Mean Chance Expectation. The results are at chance; that is, the deviation of the dependent variable meets accepted criteria for MCE. In statistical terms, we have measurements from an *unperturbed* parent distribution with *unbiased* sampling.

2. Anomalous Perturbation. Nature is modified by some anomalous interaction; that is, we expect an interaction of a "force" type. In statistical parlance, we have measurements from a *perturbed* parent distribution with *unbiased* sampling.

3. Decision Augmentation. Nature is unchanged, but the measurements are biased; that is, AC information has "distorted" the sampling. In statistical terms, we have measurements from an *unperturbed* parent distribution with *biased* sampling.

4. Combination. Nature is modified, and the measurements are based; that is, both anomalous effects are present. In statistical parlance, we have conducted *biased* sampling from a *perturbed* parent distribution.

General Considerations and Definitions

Since the formal discussion of DAT is statistical, we will describe the overall context for the development of the model from that perspective. Consider a random variable, X, that can take on continuous values (e.g., the normal distribution) or discrete values (e.g., the binomial distribution) . Examples of X might be the hit rate in an RNG experiment, the swimming velocity of single cells, or the mutation rate of bacteria. Let Y be the average of X computed over n values, where n is the number of items that are collected as the result of a single decision—one trial. Often this may be equivalent to a single effort period, but it also may include repeated efforts. The key point is that, regardless of the effort style, the average value of the dependent variable is computed over the n values resulting from one decision point. In the examples above, n is the sequence length of a single run in an RNG experiment, the number of swimming cells measured during the trial, or the number of bacteria-containing test tubes present during the trial. As we will show below, force-like effects require that the z score, which is computed from the Ys, increase as the square root of n. The square root dependence of n is not a consequence of DAT; rather, it follows naturally from a simple force-like assumption for the mechanism. In contrast, informational effects will be shown to be independent of n.

Assumptions for DAT

We assume that the parent distribution of a physical system remains *unperturbed;* however, the measurements of the physical system are systematically biased by some AC-mediated informational process.

Since the deviations seen in experiments in the statistical realm tend to be small in magnitude, it is safe to assume that the measurement biases will also be small; therefore, we assume small shifts of the mean and variance of the sampling distribution. Figure 1 shows the distributions for biased and unbiased measurements.

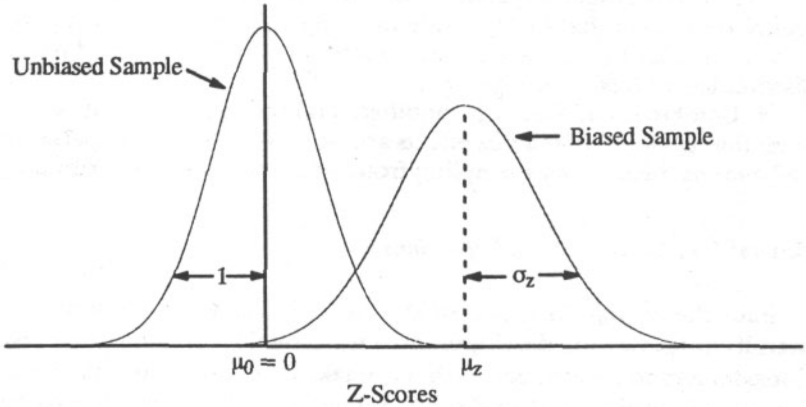

Figure 1. Sampling distribution under DAT.

The biased sampling distribution shown in Figure 1 is assumed to be normally distributed as:

$$z \sim n(\mu_z, \sigma_z^2),$$

where μ_Z and σ_Z are the mean and standard deviation of the sampling distribution and could in principle be functions of ν.

It might be possible to cast these parameters in information-theoretic terms. In a follow-on paper, May, Spottiswoode, Utts, and James (1995) show that the information concept of change-of-entropy may play a role in what is "sensed" in random number generator experiments. Although this is not a full analysis from information theory, it is suggestive that DAT might be reformulated from this perspective. We would welcome any attempt to do so.

