

# ENVIRONMENTAL MODULATION AND STATISTICAL EQUILIBRIUM IN MIND-MATTER INTERACTION

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## ABSTRACT

Mind-matter interactions observed in laboratory experiments typically manifest as minute statistical fluctuations from chance expectation. Meta-analyses suggest that these small fluctuations reflect genuine, direct interactions between mind and matter, but lack of predictability of the effect has made systematic study of the phenomenon difficult.

Two general factors that may contribute to erratic laboratory outcomes are (a) unavoidable environmental fluctuations and (b) a physical principle that tends to counterbalance mind-matter effects in time and space. Environment is used in the holistic sense, including cosmic, global, local, and personal variables. The physical principle is envisioned as a tendency for perturbations introduced into a system to be statistically balanced by opposing perturbations so as to maintain an overall condition of equilibrium.

A longitudinal experiment with the experimenter as subject was designed to explore the possible influences of these two factors in mind-matter interaction. The results found strong indicators of environmental modulation, including a successful demonstration that a neural network could learn to predict mind-matter interaction performance based upon eight environmental variables. Evidence for a time- and space-like equilibrium principle was also observed in the data.

**KEYWORDS:** Environmental, mind-matter, neural, physical

# INTRODUCTION

## THE PROBLEM OF PREDICTION

**M**eta-analyses of experiments on mind-matter interaction (MMI) involving random number generators (RNG) and other random physical systems provide strong evidence that (a) MMI effects are genuine and (b) they manifest as small perturbations from chance expectation statistics.<sup>1-3</sup>

MMI is genuine in the sense that the cumulative database shows effects that are statistically unequivocal, replicable by different experimenters, and not due to methodological artifacts or selective reporting practices. MMI is small and stochastic in that the effects typically deviate from chance expectation by only a few percent, and experimental outcomes seem to inexplicably change from one experimental session to the next.

Despite the fact that the cumulative database shows that MMI experiments are replicable, in any given experiment it is still nearly impossible to predict the outcome. Lack of predictability in experiments is sometimes caused by insufficient statistical power.<sup>4,5</sup> However, the situation for MMI appears to be more complex because an experiment involving one hundred trials seems to produce about the same statistical result as one million trials.<sup>6</sup> MMI effects apparently do not manifest at the level of the individual *trial*, but at the level of the *experiment*. This curious hint of a teleological principle has led some researchers to label the MMI effect as “goal-directed.”<sup>7</sup>

## ENVIRONMENT AND MIND-MATTER INTERACTION

Lack of experimental predictability may also be caused by limitations imposed by methodological or theoretical assumptions. For example, the vast majority of RNG experiments have focused on three general factors: psychological, physiological, and physical. *Psychological factors* include such things as examining different cognitive strategies and personality traits.<sup>8-12</sup> *Physiological factors* include such things as monitoring heart rate and electrodermal response.<sup>13-16</sup> *Physical factors* include fluctuations in the planetary geomagnetic field, local magnetic field, and sunspot number,<sup>16-19</sup> as well as the effects of distance and different physical systems on MMI performance.<sup>20</sup>

While these are all interesting theoretical and methodological topics, there has been a comparative lack of attention placed on how these factors interact with each other, and with many basic environmental variables such as barometric pressure, humidity, and temperature. To my knowledge, the effects of many more exotic geophysical variables, such as the intensity of solar flux or conditions in the ionosphere, have never been examined in MMI experiments.

In the present study, I consider the possibility that a complex assemblage of cosmic, global, local, and personal variables—some rarely monitored in parapsychological studies—conspire to modulate MMI effects. This “invisible modulation” is postulated to accommodate a fair percentage of the unexplained variance in experimental data, possibly so much variance that without taking these variables into account, experimental outcomes seem to be unpredictable.

The term *modulate* is used to suggest a causal rather than a mere correlational relationship; it seems unlikely that performance on an MMI task would affect, say, the global geomagnetic field or the number of sunspots. Instead, it seems more likely that environmental factors affect human psychophysical performance on many different levels, including mind-matter interaction.

## STATISTICAL ORDER AND MIND-MATTER INTERACTION

In addressing the “goal-oriented” nature of MMI RNG experiments, May, *et al* observed that the effect size in individual MMI experiments decreases almost exactly in proportion to the square root of the number of trials.<sup>6</sup> One implication is that MMI effects are better accounted for by an information organization or non-local correlation principle rather than the usual sort of causal, physical-type force. In other words, the cumulative database suggests that when physical target systems are subjected to MMI, they do not behave in physically unexpected ways, but rather their natural stochastic behavior is reorganized by some unknown means.<sup>21</sup>

Thus, MMI effects may be thought of as the creation of localized regions where random noise has been momentarily organized, i.e. as a paradoxical non-local production of local negentropy.<sup>9,10,22-24</sup> The term “local” refers to the idea that the statistical organization occurs only in the immediate vicinity of the

physical target, and only for a short time. The term “non-local” refers to the idea that the cause of the reorganization is not local to the target; that is, the cause is presumably related to a remote person’s mental intention. The term “negentropy” refers to the idea that local randomness has been momentarily decreased, or equivalently that local order at the target area has increased.

## PRERECORDED DATA

**S**ome studies have been reported in which random targets were successfully influenced using data that was recorded *before* the mental intention was applied.<sup>7,20</sup> The implication is that MMI effects may be time-independent, or perhaps time-reversible.

To help focus and simplify the following discussions and results, the results of the prerecorded data condition will be reported in detail in another paper.

## METHOD

The present experiment was conceived (a) as an extension of a previous study that used background ionizing radiation as the MMI “target,” (b) as a conceptual replication of a systems theoretic-inspired experiment by von Lucadou, and (c) as exploratory, both in terms of design and analysis.<sup>9,10,16,25</sup>

This last point requires some explanation. After 40 years of experiments, the existing database provides substantial evidence for the reality of genuine MMI effects. There are two general approaches one can take to increase our understanding of the phenomenon. One way is by methodically carrying out carefully pre-planned, hypothesis-testing studies, along the lines of the usual proof- and process-oriented experiments with which we are all familiar. The other way is to take what we know and speculate “what if.” Thus, in the spirit of scientific adventure, with all its risks and hopes for serendipity, the present study included both preplanned predictions and some frankly exploratory analyses.

## THE MMI TARGET

Background ionizing radiation was selected as the target because it is a natural, pervasive source of truly random events, it is easy and relatively inexpensive to measure, and it provides an interesting and unusual context for an experiment in which the target system is potentially both *influenced* (by MMI) and the *influencer* (as an environmental modulator). The consequences of creating a kind of feedback loop between influencer and “influencee” is unknown, but I reasoned that if MMI effects manifest as a form of local phase coherence in a random system, perhaps the process can be enhanced by providing a setting favorable to the establishment of a psychophysical phase-locked loop.

## EQUIPMENT

**Geiger counter:** Aware Electronics RM-60 “microRoentgen radiation monitor,” a computer-controlled, industry-standard, halogen quenched, stainless steel Geiger-Müller tube.

