NUMERICAL ANALYSIS AND THEORETICAL MODELLING OF CAUSAL EFFECTS OF CONSCIOUS INTENTION

Richard Thompson, Ph.D.

ABSTRACT

In this paper we discuss and re-analyze some phenomena involving interactions between machines and states of conscious intention that have been reported by Robert Jahn and his colleagues at Princeton University. We specifically deal with the experiments these investigators have carried out using an apparatus called the random mechanical cascade (or RMC). We introduce a class of theories, called selection theories, which might be invoked to explain the phenomena they have observed. These include some parapsychological theories that have been proposed for such phenomena in the past, and they also include the theory that the phenomena are spurious by-products of conscious or unconscious editing of the experimental data.

We have found that the data for the RMC experiments have some statistically significant features which have not been noted before, and which tend to rule out selection theories as possible explanations of the observed phenomena. Thus our findings support the conclusion that these phenomena represent a genuine anomaly, and they narrow down the range of possible theories that might account for this anomaly.

INTRODUCTION

A group at Princeton University, including R. D. Nelson, B. J. Dunne, and R. G. Jahn,[1] has for several years carried out a research program investigating correlations between human intention and the behavior of various machines. In one series of experiments the machine was a version of a device commonly used to demonstrate the law of large numbers. The Princeton device, called a "Random Mechanical Cascade" or RMC, was described as follows in Nelson *et al*.[2] The machine consists of a quincunx array of 330 3/4" nylon pins with a horizontal spacing of 3.25". A total of 9000 3/4" polystyrene spheres are allowed to cascade through the array from an inlet at the top, and these accumulate in 19 equally spaced collecting bins at the bottom. About 12 minutes are required for all of the balls to reach the bins.

As one would expect, the 9000 balls tend to fill the bins according a *Gaussian* distribution, but this distribution is somewhat irregular, and its mean and other statistical features tend to vary randomly. In the Princeton experiments an observer, called an "operator", tried to influence the mean of the distribution to shift to the left, remain at the baseline (the statistically expected position), or shift to the right. The operator did this by meditation within the mind, rather than by trying to physically interfere with the machine. Usually the operator sat in front of the machine at a distance of about eight feet and watched the cascading balls, but in some experiments the operator was at a remote location.

The operation of the machine was divided into sets of three "tripolar" runs, one for each of the three intentions of left, baseline, or right. (In some cases the operator was free to choose the order of the intentions in each set, and in other cases this was dictated by the experiment protocol.) An operator would perform a number of series, each consisting of 10 or 20 tripolar sets. The distribution of the balls in the bins was counted electronically for each run and recorded automatically in a computer file.

For a given run, let $b(k)$ be the number of balls in bin k for $k = 1, \ldots, 19$. The 19 numbers, $b(1), \ldots, b(19)$, are referred to as the bin distribution for the run, and they roughly approximate a *Gaussian* distribution. The mean of this distribution is called the bin distribution mean. We will also speak of the mean and standard deviations of the variable called "bin distribution mean" over a series of runs, each

of which produces a bin distribution and a bin distribution mean. These two uses of the word "mean" can be distinguished by context.

The performance of the operators was evaluated by examining the behavior of the quantities *lt-bl*, *rt-bl*, and *rt-lt*, where *lt*, *bl*, and *rt* are the average bin distribution means for the runs with intentions, left, baseline, and right, in a long series of tripolar sets of runs. Differences between *lt*, *bl*, and *rt* were used to offset the effect of long term trends in machine behavior caused by wear and other systematic factors. We note that since there are 19 bins, the average bin distribution mean for a perfectly symmetrical machine should come out to 10. Since the actual machine is slightly asymmetrical, this average tends to be slightly higher than 10.

One would naturally expect that there would be no relationship between human states of consciousness and the statistical behavior of the machine. However, the experiments indicated that in the long run, this behavior tended to conform with the intentions of the operators. In a total of 1131 tripolar sets of runs generated by 25 operators, it was found that *rt-lt* came out to about .0057. This corresponds to an average bin distribution mean for rightward intentions of 10.0229 and an average bin mean for leftward intentions of 10.0172.

Although the differences between these average bin means are quite small, they turn out to be statistically significant. The standard deviation corresponding to *rt-lt* was .0493, and the *t*-score was 3.891. This outcome has a probability of about 5×10^{-5}, if we assume that the individual runs were statistically independent and not influenced by operator intention.

I n these experiments the bulk of the runs were generated by two operators (10 and 55), and operator 10 achieved by far the most significant results. However, a statistically significant effect remains even if the data generated by operators 10 and 55 are excluded from the analysis.

In this paper we will analyze the results of the random mechanical cascade experiments, and show that the data generated by these experiments reveals some anomalous effects in addition to those originally reported. To do this, it was necessary for us to gain access to the original RMC data, and this was kindly provided by Roger Nelson of the engineering anomalies research group at Princeton.[1] In Section 1 we briefly discuss the possible effects of small forces generated by the observer on the RMC. In Section 2 we introduce the class of selection theories and give three

examples of such theories. In Section 3 we discuss the RMC data, and we show how it reveals hitherto unknown effects that should not occur, according to selection theories. Finally, in Section 4 we summarize our conclusions.

1.   THE EFFECT OF SMALL FORCES ON THE RMC

What happens when a conscious person desires to perform some action, such as picking up an object? Standard explanations maintain that the desire to act can be identified with particular electro-chemical phenomena in neurons within the brain. These give rise to movements of bodily parts and possible changes in the body's electrical field and other physical characteristics. Could these changes in turn influence the behavior of the RMC in a normal physical fashion?

Nelson *et. al*.[3] discuss possible mechanical, electromagnetic and gravitational interactions between the observer and the RMC, and reject these "ordinary" forces as being too weak by several orders of magnitude to produce the observed effects. Although this is basically correct, there are some fine points regarding the effect of ordinary forces on the RMC that should be taken into account.