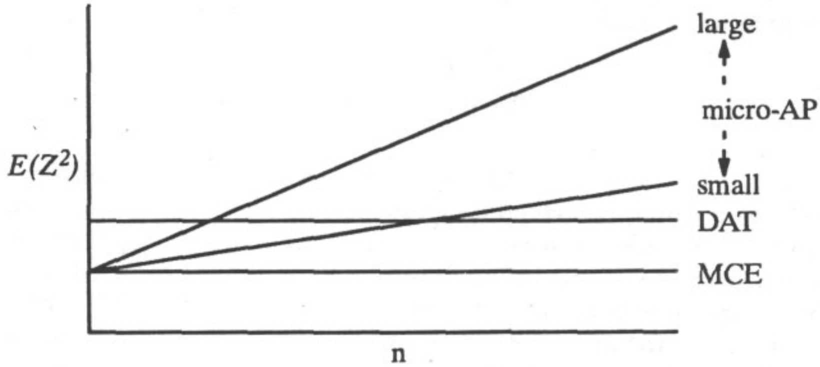

Figure 3. Predictions of MCE, micro-AP, and DAT.

Figure 3 displays these theoretical calculations for the three mechanisms graphically.

Within the constraints mentioned above, this formulation predicts grossly different outcomes for these models and, therefore, is ultimately capable of separating them, even for very small perturbations.

RETROSPECTIVE TESTS

It is possible to apply DAT retrospectively to any body of data that meet certain constraints. It is critical to keep in mind the meaning of *n*—the number of measures of the dependent variable over which to compute an average during a single trial following a single decision. In terms of their predictions for experimental results, the crucial distinction between DAT and the micro-AP model is the dependence of the results upon *n;* therefore, experiments that are used to test these theories must be those in which n is manipulated and participants are held blind to its values. May et al. (1995) retrospectively applied DAT to as many data sets as possible and examined the consequences of any violations of these criteria.

Aside from these considerations, the application of DAT is straightforward. Having identified the unit of analysis and *n,* simply create a scatter diagram of points (z^2, *n)* and compute a least square fit to a straight line. Tables 1 and 2 show that for the micro-AP model, the square of the effect size is the slope of the resulting fit. A Student's *t* test may be used to test the hypothesis that the effect size is 0, and thus test for the validity of the micro-AP model. If the slope is 0, these same tables show that the intercept may be interpreted as an AC strength parameter for DAT. The follow-on paper (May et al., 1995) will describe these techniques in detail.

PROSPECTIVE TESTS

A prospective test of DAT could not only test whether anomalous effects occurred, but would also differentiate between micro-AP and DAT. In such tests, *n* should certainly be a double-blind parameter and take on at least two values. If one wanted to check the prediction of a linear functional relationship between *n* and the $E(z^2)$ that is suggested by the micro-AP model, the more values of *n* the better. It is not possible to separate the micro-AP model from DAT at a single value of *n*.

In any prospective test, it is helpful to know the number of runs, *N*, that are necessary to determine with 95% confidence which of the two models best fits the data. Figure 4 displays the problem graphically.

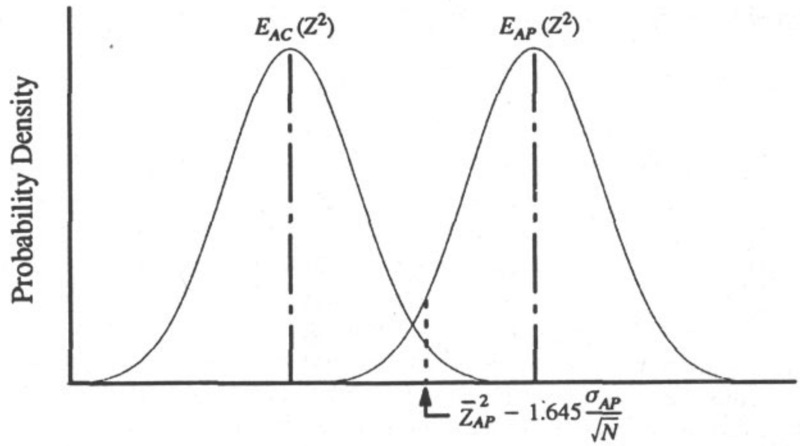

Figure 4. Model predictions for the power calculation.