**Local weather variables:** Oregon Scientific digital thermometer, barometer, hydrometer; 1% accuracy on each scale. Digital barometer calibrated using (USA) National Weather Service daily barometric readings for the Boston, Massachusetts, area.

**Body temperature:** Micronta digital temperature; 0.1° F accuracy.

**Magnetic field monitor:** Applied Physics Systems milliammeter (Model 428C), equipped with fluxgate magnetometer one-axis probe (Model APS 460). Resolution 1μ Gauss, range 1μ Gauss to 2 Gauss.

**Computer:** Gateway 2000 386-SX PC-clone.

**Software:** written by the author using Microsoft QuickBasic.

**Cosmic and global variables:** uploaded from the *Solar Daily Geophysical Bulletin* on the Internet. Raw data is collected by NASA and NOAA satellite as well as a dozen magnetic observatories around the world, then compiled for redistribution on the Internet by the University of Lethbridge, Canada.<sup>26</sup>

## EXPERIMENTAL DESIGN

An RM60 computer-controlled geiger counter (GC) was used to continuously monitor background ionizing radiation at a fixed site. One *sample* was defined as the number of radiation counts registered at the GC in 10 seconds. The data conformed to a Poisson distribution, and the expected mean (empirically determined) was about 2.

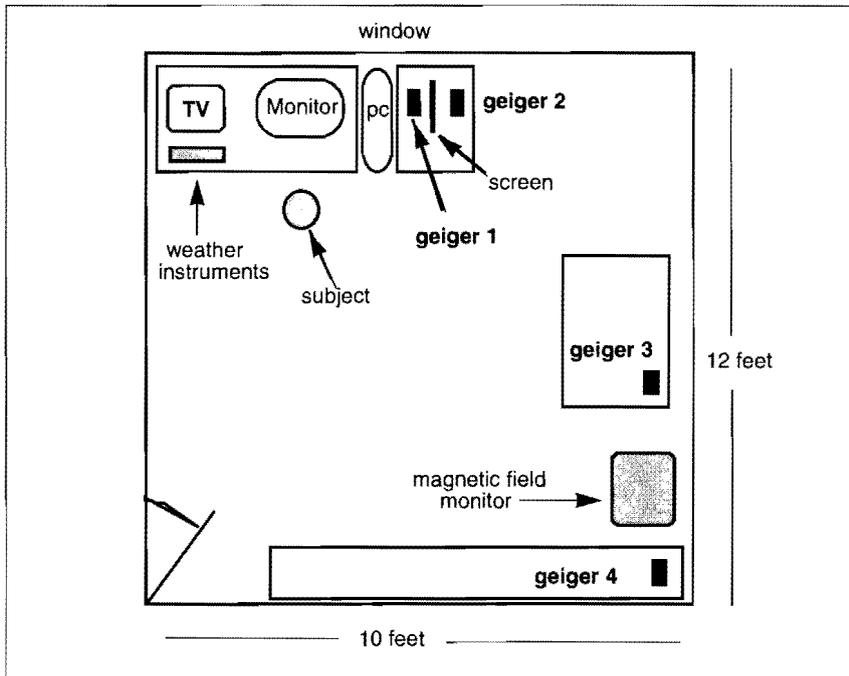
A *session* was defined as 200 contiguous samples, therefore lasting 2000 seconds, or about 33 minutes. The entire *experiment* was planned to run for 100 sessions, one session per day. The actual experiment had to end after 65 days of data collection because the computer, which was loaned to the author, had to be returned.<sup>27</sup> The plan to run sessions on successive days was followed for 63 of the 65 days; in two cases a single day was skipped.

The 200 samples per session were divided into two equal groups: 100 samples were used in a *real-time* condition and 100 were used in a *prerecorded* condition. Within each condition, 75 samples were used as *controls* and 25 as experimental *treatments*.

Four identical GCs were used; each simultaneously collected data from different locations in the laboratory. The GCs were located as shown in Figure 1. GC1 was the explicit MMI target, and the only target for which feedback was provided. The others were used to test for entropy effects (GC2) and as nominal controls (GC3 and GC4). As shown in Figure 1, an opaque screen hid GC2 from the participant's sight during experimental trials. The participant's perspective of the experiment is described in more detail later.

## COMPUTER PERSPECTIVE

To begin a session, the experimenter-subject (the author) ran the computer program that controlled the experiment. The computer created a date-stamped datafile, then it checked that each of the four GCs was operating properly by waiting until each in turn had registered 2 radiation counts. The computer then collected 100 contiguous samples. As each sample was collected, the computer monitor displayed the number of the sample, 1 to 100. These one



*Figure 1. Position of equipment in the laboratory. Geiger counter 1 (GC1), the explicit mind-matter target, was two feet from the subject. GC2 was six inches to the right of GC1, hidden behind an opaque screen. GC3 was six feet from GC1, and GC4 was nine feet. Both GC3 and GC4 were located behind the subject's view, but neither was explicitly hidden. The subject sat at a desk and either watched a TV set as a distracter during control periods or attempted to lower the radiation level at GC1 during treatment periods.*

hundred samples were used later in the *prerecorded* condition. During this data collection period, the experimenter engaged in tasks outside the laboratory room housing the equipment and GCs.

After 100 samples had been collected (about 15 minutes later), the computer beeped to alert the experimenter, then it asked for the following data to be entered: current barometric pressure, room temperature, room humidity, body temperature (of the subject), local magnetic field (vertical DC component), sunspot number, geomagnetic field (planetary A-index, a real-time estimate of

the more popular *ap* index), solar flux, background X-ray flux, wind (none, moderate, lots), precipitation (clear, cloudy, wet), physical condition (from 1 = good, to 5 = poor), mental condition (1 = high, 5 = low), confidence in the task (1 = high, 5 = low), and a line or two of general comments.

**A**fter this information was entered, the computer saved the data to the datafile and then generated a pseudorandom number between 2 and 12, using the QuickBasic "RNG" pseudorandom number generator (PRNG). Radiation counts from all four GCs were then collected until this random number of counts had been received. At this point, the PRNG was re-seeded to the current computer clock time, and a "condition" array of 200 elements was created. This array specified whether a sample was to be designated as a real-time control (N = 75, coded as 0), a real-time treatment (N = 25, code = 1), a prerecorded control (N = 75, code = 2), or a prerecorded treatment (N = 25, code = 3).

Now the computer began to run through the condition array. If the next condition was a real-time or prerecorded *treatment*, it would sound a tone to alert the subject to begin applying mental intention to cause GC1 to return a low count rate. After each treatment sample, if the count rate returned by GC1 was 2 or less, the computer sounded a higher pitched tone as feedback, otherwise there was no tone. If the next condition was a real-time (0) or prerecorded (2) control, the computer also was silent. Treatment samples were interspersed randomly throughout the controls, thus on average a treatment occurred about once in four samples.

