Experimental

SOFTWARE FOR TRAINING ANOMALOUS COGNITION: A PRELIMINARY REPORT

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ABSTRACT

The role of intuition in fields as widely divergent as science, business, and the arts has a long anecdotal history. Research into the potential for training this area of human performance, however, is not extensive. This report gives the background of anomalous cognition (AC) training devices, and describes a preliminary study involving a software program designed to enhance successful decision-making by training AC of the future and consciousness interaction with electronic systems (CIES). It was hypothesized that motivated subjects would be able to enhance their awareness of subtle internal signals or "intuitive hunches," as shown by increases in scoring. Pilot experiments by 23 experimenter/subjects yielded four who achieved significant gains in scoring at the .01 level, one who achieved both a significant increase and significant overall scoring, and two who showed significant overall scoring. Of 21 subjects who did one AC experiment, a significant percentage (71%) showed improvement. Eight of the subjects did 25 additional AC experiments, for a total of 46 AC experiments, which together showed a significant increase in scoring, with overall chance scoring. Three subjects, including two new ones, did six CIES experiments, whose combined data showed overall significant scoring. Of 11 drop-out subjects, one attained a significant increase in AC scoring. Of the total of 34 subjects, a significant number (six) achieved significant rises in scoring.

KEYWORDS: Anomalous cognition, intuition, ESP training, PK training, success

INTRODUCTION

Intuition, which is defined by Philip Goldberg[1] as "knowing something without knowing how you know it," has a long anecdotal history in fields as widely divergent as science, business, and the arts. Looking at various classes of anomalous-cognition (AC) phenomena in relation to intuitive decision-making, Goldberg suggests that only AC of the future qualifies as intuition; "the other (AC) phenomena seem more closely linked to perception than to knowing." Jeffrey Mishlove reported a survey[2] of numerous anecdotal claims of training in this area of human performance.

Douglas Dean and John Mihalasky at the New Jersey Institute of Technology have reported that the ability to display AC of the future appears to play a significant role in, and indeed to be a highly reliable indicator of, practical success.[3] In their research, over 80 percent of successful company presidents (who had doubled their profits in five years) scored above chance in computerized AC tests, while unsuccessful presidents all scored below chance. With this potential, people may be trainable to improve their AC ability. Might they not become more successful by incorporating, in a structured way, something of proven worth previously employed in an untrained manner?

AC TRAINING DEVICES

The concept that AC ability can be trained was proposed in 1966 by Charles Tart,[4] who hypothesized that immediate feedback of results to talented percipients should result in learning AC skills. Tart was reacting against the delayed feedback used in card-guessing tests, which showed declines in AC scoring. From his survey of earlier feedback studies, Tart concluded that, when small numbers of targets are used, the hits are often due only to chance; so, rewards given for chance-produced hits will produce false information leading to an extinction of AC ability.

The first commercial device for training AC skills was created by Russell Targ,[5] who devised an ESP Teaching Machine at Stanford Research Institute (SRI) International. Subjects guessed which of four buttons was preprogrammed to light up next. The device featured a pass button, which allowed subjects to skip some trials. Targ's 4-choice device produced 25 percent "false-feedback," hits by chance. A study of 147 subjects, funded by NASA, yielded 5 per cent who showed either significant inclines or above-chance scoring at the .01 level. No subjects showed significant declines. Overall scoring was at chance.

Following Targ, a more sophisticated AC training device was developed by Tart[6] at the University of California, Davis. The Ten-Choice Trainer (TCT) displayed ten playing cards arranged in a circle. The subject's challenge was to guess which of the randomly chosen target cards was being concentrated on by an agent in another room, using a duplicate console. The TCT also featured a pass button, which was seldom used. False feedback was reduced to 10 percent. Tart's first training study, which screened the student body for subjects with high initial talent, used both his device and Targ's. Five of the 15 subjects who used Targ's machine showed significant above-chance scoring with the highest scoring subject also showing significant improvement. Five out of ten subjects who used Tart's device showed highly significant above-chance scoring. The star subject achieved astronomical odds against chance and also showed significant learning within sessions. Overall scoring was highly significant.