Under micro-AP, 95% of the values of z^2 will be greater than the point indicated in Figure 4. Even if the measured value of z^2 is at this point, we would like the lower limit of the 95% confidence interval for this value to be greater than the predicted value under the DAT model. Or:

$$E(z_{AP}^2) - 1.645\frac{\sigma_{AP}}{\sqrt{N}} - 1.960\frac{\sigma_{AP}}{\sqrt{N}} \geq E_{AC}(z^2).$$

Solving for N in the equality, we find:

$$N = \left[\frac{3.605\,\sigma_{AP}}{E_{AP}(z^2) - E_{AC}(z^2)}\right]^2. \tag{1}$$

Since $\sigma_{AP} \geq \sigma_{AC}$ this value of N will always be the larger estimate than that derived from beginning with DAT and calculating the confidence intervals in the other direction.

Suppose, from an earlier experiment, that one can estimate a single-trial effect size for a specific value of n, say n_1. To determine whether the micro-AP model or DAT is the proper description of the mechanism, we must conduct another study at an additional value of n, say n_2. We use Equation 1 to compute how many runs we must conduct at n_2 to ensure a separation of mechanism with 95% confidence, and we use the variances shown in Tables 1 and 2 to compute σ_{AP}. Figure 5 shows the number of runs for an RNG-like experiment as a function of effect size for three values of n_2.

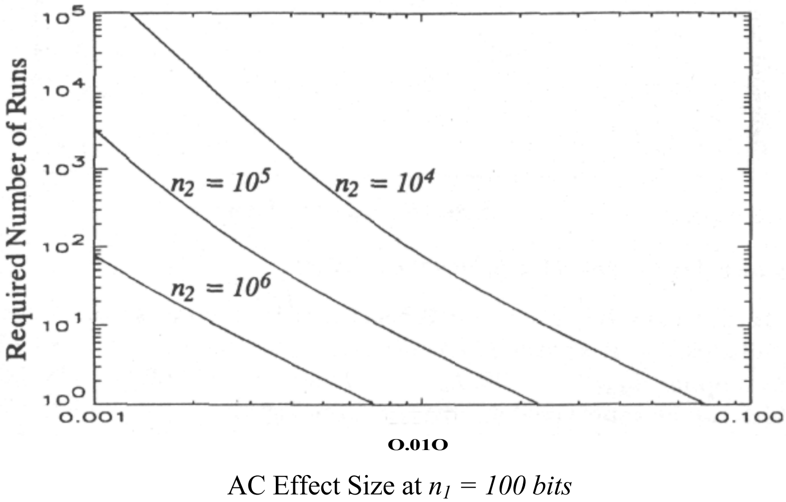

Figure 5. Runs required for RNG effect sizes.

We chose $n1$ = 100 bits because it is typical of the numbers found in the RNG database, and the values of n_2 shown are within easy reach of today's computer-based RNG devices; for example, assuming $\sigma_z = 1.0$ and assuming an effect size of 0.004, a value derived from a publication of PEAR data (Jahn, 1982), then at $n_1 = 100$, $\mu_z = 0.004 \times \sqrt{100} = 0.04$ and $E_{AC}(z^2) = 1.0016$. Suppose $n_2 = 10^4$, then $E_{AP}(z^2) = 1.160$ and $\sigma_{AP} = 1.625$. Using Equation 1, we find $N = 1368$ runs, which can be approximately obtained from Figure 5; that is, in this example, 1368 runs are needed to resolve the micro-AP model from DAT at $n_2 = 10^4$ at the 95% confidence level. Since these runs are easily obtained in most RNG experiments, an ideal prospective test of DAT, based on these calculations, would be to conduct 1500 runs randomly counterbalanced between $n = 10^2$ and $n = 10^4$ bits/trial. If the effect size at $n = 10^2$ is near 0.004, then we would be able to distinguish between micro-AP and DAT with 95% confidence. Figure 6 shows similar relationships for effect sizes that are more typical of anomalous perturbation experiments using biological target systems (May & Vilenskaya, 1992).