## PARTICIPANT'S PERSPECTIVE

From the participant's point of view, once a session began the task was to watch a TV program and wait for a low-pitched tone. This signaled the beginning of a 10-second treatment condition. During this 10 second period, the subject was to try to *lower* the radiation level at GC 1. If the returned radiation count at the end of the treatment period was 2 or less, the computer sounded a high-pitched chirp as feedback. During control samples, the computer remained silent and the subject watched the TV set as a distracter. The TV remote control "mute" button was used to switch off the TV audio during treatment samples and switch it back on during control samples.

The task was always to lower the radiation level during treatment periods because I (as subject-experimenter) found it easier to quickly produce a calm mental state and imagine the idea of “calming” a GC, than to quickly generate an aroused mental state and imagine the idea of “exciting” a GC. This bias probably reflects the author’s experience with meditation designed to produce a calm mental state. Individuals experienced in active martial arts such as karate would perhaps find it easier to quickly generate a highly focused, aroused mental state.<sup>28</sup>

In addition, the task was defined as a constant “aim low” because of the possibility that low level ionizing radiation is hazardous, thus there is intrinsic motivation to lower the level of radiation. In contrast, instructions to explicitly raise the level of radiation may invoke psychological defense mechanisms that might have suppressed the desired goal from being achieved.<sup>29</sup>

**N**o special mental technique was specified for the experiment. Typically during treatment periods I imagined the presence of a “calm field” surrounding the GC, which served as a fanciful radiation “shield.” Note that this MMI task can be accomplished by (a) lowering the sensitivity of GC1 or (b) lowering the actual level of radiation or (c) increasing the decay time of ambient radioactive sources. No attempt was made in this experiment to discriminate among these various possibilities.

## MEASURES OF MENTAL INFLUENCE

There were two MMI measures per GC, per condition, resulting in a total of  $2 \times 4 \times 2 = 16$  measures. The first measure was effect size  $r$ , calculated as

$$r = \frac{t^2}{t^2 + df}$$

where  $df = 98$ ,  $t = (\bar{x}_t - \bar{x}_c) / \sigma_d$ ,  $\bar{x}_t$  = mean of treatment samples for a GC,  $\bar{x}_c$  = mean of control samples for the same GC, and  $\sigma_d$  = combined standard error of the two samples.<sup>30</sup> The second measure was a F-score, created as  $F = \sigma_t^2 / \sigma_c^2$ , where  $\sigma_t$  was the standard deviation of the treatment samples for a given GC and  $\sigma_c$  was the standard deviation of control samples for the same GC.

Note that because this experiment consisted of the same number of samples per session, per condition,  $r$  and  $t$  can be used interchangeably as effect sizes for the present design. If one wished to compare effect sizes across different experiments consisting of different sample sizes,  $r$  would be used.

**B**ecause the defined MMI task was consistently to lower radiation counts at GC 1 during the treatment condition, success was defined in terms of statistics as  $r < 0$  (or equivalently,  $t < 0$ ) and  $F < 1$ . Note that these measures were designed to *differentially* compare treatment vs. control radiation levels at a given GC during a single session that lasted about one hour. Thus, any trends or correlations observed with MMI data *would not be due to drifts* in GC sensitivity or to natural variations in background radiation.<sup>31</sup>

## PREDICTIONS AND ANALYSES

Analyses are separated into preplanned and exploratory. Preplanned predictions were based upon observations in earlier studies; exploratory analyses were either post-hoc or were based upon speculations about the possible nature of MMI effects.

**Preplanned Prediction: MMI Effect.** The usual MMI hypothesis is to predict  $\bar{t} < \bar{c}$ , where  $t$  and  $c$  are as described above. This can be tested with a  $t$ -score, and one would hope to obtain a  $t < -1.65$  for a one-tailed test. In the majority of earlier proof-oriented studies involving RNGs this made perfect sense since the expected effect size was unknown. And while there is still some confusion over the effect size *per trial* in RNG studies, there is a good estimate of the effect size *per experiment* in these studies.

Based upon data collected for a meta-analysis of RNG studies,<sup>2</sup> we find that the mean  $z$ -score (and standard error) from 623 previously reported RNG experiments is  $\bar{z} = 0.519 \pm 0.078$ . While this mean  $z$ -score may not seem very impressive, note that it is more than 6 standard errors from a chance result (i.e.,  $.519/.078 = 6.65$ ).

Thus, this prediction is that the overall experimental outcome for the present experiment will be *negative*, meaning treatment radiation < control radiation, and the absolute value of the outcome, a  $t$ -score, will be *within* the 95% confidence interval of the population mean  $z$ -score of  $\bar{z} = 0.519 \pm 0.078$ .

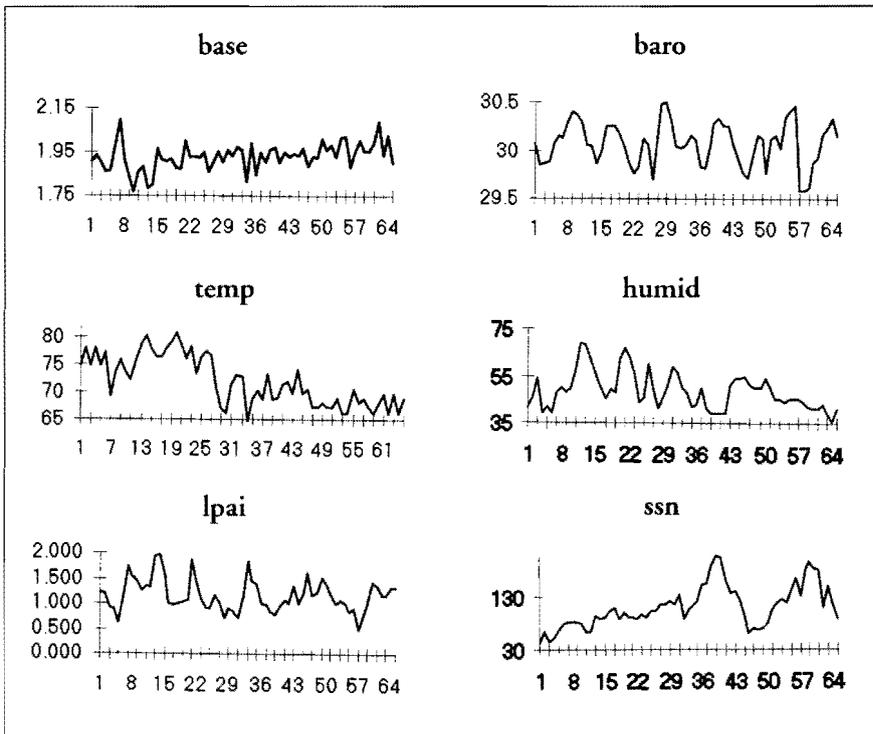
**Preplanned Prediction: Radiation Correlation.** In a previous study,<sup>16</sup> I found that successful MMI experiments (i.e., those where  $\bar{z} < \bar{r}$ ) occurred when the ambient radiation level was significantly *lower* than the radiation levels measured during unsuccessful MMI experiments. Thus, the prediction is that there should be a positive correlation between effect size and baseline radiation level recorded in each session.