In recent years a phenomenon known as deterministic chaos has been extensively investigated.[4] The essence of this phenomenon is that in physical systems with nonlinear dynamics, very small changes imposed on the state of the system can grow exponentially into very large changes in a short period of time. The consequences of this exponential growth have been dramatically illustrated by the "butterfly effect," described by E. N. Lorenz in a meteorological context: "even if the atmosphere could be described by a deterministic model in which all parameters were known, the fluttering of a butterfly's wings could alter the initial conditions, and thus (in the chaotic regime) alter the long term prediction".[5]

The dynamics of the RMC involve many nonlinear interactions, such as the nonlinear dependence of angle of bounce on angle of incidence in collisions between balls and pins. Analysis of simple mathematical models of the RMC shows that these interactions result in deterministic chaos, and we suggest that they also result in chaotic phenomena in the real RMC. If this is true, it means that extremely small forces

generated within the environment of the RMC could have a measurable effect on the bin distribution mean. Thus, in principle, the bin distribution mean could be influenced in a systematic way by small, ordinary, physical forces generated by the body of the observer.

However, if small forces can result in large effects, small variations in these forces can likewise result in large variations in the effects. According to the theory of deterministic chaos, this means that if the observed anomalous behavior of the bin distribution mean is produced by small, ordinary forces generated within the body of the observer, then these forces must be produced with great precision in accordance with the observer's intentions. Thus as Jahn and his colleagues note,[1] the observed anomalous effects cannot be produced by normal forces applied with a normal degree of precision (of the kind we would expect from a human nervous system). But they might be produced by normal forces applied with paranormal, or unexpectedly high, precision. Here we will not try to quantify "paranormal precision", but we suggest that it might be worthwhile trying to do this in future studies of PK phenomena.

2. SELECTION THEORIES

O f course, there are theories which attempt to account for the anomalous behavior of the RMC without bringing in physical forces at all. For example, there is a class of theories, called selection theories, that can be described in general terms as follows: Let us suppose that natural processes obeying known physical laws produce an ensemble of possible outcomes for runs of the RMC. This ensemble can be defined by a probability distribution, $P(x)$, where x is the information representing an RMC run. Let y represent the observer's state of intention, and let $f(x, y) > 0$ measure the degree to which a run x satisfies the intention y. (Here we write $y = RT, LT$, or BL, where these symbols stand for states of intention.) We suppose that the greater the agreement between the run and the intention, the greater is $f(x, y)$. Define the following probability distribution for a pair, (x, y), consisting of a run plus an intention:

$$P'(x, y) = f(x, y) P(x) / K \qquad (1)$$

where K is a normalization constant. In a selection theory, the actual, measured probability distribution for (x, y) is given by $P'(x, y)$, for some suitable function,

$f(x, y)$. We will give three examples of selection theories, and show in each case how one arrives at $P'(x, y)$.

Example (1), **precognition.** The first example assumes that the RMC always behaves according to known physical laws, but that the observer has a paranormal ability to foresee the future. In this example we suppose that the observer has the opportunity to make his own choice of intentions prior to each run (the "volitional" mode). We suppose that he makes his choice in accordance with what he foresees, but that his foresight is imperfect. This can be expressed by means of a Markov chain transition matrix, $M(x, y)$, which gives the probability that the observer will choose intention y, given that the future run will be x. In this model, the probability that (x, y) will come up is

$$P'(x, y) = P(x) M(x, y) \qquad (2)$$

which has the same form as Equation (1). The constant $K = 1$ since the sum of $M(x, y)$ over $y = RT, BL, LT$ is assumed to be equal to 1.

In the case where the intentions are chosen in advance by the experimenters (the "instructed" mode), a similar model can be formulated on the basis of precognition by the experimenters.

Example (2), wave function collapse. We have studied the behavior of solutions of the Schrodinger equation for an idealized model of balls bouncing from pins. The results suggest that during a run, the quantum mechanical wave function for the RMC should spread out to encompass a range of outcomes for that run. Thus, the normal physical behavior of the RMC can be expressed in terms of the collapse of the quantum mechanical wave function. We can let Ψ represent a wave function of the RMC plus observer that encompasses many possible run outcomes, and let Φ_i represent wave functions of the RMC plus observer for specific outcomes. (Just to simplify the discussion, let us suppose that the Φ_i's form an orthonormal basis for wave functions.)

In quantum mechanics, the probability of getting state Φ_i after collapse of the wave function, Ψ, is $|<\Psi, \Phi_i>|^2$. Wigner[6] has argued that the collapse of the wave function is connected with consciousness, and he proposes that a proper formulation of this connection will require modifications of the laws of quantum mechanics. So,

if we suppose that consciousness prefers Φ_i's showing harmony between intention and RMC run, we can venture to express this by replacing $| < \Psi, \Phi_i > |^2$ by $f(\Phi_i)$ $| < \Psi, \Phi_i > |^2$, where f is a positive function that favors such harmony. This modified form of quantum mechanics is also a selection theory.

Example (3), data selection. In this theory we suppose that the observed correlation between intention and RMC behavior is spurious. The probability of run outcome x is determined by a distribution $P(x)$, which is generated in accordance with the laws of physics. But in the natural course of events, some runs may seem defective for one reason or another, and the experimenter may wish to delete them from the database. We suppose that, owing to the desire for a successful experiment, the experimenter is more likely to throw out runs where x disagrees with the intention, y, than runs where x agrees. (He may do this consciously or unconsciously.) This can be expressed by means of a data selection function, $0 < f(x, y) < 1$, which represents the chances of retaining a particular run in the database, and which is somewhat smaller for cases where x and y disagree than it is for cases where they agree. The probability for (x, y) in the edited database is then given by Equation (1).

L et us suppose that the run information, x, can be expressed as $x = (u, v, w)$, where u and v are real variables describing different features of the run, and w contains whatever additional information is needed to specify x. We can suppose that v is the variable to which intentions apply (namely, the bin mean in the RMC experiments). Since $f(x, y)$ expresses the degree of agreement between v and the intention, y, we can write it as $f_1(v, y)$. The variable u is presumed to be one to which the intentions of the operator do not apply; for example, this would be the case if the operator had no knowledge of u.

If we substitute $x = (u, v, w)$ into Equation (1), and then eliminate the variable w by summing over it, we obtain an equation of the form

$$P'(u, v, y) = f_1(v, y) \, P(u, v) / K \tag{3}$$

The dependence of v on y in this model can be seen by examining the expected value of v, given y. This expectation value is

$$E(v \mid y) = \int \int v P'(u, v, y) \, dudv / \int \int P'(u, v, y) \, dudv \tag{4}$$

and we can similarly define $E(u \mid y)$, the expected value of u, given y.