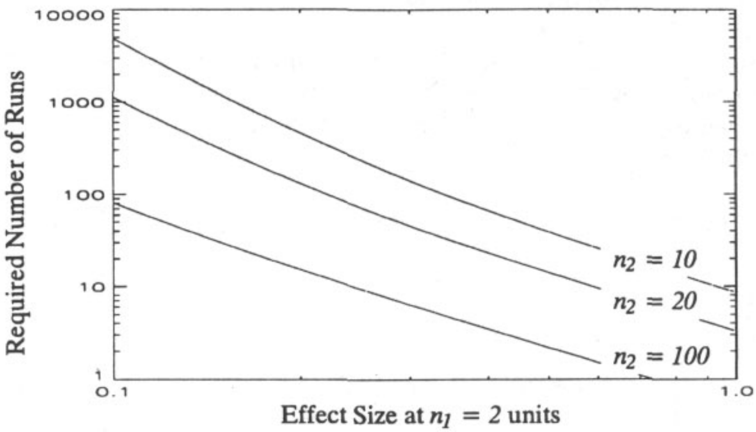

Figure 6. Runs required for biological effect sizes.

In this case, we chose $n_1 = 2$ because it is easy to use two targets simultaneously. If we assume an effect size of 0.3 and $\sigma_z = 1.0$, at $n_2 = 10$ we compute $E_{AC}(z^2) = 1.180$, $E_{AP}(z^2) = 1.900$, $\sigma_{AP} = 2.366$ and $N = 140$, which can be approximately obtained from Figure 6.

We have included $n_2 = 100$ in Figure 6, because this is within reach in cellular experiments although it is probably not practical for most biological experiments.

We chose $n_1 = 2$ units for convenience; for example, in a plant study the physiological responses can easily be averaged over two plants, and $n_2 = 10$ is within reason for a second data point. A unit could be a test tube containing cells or bacteria; the collection of all 10 test tubes would simultaneously have to be the target to meet the constraints of a valid test.

The prospective tests we have described so far are conditional; that is, given an effect size, we provide a protocol to test whether the mechanism for the anomalies is micro-AP or DAT. An unconditional test does not assume any effect size; all that is necessary is to collect data at a large number of different values of *n* and fit a straight line through the resulting z^2s. The mechanism is micro-AP if the slope is non-0 and may be DAT if the slope is 0.

STOUFFER'S Z TESTS

One consequence of DAT is that more decision points in an experiment lead to stronger results, because an operator has more opportunity to exercise AC abilities. We derive a test criterion to determine whether a force-like interaction or an informational mechanism is a better description of the data.

Consider two experiments of M decisions at n^1 and *N* decisions at n_2, respectively. Regardless of the mechanism, the Stouffer's z for the first experiment is given by:

$$z_s^{(1)} = \frac{\sqrt{n_1} \sum_{j=1}^{M} \varepsilon_{1j}}{\sqrt{M}} = \sqrt{n_1 M}\, \varepsilon_1,$$

where ε_{1j} is the effect size for one decision and where ε_1 is the average effect size over the M decisions. Under the micro-AP assumption that the effect size, 81, is constant regardless of *n,* Stouffer's z in the second

$$z_s^{(2)} = \sqrt{\frac{n_2 N}{n_1 M}}\; z_s^{(1)}.$$

Under the DAT assumption that the effect size is proportional to $1/\sqrt{n}$, the Stouffer's z in the second experiment becomes:

$$z_s^{(2)} = \sqrt{\frac{N}{M}}\; z_s^{(1)}.$$

experiment is given by:

As in the other tests of DAT, if data are collected at two values of *n,* then a test between these Stouffer's z values may yield a difference between the competing mechanisms.

DISCUSSION

We now address the possible n-dependence of the model parameters. A degenerate case arises if E_{AP} is proportional to $1/\sqrt{n}$; if that were the case, we could not distinguish between the micro-AP model and DAT by means of tests on the *n* dependence of results. If it were the case that in the analysis of the data from a variety of experiments, participants, and laboratories, the slope of a z^2 versus *n* linear least-squares fit were 0, then either $\varepsilon_{AP} = 0.0$ or ε_{AP} is proportional to $1/\sqrt{n}$, the accuracy depending upon the precision of the fit (i.e., errors on the 0 slope). An attempt might be made to rescue the micro-AP hypothesis by explaining the $1/\sqrt{n}$ dependence of ε_{AP} in the degenerate case as a fatigue or some other time dependence effect; that is, it might be hypothesized that anomalous perturbation abilities would decline as a function of *n;* however, it seems improbable that a human-based phenomenon would be so widely distributed and constant and give the $1/\sqrt{n}$ dependency in differing protocols needed to imitate DAT. We prefer to resolve the degeneracy by wielding Occam's razor: If the only type of anomalous perturbation that fits the data is indistinguishable from AC, and given that we have ample demonstrations of AC by independent means in the laboratory, then we do not need to invent an additional phenomenon called anomalous perturbation. Except for this degeneracy, a 0 slope for the fit allows us to reject all micro-AP models, regardless of their n-dependencies.