**Preplanned Prediction: Rebound in time.** A previous study<sup>16</sup> found a significant rise in radiation levels two samples past the treatment period (i.e., 20 seconds after the mental effort). This is interpreted now as an equilibrium rebound that occurs *over time*. The prediction is therefore that a similar rebound will again be found at two samples past the treatment period in GC1.

**Exploratory Analysis: Environmental-MMI Correlation Matrix.** If the environment genuinely influences MMI effects in linear ways, then we can predict that a (Pearson) correlation matrix between all environmental and MMI measures will show an excess number of significant correlations. A similar control matrix, formed from the same data except that the time sequence is randomized, is predicted to show the chance expected number of significant correlations.

**Exploratory Analysis: Predicting MMI effects With a Neural Network.** If environment influences MMI performance in either linear or non-linear ways, then a neural network may be able to learn to associate some environmental variables with some measure of MMI performance. After successfully training a neural network with half of the available data, the prediction—using the second half of the data—is that we will find a positive correlation between the neural network’s *prediction* of MMI performance based on the environmental variables, and the *actual* MMI performance observed during the experiment. Note: This analysis was preplanned, but the specific variables to be used were selected based upon examination of the above mentioned cross-correlations.

**Exploratory Post-Hoc Analysis: Rebound in Space.** If statistical order is conserved in a system in space as well as in time, we would expect that as radiation in GC1 is “influenced” to go down, radiation at GC2 will go up *at the same time*, and vice versa. The prediction is a negative correlation between MMI effects observed in GC1 vs. GC2.



*Figure 2. Example environmental fluctuations recorded over course of experiment. base is baseline radiation (as mean number of counts in a 10-second sample); baro is barometric pressure; temp is indoor temperature; humid is indoor humidity; lpai is log of the planetary A-index; and ssn is sunspot number.*

## RESULTS

### EXAMPLE OF RAW DATA

The experiment was conducted for 65 days, from August 26, 1992 to November 3, 1992. The primary reason for conducting a longitudinal experiment was to ensure that the experiment would be conducted over a wide range of environmental conditions. To illustrate how the environment varied over this period, Figure 2 presents graphs of the raw data for six environmental variables. These graphs show, as expected, that the environment is highly dynamic. Some of these variables have known relationships, for example, ambient temperature and humidity are positively correlated.

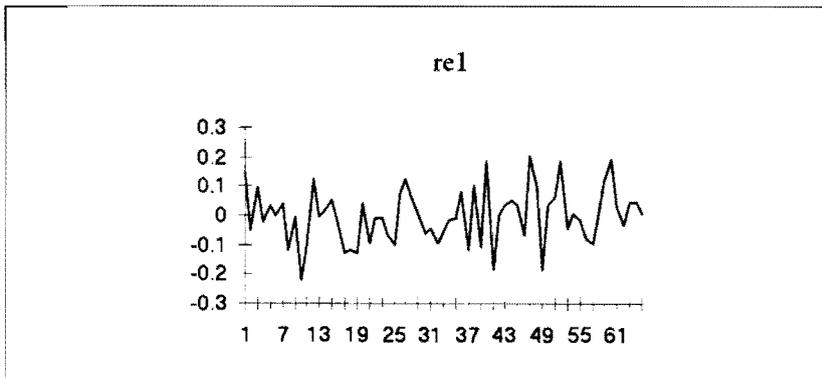


Figure 3. Realtime effect size for geiger counter 1 over the course of the experiment.

## EVIDENCE FOR MIND-MATTER INTERACTION?

As an example of the type of MMI result this experiment produced, Figure 3 shows the effect size  $r$  per session for the real-time condition. Visually there is no obvious trend, and the mean effect size appears to hover around zero.

**MMI Prediction.** The MMI prediction was that the mean overall effect size (as a terminal  $t$ -score) would be negative, and would fall within the 95% confidence interval for the meta-analytic population estimate ( $z = 0.519 \pm 0.078$ ). The terminal  $t$ -score was  $t = -.554$ , and the 95% confidence interval for the population estimate is .513 to .597, thus the MMI prediction is confirmed.

## ENVIRONMENTAL MODULATION OF MMI?

**Radiation Correlation.** A previous study<sup>16</sup> indicated that MMI effect size improved (i.e., became more negative) as baseline radiation levels dropped. The prediction was a positive correlation between overall MMI effects in GC1 (i.e., real-time and prerecorded results combined) and baseline radiation levels. The result, shown in Figure 4, is positive, but not significant ( $r = .092$ ,  $df = 63$ ,  $p = .233$  one-tail).

Now, without straying too far afield, I will momentarily jump ahead to the later discussion on equilibrium effects. Because of the counter-balancing

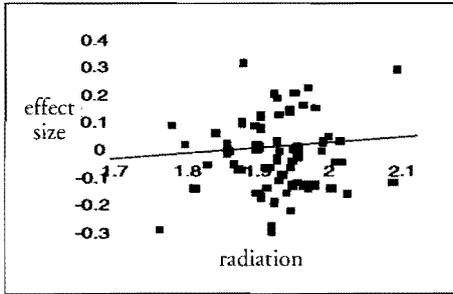


Figure 4. Correlation between MMI effects in GC1 vs. baseline radiation levels.

postulate, effects in GC2 were predicted to be *opposite* to that of GC1. Thus, given the expected positive relationship between effect and radiation in GC1, we would expect to find a *negative* correlation in GC2. This correlation is shown in Figure 5 ( $r = -.4379$ ,  $df = 63$ ,  $p = .00013$ , one-tail). This suggests that environmental and equilibrium factors may indeed be related, but in a complicated way because the correlation for GC2 is much stronger than the same correlation for GC1. The difference between G1 and G2 correlations is significant at  $p = .0008$ .

**Correlation Matrix.** A more general way of exploring relationships among environmental and MMI variables is to create a correlation matrix for these variables, then see whether the number of statistically significant correlations exceeds the number expected by chance. This is similar to von Lucadou's<sup>9,10</sup> system-theoretic approach to studying MMI effects.