The model is designed so that $E(v|y)$ varies as the intention, y, varies. But what does the model say about how the variable, u, varies as y varies? We can readily calculate this if we assume that the distribution, $P(u,v)$, for u and v is a bivariate normal distribution with means, m_u, m_v, standard deviations, s_u, s_v, and correlation coefficient, r. Given this assumption, we find that,

$$[E(u|y) - m_u]/s_u = r[E(v|y) - m_v]/s_v \qquad (5)$$

The distribution, $P(u,v)$, depends on the physics of the RMC. This equation tells us that if u and v are not strongly correlated in $P(u,v)$, then $E(u|y)$ will vary only weakly as the intention, y, is varied. This makes sense because u is not directly linked to the intention, y. It is linked with y only indirectly through $f_1(v,y)$ and $P(u,v)$.

We will show in the next section that we can find an RMC variable, u, for which $P(u,v)$ is approximated by a bivariate normal distribution with a small r, but for which $E(u|y)$ does vary strongly with y, in violation of Equation (5). Indeed, even though r is positive, $E(u|y)$ and $E(v|y)$ vary in opposite directions as y varies. This implies that the RMC data reported by Nelson et al.,[1] cannot be realistically modelled by a selection theory, and in particular, it cannot be modelled by theories (1) through (3), above.

3. ANALYSIS OF THE DATA

The information describing an RMC run is given by 19 bin numbers, $b(1),\ldots,b(19)$, indicating the number of balls that fall in each of the 19 bins. As we mentioned in the introduction, this sequence of 19 numbers is called the bin distribution for the run. The bin mean is simply the expected value of i for the distribution, $b(i)$, $i = 1,\ldots,19$. We wanted to find additional variables that (1) are functions of the 19 bin numbers, (2) are physically meaningful, and (3) are nearly statistically independent of the bin mean and of one another. Our objective in defining such variables was to find candidates for the u of Equation (5).

The distribution of balls in the bins can be approximated by a *Gaussian*. In Nelson *et. al*[7] it is observed that the bin distribution tends to deviate from a *Gaussian* in the center due to the tendency of some balls to fall straight down for some distance

without striking pins, and at the sides due to bouncing of the balls from the sides of the machine. The deviation in the center takes the form of a second, narrower *Gaussian* superimposed on the main bin distribution *Gaussian*. The bouncing of the balls from the sides contributes an additional U-shaped curve that is superimposed on these two *Gaussians*. Thus, the bin distribution can be broken down into the sum of these three curves, each of which can be explained in terms of the physics of the RMC.

Let $Dist(1),\ldots,Dist(19)$ stand for the bin distribution for a given run. We tried to break down *Dist* into the three components just mentioned. The first of these is *Gauss*1, an approximation to *Dist* by a *Gaussian*. This was obtained by fitting a quadratic to log $[Dist(3)],\ldots,$log $[Dist(7)]$, log $[Dist(13)],\ldots,$log $[Dist(17)]$ by least squares, and then expressing *Gauss* 1 as the exponential of that quadratic. In the least squares fit, we avoided the bins in the middle and on the ends since for these bins, *Dist* tends to deviate from a *Gaussian*.

The next step is to scale *Gauss*1 so that its total, *Gauss*1 $(1)+\ldots+$*Gauss*1 (19), is maximal, given that

$$Dist\,2\,(i) = Dist\,(i) - Gauss1(i) \geq 0 \qquad (6)$$

for $i = 1,\ldots,19$. When we do this we find that *Dist* 2 has the shape of a *Gaussian*, but is narrower than *Gauss* 1. We therefore define the second component as *Gauss*2, a *Gaussian* approximation to *Dist* 2. This *Gaussian* is defined to have the same mean and standard deviation as *Dist* 2 on bins 3-17 (avoiding the non-*Gaussian* behavior on the sides), and it is scaled so that its root-mean-square difference from *Dist*2 is minimal.

The total of *Gauss* 1 cannot exceed 9000, the total number of balls per run, and it generally is about 7700. The total for *Gauss* 2 is generally somewhat over 1000. The third component, called *Rem* (for remnant), is defined by

$$Rem\,(i) = Dist\,2\,(i) - Gauss2\,(i) \qquad (7)$$

for $i = 1,\ldots,19$. We note that *Rem* (i) may take on negative values.

Figure 1 illustrates the breakdown of *Dist* into *Gauss* 1, *Gauss* 2, and *Rem* in a particular case. It is interesting to note that *Rem* has a remarkably consistent form.
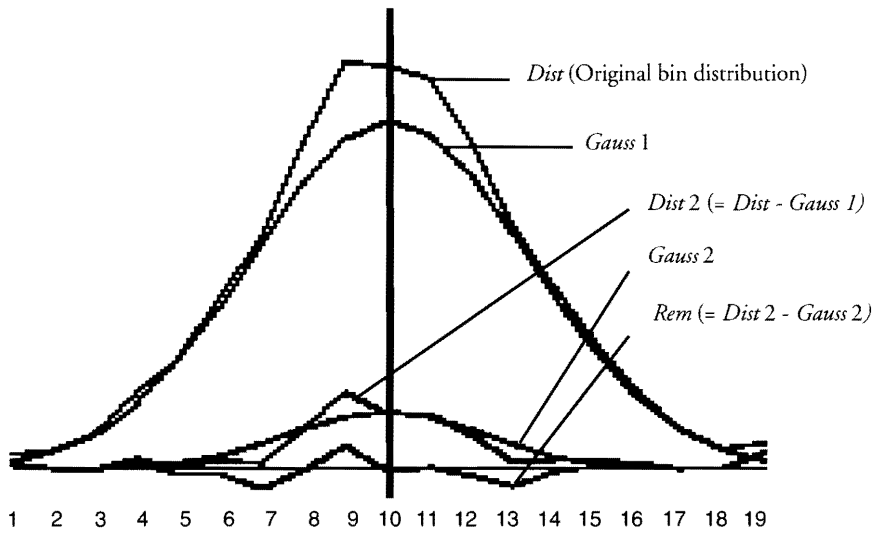
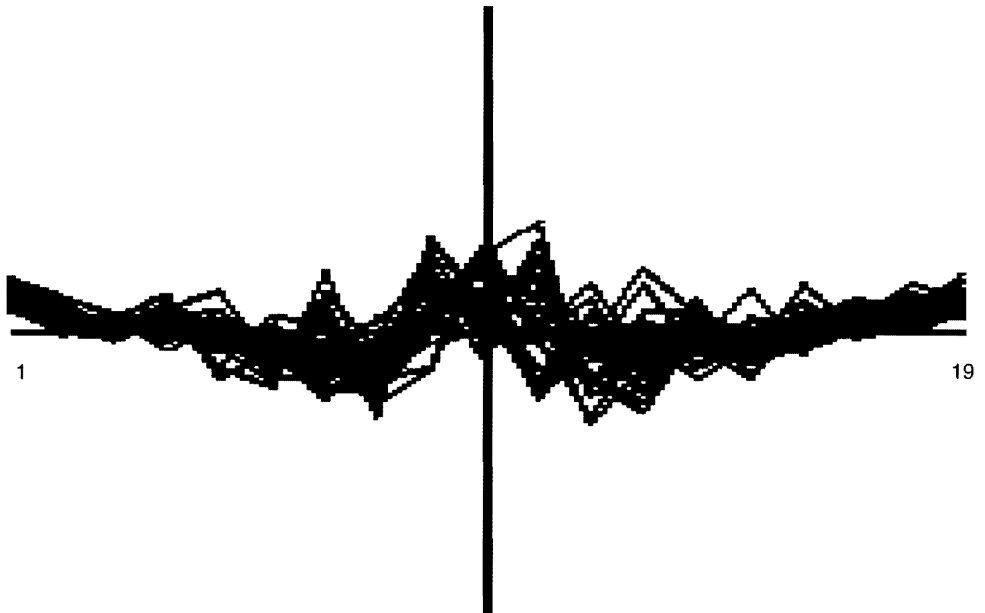Figure 1. Breakdown of bin distribution into component curves.