DAT is not limited to experiments that capture data from a dynamic system. DAT may also be the mechanism in protocols that utilize quasi-static target systems. In a quasi-static target system, a random process occurs only when a run is initiated; a mechanical dice thrower is an example. Yet, in a series of unattended runs of such a device, there is always a statistical variation in the mean of the dependent variable that may be due to a variety of factors, such as Brownian motion, temperature, humidity, and possibly the quantum mechanical uncertainty principle (Walker, 1974). Thus, the results obtained will ultimately depend upon when the run is initiated. It is also possible that a second-order DAT mechanism arises because of protocol selection—how the order in tri-polar protocols is determined and who determines it. In second-order DAT, there

$$E^B_{\mathrm{MCE}}(z) = \frac{1}{\sigma_0\sqrt{n}} \sum_{k=0}^{n} (k - np_0)B_k(n, p_0), \tag{A4}$$

where

$$B_k(n, p_0) = \binom{n}{k} p_0^k (1 - p_0)^{n-k}.$$

The first term in Equation 4 is *E(k),* which, for the binomial distribution, is np_0. Thus

$$E^B_{\mathrm{MCE}}(z) = \frac{1}{\sigma_0\sqrt{n}} \sum_{k=0}^{n}(k - np_0)B_k(n, p_0) = 0. \tag{A5}$$

The expected value of z^2 is given by:

$$E^B_{\mathrm{MCE}}(z^2) = Var(z) + E^2(z),$$

$$= \frac{Var(k - np_0)}{n\sigma_0^2} + 0,$$

$$E^B_{\mathrm{MCE}}(z^2) = \frac{n\sigma_0^2}{n\sigma_0^2} = 1. \tag{A6}$$

As in the normal case, the $Var(z^2) = E(z^4) - E^2(z^2) = E(z^4) - 1$. But*

$$E^B_{\mathrm{MCE}}(z^4) = \frac{1}{n^2\sigma_0^4} \sum_{k=0}^{n}(k - np_0)^4 B_k(n, p_0)$$

$$= 3 + \frac{1}{n\sigma_0^2}(1 - 6\sigma_0^2).$$

So,

*See Johnson and Katz (1969, p. 51).

$$Var^{B}_{\mathrm{MCE}}(z^2) = 2 + \frac{1}{n\sigma_0^2}(1 - 6\sigma_0^2) = 2 - \frac{2}{n}, \ (p_0 = 0.5). \tag{A7}$$

FORCE-LIKE INTERACTIONS

Normal Distribution

Under the perturbation assumption described in the text, we let the mean of the perturbed distribution be given by $\mu_0 + \varepsilon_{AP}\sigma_0$, where ε_{AP} is an anomalous perturbation strength parameter and in the general case may be a function of *n* and time. The parent distribution for the random variable, *X,* becomes $N(\mu_0 + \varepsilon_{AP}\sigma_0, \sigma_0^2)$. As in the mean-chance-expectation case, the average of *n* independent values of X is Y is distributed as $N(\mu_0 + \varepsilon_{AP}\sigma_0, \sigma_n^2)$. Let

$$y = \mu_0 + \varepsilon_{AP}\sigma_0 + \Delta y.$$

For a mean of *n* samples, the z score is given by

$$z = \frac{y - \mu_0}{\sigma_n} = \frac{\varepsilon_{AP}\sigma_0 + \Delta y}{\sigma_n} = \varepsilon_{AP}\sqrt{n} + \zeta,$$

where ζ is distributed as $N(0,1)$ and is given by $\Delta y/\sigma_n$. Then the expected value of z is given by

$$E^{N}_{AP}(z) = E_{AP}(\varepsilon_{AP}\sqrt{n} + \zeta) = \varepsilon_{AP}\sqrt{n} + E(\zeta) = \varepsilon_{AP}\sqrt{n}\,, \tag{A8}$$

and the expected value of z^2 is given by

$$E^{N}_{AP}(z^2) = E_{AP}([\varepsilon_{AP}\sqrt{n} + \zeta]^2) = n\varepsilon^2_{AP} + E(\zeta^2) + 2\varepsilon_{AP}\sqrt{n}\ E(\zeta)$$

$$= 1 + \varepsilon^2_{AP} n, \tag{A9}$$

since $E(\zeta) = 0$ and $E(\zeta^2) = 1$.