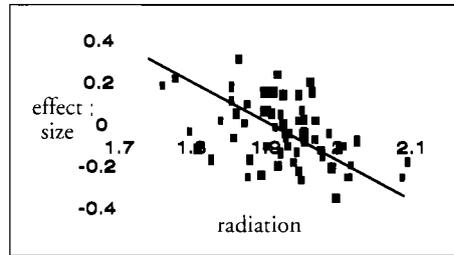
The experimental dataset consisted of a spreadsheet of 65 rows, one row per session, and 49 columns, one column per variable of interest. The 49 columns included the following *environmental variables*:

session number, time of day, baseline radiation, barometric pressure, baseline radiation one day before the experiment,<sup>32</sup> barometric pressure -1, change in barometric pressure,<sup>33</sup> wind, indoor temperature, indoor humidity, change in humidity, humidity -1, local magnetic field, background xray, log of background xray, local magnetic field -1, log of background xray -1, change in log of background xray, sunspot number, planetary A-index, log of planetary A-index, sunspot number -1, planetary A-Index -1, log of planetary A-Index -1, solar flux, body temperature, precipitation, physical status, precipitation -1, physical status -1, mental status, mood, confidence,

and the following *mind-matter interaction variables*,

r1, F1, r2, F2, r3, F3, r4, and F4 for realtime effects, and p1, f1, p2, f2, p3, f3, p4, and f4 for prerecorded effects.

The *log*, *change*, and “-1” variables in the list were included to study the effects of normalizing some of the more skewed geophysical variables, and to examine time-change and time-delay factors, respectively.



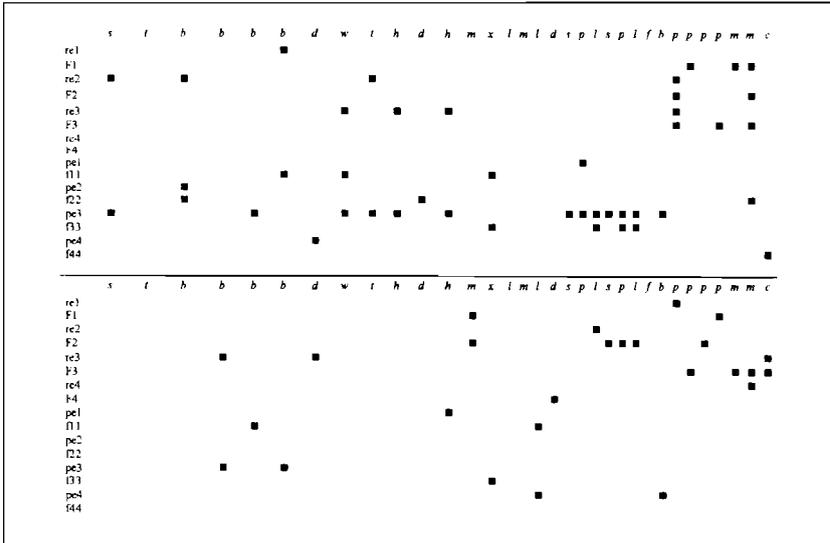
*Figure 5. Correlation between MMI effects in GC2 vs. baseline radiation levels;  $r = -.4379$ ,  $df = 63$ ,  $p = .00013$  (one-tail).*

Figure 6 shows two correlation matrices: The little boxes indicate statistically significant ( $p < .05$ , two-tail) correlations. The matrix on top shows correlations in actual data; the matrix on the bottom is a control dataset created by using the original data but *randomly scrambling the chronological order of the MMI variables*. This maintained the original time-sequence for all of the environmental variables but randomized the MMI variables (which, under the null hypothesis, should not be related in any way to the environmental outcome).

Each matrix above shows 16 MMI by 33 environmental variables, for a total of  $16 \times 33 = 528$  correlations. By chance, one would expect to find  $528 \times .05 = 26$  significant correlations. The experimental dataset resulted in 44 significant ( $p < .05$  two-tail) correlations (exact binomial  $p = .0004$ ); the comparable number for the control data was 26 ( $p = .4801$ ). At the  $p \leq .10$  (two-tail) level, there were 68 correlations in the actual dataset (exact binomial  $p = .013$ ) and 59 in the control dataset ( $p = .165$ ). Thus, the prediction is confirmed: The actual data resulted in more significant correlations than expected by chance.

Separating the above correlations significant at the  $p \leq .10$  level results in the distributions shown in Figure 7. A chi-squared test of the experimental distribution in Figure 7 results in  $\chi^2 = 26.47$ ,  $p = .000008$ . By inspection, it is clear that GC 3 and GC 4 were responsible for this significance. A similar distributional test for the control data results in a nonsignificant  $\chi^2 = .864$ ,  $p = .834$ .

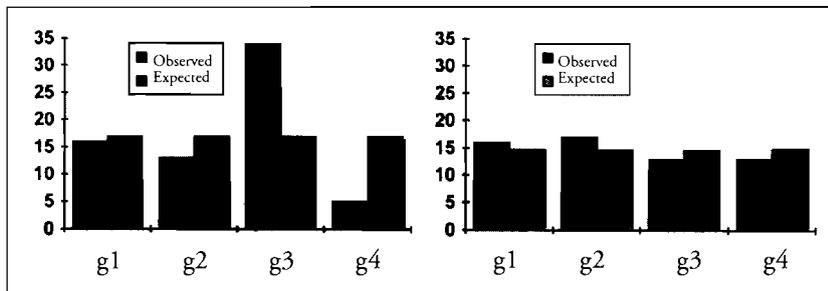
It might be argued that some of the excess significant correlations in the experimental data might have been due to the fact that some of the environmental variables tested were intercorrelated with each other. That is, ten of the environmental variables were created by simply shifting the data sequence by one day.<sup>34</sup>



*Figure 6. Correlation matrices for environmental (abscissa) vs. MMI (ordinate) variables. Top matrix shows actual data; bottom matrix shows control data. The environmental variables correspond to the 49 variables listed in the text.*

To test the possibility that these time-shifted variables might have been responsible for the large number of significant correlations in the experimental matrix, all ten time-shifted variables were removed from the correlation matrix and the number of remaining significant correlations was determined. This new matrix consisted of  $16 \times 23 = 368$  correlations. By chance, we would expect to find  $368 \times .05 = 18.4$  correlations significant at  $p \leq .05$ ; in fact, 32 were observed (exact binomial  $p = .0009$ ). Thus, we can have some confidence that there were genuine environmental relationships with MMI performance.

**Neural Network Analysis.** Artificial neural networks are a recent technological development useful in discovering patterns in noisy and complex data.<sup>35</sup> This technology is based upon how information is processed in biological neural networks. The technique has proven to be exceptionally valuable in difficult computational applications such as automatic speech recognition, radar signal identification, and stock market predictions. More pertinent to the present study, previous work has shown that neural networks can be used to discover complex person-unique patterns in MMI RNG data.<sup>36</sup>



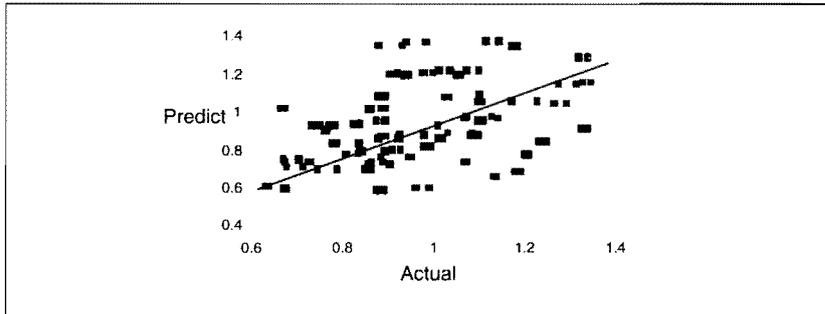
*Figure 7. Distribution of expected and observed number of significant correlations for experimental (left) and control (right) datasets.*

A neural network was used to analyze the present dataset to see if one of the MMI variables could be predicted from a set of environmental variables. If this were possible, it would provide further evidence of genuine relationships between environmental and MMI performance as well as demonstrate the viability of building a predictive model of MMI performance.