Legend (from top to bottom):
- *Dist* (Original bin distribution)
- *Gauss* 1
- *Dist* 2 (= *Dist* - *Gauss* 1)
- *Gauss* 2
- *Rem* (= *Dist* 2 - *Gauss* 2)

Figure 2. Superposition of 30 examples of Rem (= Dist - Gauss1 - Gauss2).

Table I

A set of 14 bin distribution variables,
based on *Dist*, *Gauss*1, *Gauss*2, and *Rem*.

Vble.	Mean	S.D.	Description
V1	10.0082	.2449	Mean of *Dist-Gauss* 1
V2	10.0341	.0774	Mean of *Dist* restricted to bins 3-7,13-17
V3	115.9227	11.8348	*Dist* (18) + *Dist* (19)
V4	10.0178	.0382	Mean of *Dist*
V5	10.0194	.0528	Mean of *Gauss* 1
V6	10.0480	.2120	Mean of *Gauss* 2
V7	3.2750	.0383	S.D. of *Dist*
V8	38.3002	12.2195	*Rem* (18) + *Rem* (19)
V9	3.3052	.0684	S.D. of *Gauss* 1
V10	2.6706	.2378	S.D. of *Gauss* 2
V11	7774.6040	443.9916	Total of *Gauss* 1
V12	1157.4250	447.0527	Total of *Gauss* 2
V13	67.9623	27.9438	Total of *Rem*
V14	42.3580	12.3441	*Rem* (1) + *Rem* (2)

Figure 2 shows the superposition of *Rem* curves obtained from 30 different bin distributions. The elevation at the sides is presumably due to reflection of balls from the side walls, and the other characteristics must be due to asymmetries in the structure of the machine.

For each run, we can compute a number of standard parameters for the distributions, *Dist*, *Gauss* 1, and *Gauss* 2, including their totals, means, and standard deviations. We can also compute such quantities as *Rem* (1) + *Rem* (2) and *Rem* (18) + *Rem* (19), which indicate the behavior of the bouncing balls near the sides of the RMC.

Table II
Statistical correlations over the total data set for variables $v1,\ldots,v14$.
The total data set contains 4530 bin distributions.

	2	3	4	5	6	7	8	9	10	11	12	13	14
1	-.11	.29	.18	-.46	.85	-.04	.38	-.02	-.01	-.04	.04	.01	-.33
2		.05	.89	.85	.00	-.08	-.13	-.01	-.09	-.01	.02	-.04	.18
3			.28	.03	.01	.53	.82	.22	-.11	.04	-.06	.27	.05
4				.74	.12	-.10	.12	-.03	-.08	-.04	.04	-.04	-.08
5					-.42	-.07	-.17	-.01	-.07	.00	.00	-.05	.17
6						.00	.08	-.04	.00	.03	-.03	.02	.00
7							.10	.59	.12	.04	-.05	.16	.17
8								-.28	.05	.09	-.12	.52	.14
9									-.41	-.45	.48	-.55	-.26
10										.03	-.08	.68	.03
11											-1.00	.09	.18
12												-.15	-.21
13													.49

Table I gives a list of 14 of these quantities, called $v1,\ldots,v14$, along with their means and standard deviations over our entire set of RMC data, which consists of 4530 (= 3 × 1510) runs. Table II lists the correlation coefficients for pairs of the variables $v1,\ldots,v14$. These are also computed using the entire data set.

We wanted to study a set of bin distribution variables that have as little statistical correlation as possible, but are also physically meaningful. One way of doing this is to eliminate strongly correlated variables from the set $v1,\ldots,v14$ until a set of nearly uncorrelated variables remains. Table III shows the result of doing this.

Table III
A subset of the variables $v1,\ldots,v14$ which are nearly
statistically independent of one another.

		6	7	8	10	11	14
4	Mean of *Dist*	.12	-.10	.12	-.08	-.04	-.08
6	Mean of *Gauss* 2		.00	.08	.00	.03	.00
7	S.D. of *Dist*			.10	.12	.04	.17
8	*Rem* (18) + *Rem* (19)				.05	.09	.14
10	S.D. of *Gauss* 2					.03	.03
11	Total of *Gauss* 1						.18
14	*Rem* (1) + *Rem* (2)						

In the set of variables of Table III, $v4$ is the bin mean, which the RMC operators tried to directly influence. The other 6 variables were presumably not the object of operator or experimenter intentions, and they would be hard for the operator to recognize by observing the machine. Our question is: Do these other variables display behavior significantly correlated with operator intention? A selection theory would imply they should not do this, but it turns out that some of them do.

In Table IV we list the results of an analysis similar to that reported in Tables I.A-C in Nelson *et. al.*[1] Their table was computed for a 1131 run subset of the total data set, generated by 25 out of the 35 operators. These comprise all the runs in the total data set in which a single operator observed the RMC machine in operation, in the same room. (Other runs involved multiple operators, or an operator trying to influence the machine at a remote location or at a time before or after the time of the run.) In our analysis we also made use of this 1131 run subset.