In general, z^2 is distributed as a noncentral χ^2 with one degree of freedom and noncentrality parameter $n\varepsilon_{AP}^2$, $\chi^2(1, n\varepsilon_{AP}^2)$. Thus, the variance of z^2 is given by*

*See Johnson and Katz (1970, p. 134).

$$Var_{\mathrm{AP}}^{N}(z^2) = 2\,(1 + 2n\varepsilon_{\mathrm{AP}}^2). \tag{A10}$$

Bernoulli Sampling

As before, let the probability of observing a one under mean chance expectation be given by p_0 and the discrete z score be given by:

$$z = \frac{k - np_0}{\sigma_0\sqrt{n}},$$

where k is the number of observed ones ($0 \le k \le n$). Under the perturbation assumption, we let the mean of the distribution of the single-bit probability be given by $p_1 = p_0 + \varepsilon_{\mathrm{AP}}\sigma_0$, where $\varepsilon_{\mathrm{AP}}$ is an anomalous-perturbation strength parameter. The expected value of z is given by:

$$E_{\mathrm{AP}}^{B}(z) = \frac{1}{\sigma_0\sqrt{n}} \sum_{k=0}^{n} (k - np_0) B_k(n, p_1),$$

where

$$B_k(n, p_1) = \binom{n}{k} p_1^k (1 - p_1)^{n-k}.$$

The expected value of z becomes

$$E_{\mathrm{AP}}^{B}(z) = \frac{1}{\sigma_0\sqrt{n}} \left[\sum_{k=0}^{n} kB_k(n, p_1) - np_0 \right]$$

$$= \frac{(p_1 - p_0)\sqrt{n}}{\sigma_0} = \varepsilon_{\mathrm{AP}}\sqrt{n}\ . \tag{A11}$$

Since $\varepsilon_{\mathrm{AP}} = E(z)/\sqrt{n}$, so $\varepsilon_{\mathrm{AP}}$ is also the binomial effect size. The expected value of z^2 is given by:

$$E_{\mathrm{AP}}^{B}(z^2) = Var(z) + E^2(z),$$

$$= \frac{Var(K - np_0)}{n\sigma_0^2} + \varepsilon_{\mathrm{AP}}^2 n,$$

$$= \frac{p_1(1-p_1)}{\sigma_0^2} + \varepsilon_{AP}^2 n.$$

Expanding in terms of $p_1 = p_0 + \varepsilon_{AP}\sigma_0$,

$$E_{AP}^B(z^2) = 1 + \varepsilon_{AP}^2(n-1) + \frac{\varepsilon_{AP}}{\sigma_0}(1-2p_0). \tag{A12}$$

If $p_0 = .5$ (i.e., a binary case) and $n \gg 1$, then Equation 12 reduces to the $E(z^2)$ in the normal case, Equation 9.

We begin the calculation of $Var(z^2)$ by using the equation for the jth moment of a binomial distribution

$$m_j = \frac{d^j}{dt^j}[(q + pe^t)^n \Big|_{t=0}.$$

Because $Var(z^2) = E(z^4) - E^2(z^2)$, we must evaluate $E(z^4)$. Or,

$$E_{AP}^B(z^2) = 1 + \varepsilon_{AP}^2(n-1) + \frac{\varepsilon_{AP}}{\sigma_0}(1-2p_0).$$

Expanding $n^{-2}\sigma_0^4(k - np_0)^4$, using the appropriate moments, and subtracting $E^2(z^2)$, yields

$$Var(z^2) = C_0 + C_1 n + C_{-1} n^{-1}, \tag{A13}$$

where,

$$C_0 = 2 - 36\varepsilon_{AP}^2 + 10\varepsilon_{AP}^4 + 8\frac{\varepsilon_{AP}}{\sigma_0}(1-2p_0)(1-2\varepsilon_{AP}^2) + 6\frac{\varepsilon_{AP}^2}{\sigma_0^2},$$

$$C_1 = 4\varepsilon_{AP}^2(1-\varepsilon_{AP}^2) + 4\frac{\varepsilon_{AP}^3}{\sigma_0}(1-2p_0), \text{ and}$$

$$C_{-1} = 48 - 6[\varepsilon_{AP}^2 - 3]^2 + 12\frac{\varepsilon_{AP}^3}{\sigma_0}(1-2p_0) + \frac{(1-7\varepsilon_{AP}^2)}{\sigma_0^2} + \frac{\varepsilon_{AP}}{\sigma_0^2}(1-2p_0)(12p_0^2 - 12p_0 + 1).$$