Eight predictors were selected: one cosmic variable (log of background X-ray flux in the ionosphere), one global variable (log of the geomagnetic field planetary A-index), four local variables (ambient ionizing radiation level, wind, precipitation, barometric pressure the day before the experiment), and two psychological variables (mood and confidence).<sup>37</sup> The MMI variable to be predicted was F1, the ratio of the real-time treatment standard deviation to the control standard deviation in the explicit MMI target, GC 1. These variables were selected by choosing representative variables from each of the environmental “bands,” and by inspection of the above-mentioned MMI vs. environment correlation matrix.

Half of the data was used to teach the neural network the association between the inputs and the output; the remaining half of the data was used to test whether what the network had learned would generalize to new data it had not yet “seen.” If the network had learned a genuine relationship between the inputs and output, then after passing the second half of the data through the trained network, one would expect that the correlation between the predicted output and the actual output would be significantly positive.

Figure 8 shows the correlation between the actual and predicted neural network results for the output, F1. The correlation is positive,  $r = .405$



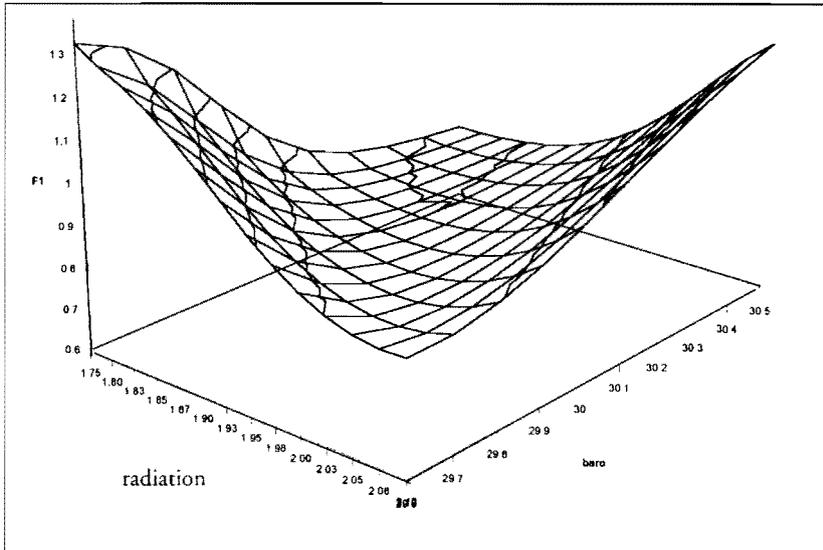
*Figure 8. Correlation between neural-network predicted MMI outcome and actual outcome,  $r = .405$ ,  $p = .000002$ .*

(126 *df*),  $p = .000002$ . This correlation indicates that the network successfully learned to identify an MMI effect based on eight environmental predictor variables.

**Neural network training-testing process.** Where did the 126 degrees of freedom come from in the above correlation? The answer helps to explain the neural network training-testing process, but because it is a technical diversion, the discussion is presented in Appendix A.

**What did the network learn?** Given the evidence that the network learned how to predict MMI performance based upon eight environmental factors, how can we come to understand this knowledge? Unfortunately, the answer is not simple because the neural network captures its knowledge in an abstract higher-dimensional space.

However, we can begin to study the knowledge by creating a three-dimensional representation for how two of the eight variables covary in this higher-order space. Figure 9 shows how the neural network has captured the relationship between the input variables *baseline radiation*, *barometric pressure*, and the output variable *FI*, while all over variables are held constant.<sup>38</sup> This graph tells us that the neural learned that MMI performance would improve on GC 1 (i.e., when  $FI < 1$ ) when the ambient radiation level is low *and* the barometric pressure is high. The graph also indicates that performance will be poor when there is low barometric pressure *and* low baseline radiation.



*Figure 9. Relationship between background radiation (x-axis), barometric pressure (y-axis), and the MMI variable F1 (z-axis).*

As another example, Figure 10 shows the relationships between the log of the planetary A-index (*geomagnetic fluctuations*), *baseline radiation*, and *F1*. This saddle-shaped curve reveals that the network learned that MMI performance is better when radiation or geomagnetic fluctuations are at average levels, but performance suffers if either variable goes to extremes, especially if they move in opposite directions (i.e., radiation low, geomagnetic fluctuations high, or vice versa).

Many similar analyses will be required to understand what the neural network has learned, but in the meantime it is encouraging to know that there is very likely a model waiting to be discovered—a non-linear, multidimensional, multi-factorial model—which may some day be able to reliably predict MMI functioning.

**Rebound in space?** A speculative analysis postulated that when the MMI task was successful, radiation in GC1 would *drop* during the treatment samples and radiation in GC2 would *rise*. This can be tested by examining the correlation between individual session scores in GC1 vs. GC2, where we would predict a negative correlation.

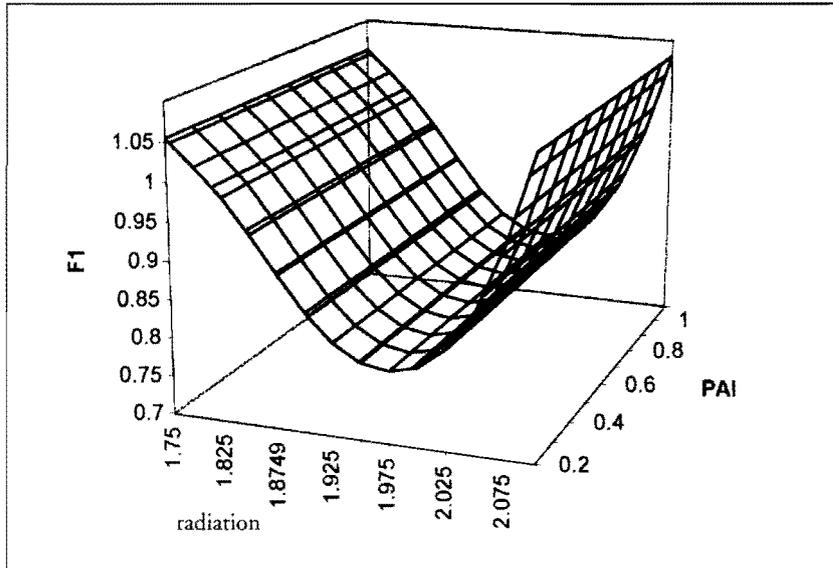


Figure 10. Relationship between baseline radiation, log of planetary A-index, and MMI variable F1.