For each tripolar set of runs, the differences $v4\,(i,LT) - v4\,(i,BL)$, $v4\,(i,RT) - v4\,(i,BL)$, and $v4\,(i,RT) - v4\,(i,LT)$ were computed, where $v4\,(i,LT)$, $v4\,(i,BL)$, and $v4\,(i,RT)$ are the bin means obtained under leftward,

Table IV

Comparison between the behavior of the bin mean, $v4$, and variables $v5$, $v6$, $v7$, $v8$, $v10$, $v11$, $v14$, $v15$, and $v16$ for 1131 runs generated by 25 operators.

Vble	Intent	Mean	S.D.	t-score	Prob.	Correlation
4	LT-BL	-.00564	.05005	-3.7870	.76E-04	
4	RT-BL	.00007	.05008	.0472	.48E+00	
4	RT-LT	.00571	.04931	3.8913	.50E-04	
5	LT-BL	-.00789	.07090	-3.7420	.91E-04	.70955
5	RT-BL	.00001	.06938	.0065	.50E+00	.72223
5	RT-LT	.00790	.06927	3.8364	.62E-04	.71710
6	LT-BL	.01124	.29531	1.2799	.10E+00	.09233
6	RT-BL	.00373	.29996	.4178	.34E+00	.12404
6	RT-LT	-.00751	.29278	-.8629	.19E+00	.12407
7	LT-BL	.00321	.03500	3.0875	.10E-02	-.04128
7	RT-BL	.00085	.03578	.8003	.21E+00	-.03315
7	RT-LT	-.00236	.03630	-2.1881	.14E-01	.01918
8	LT-BL	.70664	17.63451	1.3476	.89E-01	.16174
8	RT-BL	-.59116	17.25134	-1.1524	.12E+00	.08853
8	RT-LT	-1.29780	16.99774	-2.5677	.51E-02	.12033
10	LT-BL	-.00397	.30761	-.4343	.33E+00	.00937
10	RT-BL	-.01122	.31699	-1.1900	.12E+00	.02250
10	RT-LT	-.00724	.31543	-.7724	.22E+00	-.00912
11	LT-BL	-18.69107	630.79480	-.9965	.16E+00	.01230
11	RT-BL	-4.65074	632.71381	-.2472	.40E+00	.00503
11	RT-LT	14.03979	627.16571	.7529	.23E+00	.03185
14	LT-BL	1.02498	16.41335	2.1001	.18E-01	-.10295
14	RT-BL	-.10467	16.80345	-.2095	.42E+00	-.10887
14	RT-LT	-1.12965	17.39774	-2.1836	.14E-01	-.07294
15	LT-BL	.33160	3.08571	3.6140	.15E-03	.05171
15	RT-BL	.03976	3.08411	.4336	.33E+00	.02832
15	RT-LT	-.29184	3.08992	-3.1764	.75E-03	.07167
16	LT-BL	.27337	2.82734	3.2517	.57E-03	.06682
16	RT-BL	-.01755	2.87298	-.2055	.42E+00	.04326
16	RT-LT	-.29093	2.88306	-3.3936	.34E-03	.08805

baseline, and rightward intentions for the ith tripolar set. (Here $i = 1, \ldots, 1131$.) The means and standard deviations for these three differences were computed for the 1131 cases, and these were used to compute corresponding t-scores and probabilities. The probabilities indicate how likely it is that the means of the differences would be displaced by chance from 0 to their observed values. The main point made by Jahn and his colleagues is that these probabilities turn out to be unexpectedly low.

We performed the same computations for each of the remaining 6 variables of Table III, plus the additional variable, $v5$. For example, for variable $v14$ the computations were done for the differences, $v14 (i, LT) - v14 (i, BL)$, $v14 (i, RT) - v14 (i, BL)$, and $v14 (i, RT) - v14 (i, LT)$. Table IV enables us to compare the probabilities computed for each of these 7 variables (namely, $v5$, $v6$, $v7$, $v8$, $v10$, $v11$, and $v14$) with the probabilities computed for the bin mean, $v4$. In the table, the three differences are indicated for each variable by the symbols LT-BL (left minus baseline), RT-BL (right minus baseline), and RT-LT (right minus left). The t-scores are written with a minus sign if the corresponding quantity had a negative displacement. The correlation coefficients between the difference pairs for each of the 7 variables and the difference pairs for $v4$ are also indicated.

It is natural for the displacement probabilities for variables $v4$ and $v5$ to be similar, since these variables have a correlation of about .71 for each of the three differences. Thus $v4$ has probabilities of .000076 and .00005 for LT-BL and RT-LT, and $v5$ has similar probabilities for these differences. These small probabilities represent the main anomalous effect. However, if we look at variables $v6$, $v7$, $v8$, $v10$, $v11$, and $v14$, we can see that they also tend to have moderately low probabilities for LT-BL and RT-LT, even though they have very small correlations with $v4$.

One should ask whether or not this might be statistically significant. The answer is that, individually, the displacements of these variables are not highly significant, but they *are* highly significant when taken together as a group. Since the variables tend to be mutually uncorrelated, this can be shown by summing them up and examining the displacement of the sum.

With this aim in mind, the calculations of Table IV were also performed for two composite variables:

$$v\,15 = Z(v\,6) + Z(v\,7) + Z(v\,8) - Z(v\,10) - Z(v\,11) + Z(v\,14) \quad (8)$$

and

$$v\,16 = Z(v\,6) + Z(v\,7) + Z(v\,8) + Z(v\,14) \quad\quad\quad (9)$$

where Z(variable) is that variable shifted so as to have mean 0 and scaled so as to have a standard deviation of 1 over the 1510 tripolar sets. The transformation Z was applied so as to make the magnitudes of the variables comparable, and thereby prevent the high magnitude variables in the sum from overshadowing the contributions of the low magnitude variables. In $v\,15$ the variables $v\,10$ and $v\,11$ were given a minus sign due to the fact that they vary in a direction opposite to that of variables $v\,6$, $v\,7$, $v\,8$, and $v\,14$. (This can be seen by examining Table IV.)

The same computations were performed for $v\,15$ and $v\,16$ that were performed for $v\,4$, $v\,5$, $v\,6$, $v\,7$, $v\,8$, $v\,10$, $v\,11$, and $v\,14$, and the results are listed in Table IV. These results indicate that the mild effects noted for the constituent variables of $v\,15$ and $v\,16$ do seem to add up. We see from the table that $v\,15$ has probabilities of .00015 and .00075 for LT-BL and RT-LT, and $v16$ has corresponding probabilities of .00057 and .00034. These probabilities indicate that the group behavior of the variables making up $v15$ and $v16$ is significantly different from what would be expected by chance.