Under the condition that $\varepsilon_{AP} \ll 1$ (a frequent occurrence in many experiments), we ignore any terms of higher order than ε_{AP}^2. Then the variance reduces to

$$Var(z^2) = 2 - 36\varepsilon_{AP}^2 + 8\frac{\varepsilon_{AP}}{\sigma_0}(1-2p_0) + 6\frac{\varepsilon_{AP}^2}{\sigma_0^2} + 4\varepsilon_{AP}^2 n +$$

$$\frac{1}{n}\left[-6 + 36\varepsilon_{AP}^2 + \frac{(1-7\varepsilon_{AP}^2)}{\sigma_0^2} + \frac{\varepsilon_{AP}}{\sigma_0^3}(1-2p_0)(12p_0^2 - 12p_0 + 1)\right].$$

We notice that when $\varepsilon_{AP} = 0$, the variance reduces to the mean chance expectation case for Bernoulli sampling. When $n \gg 1$, $\varepsilon_{AP} \ll 1$, and $p_0 = .5$, the variance reduces to that derived under the normal distribution assumption. Or,

$$Var_{AP}^B(z^2) \approx 2(1 + 2n\varepsilon_{AP}^2). \qquad \text{(A14)}$$

INFORMATIONAL PROCESS

Normal Distribution

The primary assumption in this case is that the parent distribution remains unchanged (i.e., $N(\mu_0,\sigma_0^2)$). We further assume that because of an AC-mediated bias, the sampling distribution is distorted, leading to a z-distribution of $N(\mu_{AC}, \sigma_{AC}^2)$. In the most general case, μ_{AC} and σ_{AC} may be functions of n and time.

The expected value of 2 is given by definition as

$$E_{AC}^N(z) = \mu_{AC}\,. \qquad \text{(A15)}$$

The expected value of z^2 is given by definition as

$$E_{AC}^N(z^2) = \mu_{AC}^2 + \sigma_{AC}^2\,. \qquad \text{(A16)}$$

The $Var(z^2)$ can be calculated by noticing that

$$\frac{z^2}{\sigma_{AC}^2} \sim \chi_{nc}^2\left(1, \frac{\mu_{AC}^2}{\sigma_{AC}^2}\right).$$

So the *Var(z²)* is given by

$$Var\left(\frac{z^2}{\sigma_{AC}^2}\right) = 2\left(1 + 2\frac{\mu_{AC}^2}{\sigma_{AC}^2}\right)$$

Thus,

$$Var_{AC}^{N}(z^2) = 2(\sigma_{AC}^4 + 2\mu_{AC}^2\sigma_{AC}^2). \tag{A17}$$

Bernoulli Sampling

As in the normal case, the primary assumption is that the parent distribution remains unchanged and that because of an AC-mediated bias the sampling distribution is distorted, leading to a discrete z distribution characterized by $\mu_{AC}(n)$ and $\sigma_{AC}^2(n)$. Thus, by definition, the expected values of z and z^2 are given by

$$E_{AC}^{B}(z) = \mu_{AC} \tag{A18}$$

$$E_{AC}^{B}(z^2) = \mu_{AC}^2 + \sigma_{AC}^2$$

respectively. For any value of *n,* estimates of these parameters are calculated from M data points as

$$\hat{\mu}_{AC} = \frac{1}{M}\sum_{j=1}^{M} z_j, \quad \text{and}$$

$$\hat{\sigma}_{AC}^2 = \frac{M}{(M-1)}\left(\sum_{j=1}^{M}\frac{z_j^2}{M} - \hat{\mu}_{AC}^2\right)$$

The *Var(z²)* for the discrete case is identical to the continuous case. Therefore

$$Var_{AC}^{B}(z^2) = 2(\sigma_{AC}^4 + 2\mu_{AC}^2\sigma_{AC}^2). \tag{A19}$$

REFERENCES

BEM, D. J., & HONORTON, C. (1994). Does psi exist? Replicable evidence for an anomalous process of information transfer. *Psychological Bulletin,* 115, 4—18.