To form individual session scores, rather than use  $t$ -scores as described above, I calculated a Mann-Whitney sum of ranks score for the data in each session, then transformed this into a  $z$ -score.<sup>39</sup> This was performed to avoid the parametric assumptions of  $t$ -scores.<sup>40</sup> Figure 11 shows this correlation, which is significantly negative as predicted ( $r = -.153$ ,  $t = -1.73$ ,  $p = .04$ , one-tailed).

To test the possibility that this apparent space-like rebound is spurious, the cross-correlation matrix between all GCs is shown in Table 1, along with the associated  $t$ -scores. This reveals that the only significant (one-tailed) correlation was between GC 1 and GC 2.

**Rebound in time** The previous study<sup>16</sup> observed a statistically significant time-like rebound in GC 1 two samples after the explicit effort (labeled "0" in Figure 12). It was predicted again in the present data.

Table 2 compares time-shifted means in Figure 12 against the mean at time 0 as  $t$ -scores. This reveals that only the sample mean at +2 is significantly higher, with  $t(64 df) = 2.990$ ,  $p < .01$ , in conformance with the previously observed statistical rebound in time.

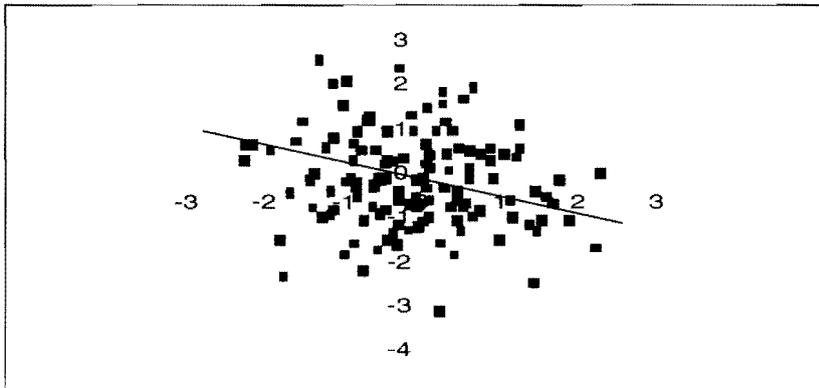


Figure 11. Correlation between individual session z-scores, GC1 on the x-axis, GC2 on the y-axis.

## DISCUSSION

This experiment was designed to explore two general factors that may influence mind-matter interaction: environmental fluctuations and a postulated equilibrium principle that manifests as MMI rebounds in space and time. The picture that emerges is the following: (a) the environment does appear to modulate MMI performance, (b) there are intriguing hints of space-like and time-like rebounds, and (c) there is reason to believe that fairly good predictive models of MMI performance are realistically attainable. This last point is most important from a pragmatic point of view because it suggests that neural network and other pattern-matching technologies may be of significant value in creating practical applications out of MMI phenomena *far in advance* of our gaining a clear understanding of how and why MMI works.

Among other things, the emerging complexity of MMI suggests that the issue of clearly isolating independent from dependent variables is probably more complicated than we had previously imagined.<sup>41</sup> In the meantime, is there a schema we can use to begin to understand the interactions observed among environment, statistical rebounds, and MMI? To begin, we may consider the question as to what is “influenced.”

*Table 1*

Cross-correlations for all GCs, showing that only GC 1 vs. GC 2 resulted in a significantly negative correlation.

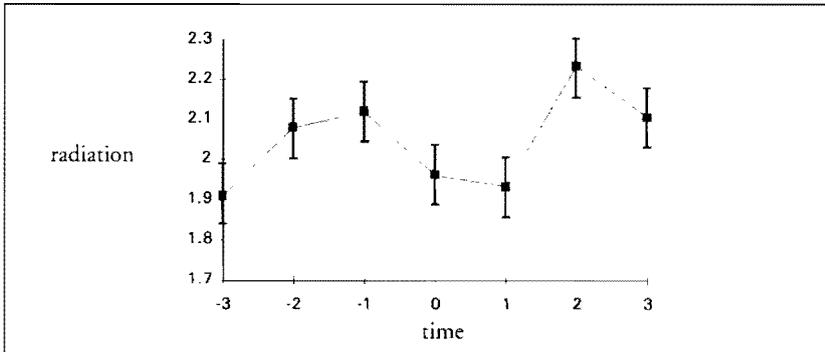
Correlation	g1	g2	g3
g1	1		
g2	-0.153	1	
g3	-0.102	0.061	1
g4	0.111	0.108	0.111
<i>t</i> -score			
g2	-1.73		
g3	-1.15	0.68	
g4	1.25	1.21	1.26

## WHAT IS INFLUENCED IN MIND-MATTER INTERACTION?

One attractive possibility, proposed by Puthoff and Targ<sup>22</sup> and others, is that the MMI effect is a phase coherence phenomenon involving short-term mobilization of system noise. This is attractive because most, if not all, MMI effects observed in the laboratory can be produced in principle by slightly shifting the random target system's boundary conditions. This can be explained by analogy with a common phase coherence phenomenon at the heart of the compact disc player, the supermarket scanner, and the telephone network, namely, the laser.

The laser is a light amplification device. Lasers come in many forms, ranging from solid state to gas, but the basic operating principle is essentially the same. If you can manage to nudge random electromagnetic waves into phase coherence, you can produce an intensely powerful output beam.

To expand upon this idea, let's say you take a gas laser tube and heat up the gas until it becomes a plasma, much like the plasma inside a softly glowing neon sign. To turn that soft glow into a laser beam, you align two mirrors at either end of the tube. The light reflecting off the mirrors bounces back inside



*Figure 12. Time-offset graph for GC1, real-time condition only, showing the mean absolute level of radiation in GC1 at the time when MMI effort was applied (time 0), and plus and minus three samples from that time. Error bars are plus and minus one standard error.*

the plasma and a resonance effect is set up. If the mirrors are perfectly aligned and the distance between the mirrors is precisely right, the plasma resonance will quickly increase and the system will start to “lase.”

**N**ow let’s say you slightly detune the mirrors so that the plasma is not lasing. The tube now resembles an ordinary, softly glowing neon lamp. If you had asked a physicist of the last century to look at that plasma and to calculate the statistics for the photons coming out, he (physicists were mostly “he” in the last century) would have drawn a nice smooth distribution.