Here the objection could be raised that perhaps we have tried our analysis with many different variables, and have presented the results for $v15$ and $v16$ because they turned out to give us low probability values. These values would then be of no real significance, because one can always find a spurious effect that looks significant if one juggles the data sufficiently.

The answer to this objection is that we did not do this. The variables in Table I were selected initially on the basis of our understanding of the RMC, and no other variables of this type have been considered. The subset of these 14 variables listed in Table III was chosen solely on the basis of the correlation coefficients listed in Table II, the object being to find a subset of $v\,1,\ldots,v\,14$ with mutual correlations of the smallest possible magnitudes.

We can see from Table IV that all 6 of the variables of Table III show a noticeable tendency towards systematic drift in the cases LT-BL and RT-LT. The two sums,

$v\,15$ and $v\,16$, show that these tendencies, taken together, are statistically significant. The composite variables $v\,15$ and $v\,16$ are the only ones considered; they were not chosen from a larger set of composite variables.

We also performed the calculations of Table IV for the full collection of 1510 tripolar sets of runs. In this case it turned out that $v\,15$ has probabilities of .0079 and .0081 for $LT\text{-}BL$ and $RT\text{-}LT$, and $v\,16$ has probabilities of .024 and .0034. In general, one tends to obtain lower probabilities for the 1131 case subset than for the full data set of 1510 cases. What is happening here is that anomalous effects are much weaker in the part of the data set involving either multiple operators or operators who could not see the RMC in operation.

We note that the correlation coefficient of $v\,4$ and $v\,15$ is .073 (over the entire data set), and that of $v\,4$ and $v\,16$ is .028. The correlation coefficients between the difference pairs for $v\,15$ and $v\,16$ and the corresponding difference pairs for $v\,4$ are listed in Table IV, and also lie between 0 and .1. (Recall that the difference pairs are $v\,15\,(\,i\,,LT\,) - v\,15\,(\,i\,,BL\,)$, and so on.) Although these correlation coefficients are small, they are significantly different from 0 in the positive direction. This can be seen by applying the formula,

$$t = r\,[\,(\,N-2\,)\,/\,(\,1-r^{\,2}\,)\,]^{1/2} \tag{10}$$

where N is the number of cases (1510 for the whole data set and 1131 for the subset), r is the correlation coefficient, and t is interpreted as a t value.[8] For the correlation coefficients in question we obtain t values ranging from 1.09 to 2.97.

The improbable displacements of $v\,15$ and $v\,16$ cannot be accounted for by the hypothesis that $v\,15$ and $v\,16$ shift in correlation with the shift in $v\,4$. In fact, the displacements of $v\,15$ and $v\,16$ for $LT\text{-}BL$ and $RT\text{-}LT$ go in the direction opposite to the corresponding displacements of $v\,4$, even though $v\,15$ and $v\,16$ are positively correlated with $v\,4$. These displacements constitute an anomalous effect that is independent of the original anomalous effect reported by Jahn and his colleagues. Moreover, this effect is due to the behavior of variables (the constituents of $v\,15$ and $v\,16$) which could not be observed by the operators, and were not the objects of operator intentions.

We have examined the 4530 pairs, $(v4, v15)$, and we find that their distribution can be approximated by a bivariate normal distribution. The same is true of the pairs, $(v4, v16)$. This means that Equation (5) should apply with $v = v4$ and $u = v15$ or $v16$. This equation implies, for example, that

$$[E(v15 \mid LT) - E(v15 \mid BL)] / s_{v15} = r[E(v4 \mid LT) - E(v4 \mid BL)] / s_{v4} \quad (11)$$

where r lies between 0 and .1. But this is contradicted by the actual behavior of $v15$, which shifts strongly in the positive direction in this case, even though $v4$ shifts strongly in the negative direction.

In addition to the calculations presented in Table IV, we produced graphs showing the behavior of the 10 variables, $v4, \ldots, v16$. For these graphs we adopted the following procedure. First, the variables were all scaled so as to have mean 0 and standard deviation 1. That is, we replaced vk by $Z(vk)$ for each of the variables. We then formed all of the pairs, $(v4, vk)$, for $k = 5,6,7,8,10,11,14,15,16$. For the pair, $(v4, vk)$, define the two dimensional random variable (X_{2n-1}, Y_{2n-1}) to be $(v4, vk)$, computed for the nth tripolar set with leftward intention. Similarly, define (X_{2n}, Y_{2n}) to be $(-v4, -vk)$, computed for the nth tripolar set with baseline intention. We plotted the random walk generated by steps of (X_n, Y_n) for $n = 1, \ldots 2 \times 1510$.

We will let (S_n, T_n) represent the random walk generated by steps of (X_n, Y_n). Thus, $S_0 = T_0 = 0$ and

$$(S_n, T_n) = (X_n, Y_n) + (S_{n-1}, T_{n-1}) \quad (12)$$

For each tripolar set of runs, this random walk takes one step of $(v4, vk)$ for the run of intention, LT, and one oppositely directed step of $(-v4, -vk)$ for the run of intention, BL. This gives us an idea of the comparative behavior of $v4$ and vk in the case LT-BL. Similar random walks were plotted for the cases RT-BL and RT-LT. We also plotted these random walks for the subset of 1131 tripolar sets in which a single operator was watching the RMC, for the subset of tripolar sets generated by operator 10, and for the subset in which operator 10 was watching the RMC.

For a given angle, ϕ, the random walk can be projected onto the line through the origin at angle ϕ. This projected random walk is

$$U_n = \cos(\phi) S_n + \sin(\phi) T_n \quad (13)$$

The standard deviation of U_n is $[n(1 + \sin(2\phi)\,r)]^{.1/2}$, where r is the correlation coefficient for X_n and Y_n. If we assume that $v4$ and vk keep the same statistical properties for tripolar sets in the interval from $n = 1$ to 2×1510, and that operator intention is irrelevant to their behavior, then r is the correlation coefficient between $v4$ and vk, as estimated in Table III. (This table should be supplemented with values for r of .073, .028, .814 for $(v4, v15)$, $(v4, v16)$, and $(v15, v16)$, respectively.) Although there is some change in the statistical properties of the vk's with the passage of time (represented by n), the curve,

$$R = 2[N(1 + \sin(2\phi)\,r)]^{1/2} \tag{14}$$

provides a two standard deviation limit that can be used to evaluate the behavior of (S_n, T_n) for $n = 1, \ldots, N$.