DRUCKMAN, D., & SWETS, J. A. (Eds.) (1988). *Enhancing human performance: Issues, theories, and techniques.* Washington DC: National Academy Press.

HONORTON, C., BERGER, R. E., VARVOGLIS, M. P., QUANT, M., DERR, P., SCHECHTER, E. I., & FERRARI, D. C. (1990). Psi communication in the Ganzfeld. *Journal of' Parapsychology,* 54, 99-139.

HUBBARD, G. S., BENTLEY, P. P., PASTUREL, P. K., & ISAACS, J. (1987). A remote action experiment with a piezoelectric transducer. *Final Report—Objective H, Task 3 and 3a.* SRI International Project 1291, Menlo Park, CA.

HYMAN, R., & HONORTON, C. (1986). A joint communiqué: The psi ganzfeld *controversy. Journal of Parapsychology,* 50, 351-364.

JAHN, R. G. (1982). The persistent paradox of psychic phenomena: An engineering perspective. *Proceedings of the IEEE,* 70, 136-170.

JAHN R. G., & DUNNE, B. J. (1986). On the quantum mechanics of consciousness, with application to anomalous phenomena. *Foundations of Physics,* 16, 721—772.

JOHNSON, N. L., & KATZ, S. (1969). *Discrete distributions.* New York: John Wiley and Sons.

JOHNSON, N. L., & KATZ, S. (1970). *Continuous univariate distributions: 2.* New York: John Wiley and Sons.

MAY, E. C., HUMPHREY, B. S., & HUBBARD, G. S. (1980). *Electronic system perturbation techniques: Final Report.* Menlo Park, CA: SRI International.

MAY, E. C., RADIN, D. I., HUBBARD, G. S., HUMPHREY, B. S., & UTTS, J. (1985). Psi experiments with random number generators: An informational model. *Proceedings of Presented Papers Vol 1: The Parapsychological Association 28th Annual Convention,* 237-266.

MAY, E. C. SPOTTISWOODE, S. J. P., UTTS, J. M., & JAMES, C. L. (1995). Applications of decision augmentation *theory. Journal of Parapsychology,* 59, 221-250.

MAY, E. C., & VILENSKAYA, L. (1992). Overview of current parapsychology research in the former Soviet Union. *Subtle Energies,* 3, 45-67.

RADIN, D. I., & NELSON, R. D. (1989). Evidence for consciousness-related anomalies in random physical systems. *Foundations of Physics,* 19, 1499-1514.

STANFORD, R G. (1974a). An experimentally testable model for spontaneous psi events I. Extrasensory events. *Journal of the American Society for Psychical Research,* 68, 34-57.

STANFORD, R. G. (1974b). An experimentally testable model for spontaneous psi events II. Psychokinetic *events. Journal of the American Society for Psychical Re=search,* 68, 321-356.

STANFORD, R. G., ZENHAUSERN R., TAYLOR, A., & DWYER, M. A. (1975). Psychokinesis as psi-mediated instrumental response. *Journal of the American Society for Psychical Research,* 69,127-133.

STOKES, D. M. (1987). Theoretical parapsychology. In S. Krippner (Ed.), *Advances inparapsychologicalresearch5* (pp. 77-189). Jefferson, NC: McFarland.

UTTS.J. (1991). Replication and meta-analysis in parapsychology. *Statistical Science,* 6, 363-403.

WALKER, E. H. (1974). Foundations of paraphysical and parapsychological phenomena. In E. Oteri (Ed.), *Proceedings of an international conference: Quantum physics and parapsychology* (pp. 1-53). New York: Parapsychology Foundation.

WALKER, E. H. (1984). A review of criticisms of the quantum mechanical theory of psi phenomena. *Journal of Parapsychology,* 48, 277-332.

WASHBURN S., & WEBB, R. A. (1986). Effects of dissipation and temperature on macroscopic quantum tunneling in Josephson junctions. In D. M. Greenburger (Ed.), New *techniques and ideas in quantum measurement theory* (pp. 66-77). New York: New York Academy of Sciences.

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