Then you would say to him, ‘What’s the probability that all the light will come out in one mode?’ He would say, ‘that’s permissible as far as the physics goes, but it’s highly unlikely.’ So then [you] come along and rotate the mirror into place, and this suddenly produces [the intense beam of the laser,] which is basically only a change in the statistics of the situation.<sup>22</sup>

offset	-3	-2	-1	0	+1	+2	+3
<i>t</i> -score	-0.581	1.368	1.764	0	-0.305	2.990	1.630

In other words, an infinitesimal change in the boundary conditions of a random system (aligning the mirrors in a laser tube) results in phase coherence that produces an unexpected effect with macroscopic consequences (e.g., a light beam so intense it can punch a hole through a metal sheet). Likewise, in a random generator system, an infinitesimal nudge may result in a momentary phase change that we measure as a shift in the system's statistics. A properly designed MMI experiment that repeatedly nudged a random system in just the right way might be able to create the equivalent of an intense beam. What would such unexpected order do to the random system (say, to a geiger counter or electronic random number generator)? It may appear to anomalously "freeze up," or if computer-based, cause the system to crash.<sup>42</sup>

## ENTROPY REBOUNDS?

If MMI effects are reflections of order or negentropy impressed into a system, we would not *necessarily* expect to find evidence for statistical rebounds because entropy is not conserved; in an isolated system entropy increases. However, as living creatures, we maintain a state of constant low entropy (to remain alive) by eating lower-entropy food and discarding higher-entropy waste as heat, carbon dioxide, etc.<sup>43</sup>

Perhaps MMI manifests because we are able to somehow non-locally "loan" some of our low-entropy to a remote location. If this were the case, we could predict that the process of performing MMI causes entropy to rise in the "sending" organism. This could be tested by seeing whether the strength of MMI results are correlated with say, levels of bodily fatigue or vitality (assuming that fatigue and vitality are associated in some way with individual entropy).

## OTHER EVIDENCE FOR SPACE- & TIME-LIKE STATISTICAL REBOUNDS

However we conceptualize the MMI rebound effect, besides the observations in the present experiment, there is prior evidence for space- and time-like statistical rebounds in MMI experiments. The effects are reported variously as

constricted variance in control data, as a “balancing effect,” and as unexpected effects in “silent” and “hidden” sources of randomness.<sup>9,16,42,42,45,46</sup>

There is also evidence for time-like rebounds, described variously as linger and as release-of-effort effects.<sup>47</sup> Of particular interest is that release-of-effort effects observed in experiments by Watkins, Watkins & Wells<sup>48</sup> and Stanford & Fox<sup>49</sup> were significantly larger than results observed during periods of explicit mental effort. It is of theoretical interest that both space-like and time-like MMI effects seem to occur without explicit observation, suggesting that so-called silent and linger effects may reflect physical conservation principles rather than “purely” psychological principles.

## MUSINGS ABOUT THE NATURE OF MIND-MATTER INTERACTION

**C**onsider the surface of a shimmering pool (a random system). When the weather is calm, the surface is relatively smooth (favorable environment); when a storm arises, the surface is whipped into a frenzy (unfavorable environment). Regardless of the weather, the volume of water remains the same.

Now imagine that every so often, an infinitesimal bubble from deep below rises to the surface. As it rises, the water pressure relaxes and the bubble grows. On a calm day, when the bubble breaks the surface, it causes the same sort of ripples that a tossed pebble would create, except that this “cause” came from the same medium whose surface is now disturbed.

The bubble represents an event that occurs in the world of the very small (or very low energy). How this bubble is formed may be related to quantum observational effects, but the precise method does not matter for this discussion. What is proposed is that once the bubble is set on its course, it eventually causes a noticeable disturbance on the surface of the pond; the disturbing element and the disturbed are, in a sense, the same. (This is similar to Bohm’s notion of an implicate order.)

If the deep pond represents the deep structure of the world, which we struggle to imagine using quantum and other theories, and the surface represents observ-

able events, then perhaps what we see in MMI experiments using random generators are tiny “probability bubbles” that cause corresponding ripples of probability in the vicinity of the explicit target. These ripples are postulated to manifest as statistical rebound effects, which in turn serve to maintain overall system equilibrium.

## CONCLUSION

This study suggests that fluctuations in the environment modulate mind-matter interactions in predictable ways. The specific variables and circumstances have yet to be explicitly identified, but it is encouraging to find evidence for lawful principles at work behind the otherwise erratic nature of MMI phenomena. This experiment also found indications that when the environment is favorable, MMI effects may produce short-term rebounds in space and time.

The present experiment was not designed to answer interesting and relevant questions such as:

- What did MMI affect? Background radiation, sensitivity of the GCs, something else?
- Why did GC 3 and GC 4 show unexpected MMI-related effects?
- What specific model of the environment did the neural network actually learn?

To explore these factors in more detail, I recommend that future MMI experiments use physical target systems with multiple detectors to look for inter-detector correlations, the time between mental treatments should be systematically varied, and experimental designs should be used which can discriminate between MMI influence of the physical target system and the detectors used to measure that system. In addition, even more environmental variables should be formally incorporated into experimental designs, especially physiological measurements, local electromagnetic fluctuations, and better real-time estimates of psychological factors.

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32. Hereafter time-shifted data is referred to by using the suffix "-1".
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- until all network outputs were within 10% of the values of their associated training examples. A commercial software product called "Brainmaker" (California Scientific Software, Nevada City, CA) was used to implement the network on an 80486 33 MHz, DOS-based PC. Further details are available upon request from the author.
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## APPENDIX A: NEURAL NETWORK TRAINING/TESTING DETAILS

In the process of forming time-shifted variables, such as barometric pressure -1, the first line of the experimental dataset had to be dropped because there was no data for the day before the first experimental session. Thus, half of the dataset of now 64 (no longer 65) items was 32. The network was trained on 32 items and tested on 32 items.

Typically one tries to give a neural network a minimum of 5 times as many examples to learn from as there are input variables. Since I used an 8-input model, this means I needed a minimum of 40 examples. However, as noted above, there were only 32 items available. Fortunately, there is a way to increase the effective number of input examples, and at the same time help the network generalize its knowledge—by “blurring” the inputs.

Blurring the input examples is performed by generating a random variable based upon the gaussian-estimated distribution of the actual inputs. Using this approach, the neural network is presented with each training example twice, once with actual inputs and once with blurred inputs. Every other time the data is passed through the network (one “pass” occurs when all 32 examples go through the network once), new inputs are randomly generated. This automatically doubles the number of training examples that the network is exposed to. When the 32 test inputs are passed through the network to see if it has learned to generalize properly, the same blurring procedure is also applied to these inputs, thereby creating 64 predicted outputs in one pass.

The training-testing process was performed *twice* in this analysis, each time training the network from scratch. This was done because neural networks learn from example starting with random initial conditions. It is possible that one training session may be successful in learning to extract knowledge from a dataset, but fail in transferring that knowledge to new data. Thus, to test the generalizability of the learned knowledge, it is often useful to train and test the network several times to see how well the learned knowledge “holds up.” Therefore, 64 training outputs for the first train-test run, plus 64 from the second train-test run gives 128 predictions; hence, the correlation reported here contains 126 degrees of freedom. For general information about neural network testing-training mechanisms, and for specifics about the Brainmaker software, refer to Lawrence & Lawrence.<sup>51</sup>