Figures 3 (a-e), 4, and 5 (a-c) show some of the plots of these random walks, along with their estimated two standard deviation limits. In each graph, S_n is plotted along the x-axis and T_n is plotted on the y-axis. Figure 3 (a) shows the behavior of $v4$ and $v16$ for the subset of the 1510 tripolar sets generated by operator 10, the most successful operator in the RMC experiments. This figure shows the case of *LT-BL*, or left minus baseline. In this figure we see that the random walk moves to the left and up in nearly a straight line. The leftward movement is the anomalous displacement of the bin mean, $v4$, and the upward movement is the anomalous displacement of $v16$. Figures 3(b-e) show the corresponding behavior of $v4$ and vk, where $k = 6$, 7, 8, and 14. These are the variables that sum up to form $v16$ (see Equation 9).

Figure 3 (a) should be compared with Figure 4, which shows the $(v4, v16)$ random walk in the case of *LT-BL* for the subset of runs in which operator 10 watched the RMC in action. We note that the random walk in Figure 4 moves further out from the two standard deviation limit than does the random walk in Figure 3 (a); this is due to the fact that the anomalous effects seem to occur predominantly in the runs involving a single operator who is able to observe the RMC.

Figures 5 (a-c) show the behavior of $v4$ and $v16$ for all 1510 tripolar sets. In this figure, parts (a), (b), and (c) are for the respective cases of *LT-BL*, *RT-BL*, and *RT-LT*. Figure 5 (b) shows that in the *RT-BL* case, $v4$ barely moves from the origin, while $v16$ shows considerable activity. This rather puzzling non-random behavior occurs in the *RT-BL* cases for practically all of the variables.
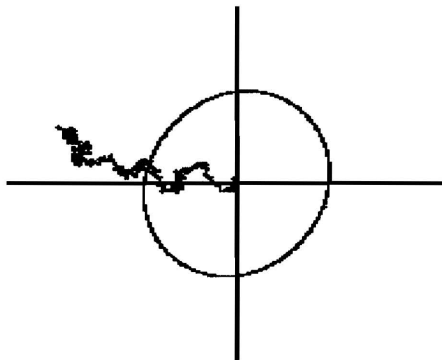
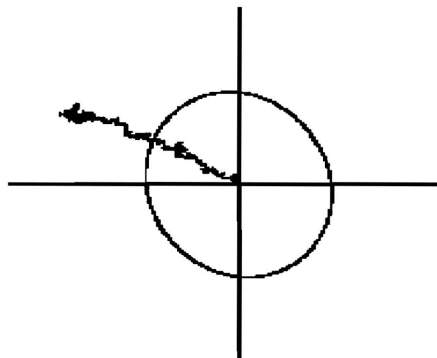**Figure 3(a).** *Operator 10, left-baseline. Parameters (4,6) are the (x,y) axes.*

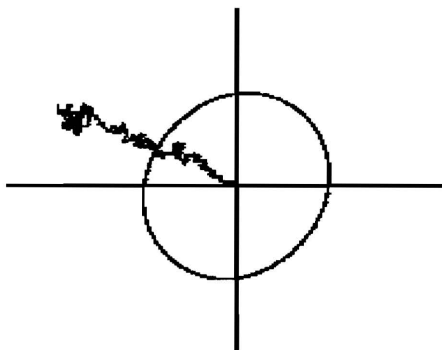**Figure 3(b).** *Operator 10, left-baseline. Parameters (4,7) are the (x,y) axes.*

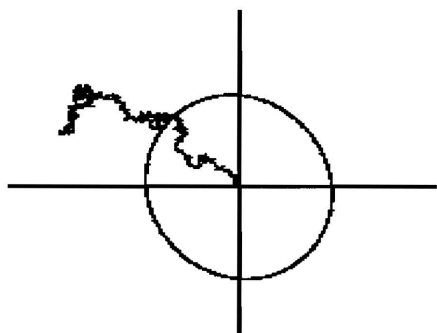**Figure 3(c).** *Operator 10, left-baseline. Parameters (4,8) are the (x,y) axes.*

Figure 3(d). *Operator 10, left-baseline. Parameters (4,14) are the (x,y) axes.*
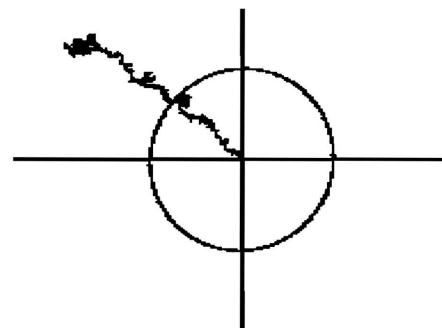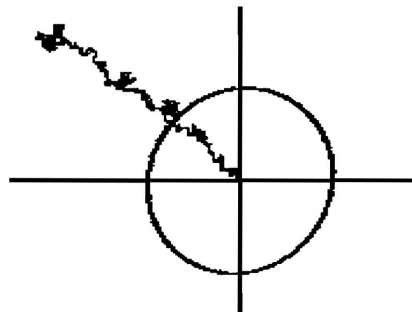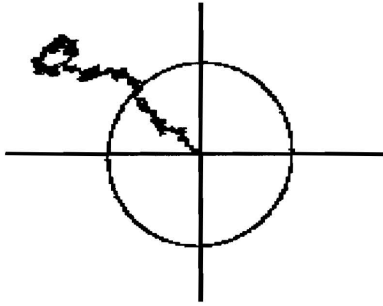

Figure 3(e). *Operator 10, left-baseline. Parameters (4,16) are the (x,y) axes.*

Figure 4. *Operator 10, left-baseline. Parameters (4,16) are the (x,y) axes. Case of 1131 runs.*

To test whether or not the apparent non-randomness of these random walks is illusory, we performed a number of probabilistic experiments using the RMC data. The results of the first of these experiments are summed up in Figure 6. There we have superimposed 100 random walks which are generated in nearly the same way as the random walks in the case of $v4$ vs. $v16$ for all tripolar sets. The only difference is that in each tripolar set, the + ($v4$, $v16$) and - ($v4$, $v16$) steps of the random walk are chosen at random from the three runs in that set, instead of being chosen on the basis of intention. The random choices were made using a pseudo-random number generator. The idea here is to create random walks that are identical to the random walks of Figures 5 (a-c), with the exception that information concerning operator intentions is erased by random scrambling. Figure 6 shows that these random walks show no particular tendency for systematic drift, apart from a slight tilt with positive slope which may be due to the small positive correlation between $v4$ and $v16$. Thus, all of the anomalous effects in Figures 5 (a-c) seem to depend on the information regarding operator intentions.

The results of the second experiment are shown in Figure 7. This experiment is the same as the first, with one exception: In the random walks, if a step is positive in $v4$, then it is rejected with a certain probability; if it is negative then it is always accepted. This rule has the effect of imposing an artificial bias against movement in the positive $v4$ direction (the positive x-axis in the plots). This is exactly the kind of bias we would postulate in the "data selection" theory described in the previous section. If that theory is correct, then these random walks should be similar to the one plotted in Figure 5(a).

We can see from Figure 7 that, with a couple of exceptions, there is no tendency for the random walks generated in this way to mimic Figure 5(a), the real random walk for variables $v4$ and $v16$ and intentions *LT-BL*. The artificially generated random walks do show a tendency to drift systematically to the left, but instead of also drifting in the positive y direction, they exhibit, if anything, the opposite tendency.

We also considered the following hypothesis: Suppose that there is a variable w that is weakly correlated with both $v4$ and $v16$. Perhaps the joint displacements of $v4$ and $v16$ can be explained as a result of selection applied to w. To investigate this hypothesis properly, one would have to consider many different candidates for w. We investigated only two possible w's, and it turned out that neither one could account for the observed displacements of $v4$ and $v16$.

Figure 5(a). All operators, left-baseline. Parameters (4,16) are the (x,y) axes.
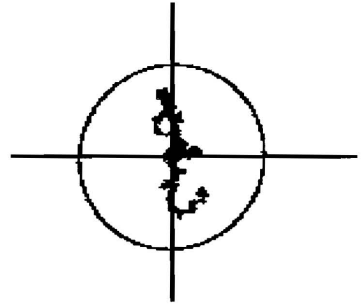
Figure 5(b). All operators, right-baseline. Parameters (4,16) are the (x,y) axes.
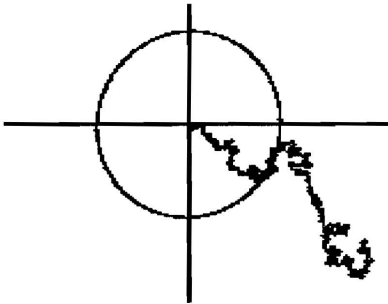
Figure 5(c). All operators, right-left. Parameters (4,16) are the (x,y) axes.

Figure 6. Superposition of 100 RMC random walks with randomized intention. Parameters (4,16) are the (x,y) axes.
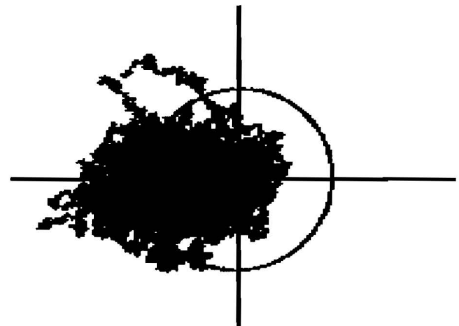

Figure 7. Superposition of 100 RMC random walks with randomized intention and artificial selection of parameter 4 low (i.e. to the left). Parameters (4,16) are the (x,y) axes.

4. CONCLUSION

The basic conclusion that emerges from this study is that in addition to the original anomalies reported by Jahn and his colleagues, the statistical behavior of the bin distributions seems to display systematic patterns that correlate with human intentions, but are not related in an obvious way to the conscious content of those intentions. Thus, the data show a systematic shift in $v4$, the bin mean, but they also show shifts in $v15$, and $v16$. These, in turn, are due to the summing up of shifts in the constituent variables of $v15$ and $v16$, namely $v6$, $v7$, $v8$, $v10$, $v11$, and $v14$ (see Table I). The shifts in $v15$ and $v16$ are somewhat less improbable than the shift in the bin mean, but they are nonetheless statistically significant. This is especially true for the set of 1131 runs in which a single operator was present during the running of the RMC (see Table IV).

The shifts in $v15$, $v16$ cannot be accounted for by inter-variable correlations with the bin mean that could be due to the physical characteristics of the RMC device. The reason for this is that we can calculate the correlations between $v4$ and these two variables over the whole data set, without taking operator intentions into account. When this is done, it is found that the resulting correlations go in the wrong direction to account for the observed shifts in $v15$ and $v16$.

These findings tend to rule out a class of theories, called selection theories, which might be invoked to explain the anomalies in the RMC data. In particular, they tend to rule out the possibility that the main anomalous effect in the bin mean was obtained by conscious or unconscious data selection by the experimenters. Certainly a drift in $v4$ in a given direction can be obtained by systematically throwing out a certain percentage of the runs which do not tend in that direction. However, as we have seen, such editing of the data will not generate the additional shifts that we have observed in certain other variables, and it seems unlikely that these variables could have been the object of additional data selection by the experimenters.

Theoretical calculations suggest that it would be difficult for the experimenters to generate the observed anomalous effects by exerting small, normal forces on the RMC (of the kind that could be produced by a human body at a distance from the machine). Forces of the strength that could be produced by an observer watching the RMC *could* influence the RMC in accordance with the observer's intention, if

these forces could be generated with very precisely specified magnitudes. But to do this, it would be necessary for the observer to somehow unconsciously determine what these magnitudes should be—a task which would be difficult to carry out even with a supercomputer and an accurate mathematical model of the RMC.

What we are left with is the conclusion that some unknown agency affects the behavior of the RMC in accordance with conscious intentions of the operators. This agency not only affects the bin mean, which is the object of the operators' intentions, but it also strongly affects other aspects of RMC behavior which would be expected to vary almost independently of this variable. To learn more about what is happening here, we would recommend future experiments in which many different aspects of a physical process are monitored, while efforts are being made to influence particular features of that process. Such experiments would reveal whether or not the phenomena we have observed here generally occur, and they may give further insight into the causes of these phenomena.

CORRESPONDENCE: Richard Thompson, Ph.D. • Bhaktivedanta Institute • 1136 Grand Avenue • San Diego, CA 92109

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