Tart's second training study[7] was less successful. A new group of students was screened. Out of seven subjects who trained on the TCT or a more sophisticated version, the ADEPT (Advanced Decimal Extrasensory Perception Trainer), one scored significantly above chance, which was canceled out by another subject who scored significantly below chance. Three additional subjects who trained on Targ's machine showed a combined significant score. None of the ten subjects showed significant inclines. Nor did they show significant declines. Of the total of 35 subjects in both studies, 6 percent showed significant inclines in scoring.

CIES Training

In 1982 Tart[8] extended his learning hypothesis to consciousness interaction with electronic systems (CIES). He theorized that strong initial talent was needed to overcome the inherent noise level and the extinction procedure caused by chance-produced hits in the binary random-event generators most commonly used in experiments where agents attempt to influence the outcome of the random event generators. This remains incompletely tested and other research suggests the actual AC learning dynamic is far from simple. Indeed, some researchers doubted whether it was possible. Gertrude Schmeidler,[9] after reviewing both AC and CIES training studies, concluded that there is no replicated evidence to show that these abilities can be learned. Rex Stanford[10] notes that decline effects are common and incline effects, even nonsignificant ones, are quite rare.

Such a rare incline effect, however, was achieved by seven subjects who were trained in a pilot study by William Braud[11] using a binary random-event generator. Braud augmented the usual testing protocol with visualization exercises over six weeks prior to the second test. He achieved a significant increase in scoring, and his study suggests that psychophysical self-regulation strategies may prove a fruitful area for exploration in any attempt to develop AC or CIES training.

Feedback Design

The design of the present study was based on a speculation first advanced by Tart. He reasoned that reducing "false feedback" or chance-produced hits would enable subjects to better learn from internal signals that accompany accurate hunches. Yet, we questioned, what about the negative feedback from misses? If most of the time, subjects' feedbacks are "misses," they grow bored at being just plain wrong. We postulated: If most of the negative feedback could be converted into graduated-and-weighted positive feedback, such that subjects would get rewards roughly proportional to how close they got to the target, they might become more sensitive to the internal signals that Tart hypothesized. And, of course, "false feedback" of direct hits should be kept to a minimum.

A conceptual ancestor of this feedback design was the ESP clock test devised forty years ago by G. W. Fisk and A. M. Mitchell.[12] The 12 positions of a clock face were scored: a direct hit as 0, one off as 1, two off as 2, and so on, with a low score being desirable. Our innovation was to weight the scoring. A direct hit is 10,000, one off is 40 percent of the direct-hit value, two off is 20 percent, three off is 7.5 percent, as shown below. This study was designed to test the value of using a weighted feedback strategy and its role in putative AC learning curves.

> Direct Hit: $10,000; 1 off: $4,000; 2 off: $2,000; 3 off: $750; 4 off: $500; 5 off: $200; 6 off: $100; 7-12 off: $75; 13 off: $0.

HYPOTHESIS

The null hypothesis predicts that AC testing with whatever system of feedback will not show a significant increase between the first third of scores (600 trials) and the last third of scores when subjects do 1,800 trials. We predict that a computerized AC testing system with weighted 96 percent positive feedback, 4 percent negative feedback, and 4 percent "false feedback" of direct hits should enable motivated subjects to show AC learning over 1,800 trials, as measured by a significant increase in scoring from first third to last third of scores.

COMPUTERIZED AC TESTING SYSTEM

DESIGN

A software program was written in Basic, which we called Psychic Reward: An Intuition Trainer. It was designed for IBM and Macintosh systems, and had the overt purpose of enhancing successful decision-making by testing and training AC ability. The name is inspired by the business literature, which speaks of "psychic rewards" to mean intangible job satisfactions that outweigh financial rewards. A wheel display operates like an electronic wheel of fortune (Figure 1). It was designed to simulate a game-show wheel that gives money rewards, in line with the Dean-Mihalasky finding that "prophets make profits." The subject's challenge is to predict which of the wheel's 26 lettered slots, A-Z clockwise, will be chosen by the computer as the random target, as shown by an arrow.

The program's novel design gives weighted, positive feedback 96 percent of the time according to how accurate the guess is: the closer the guess is to the target, the higher the score in money points. False feedback of direct hits is reduced

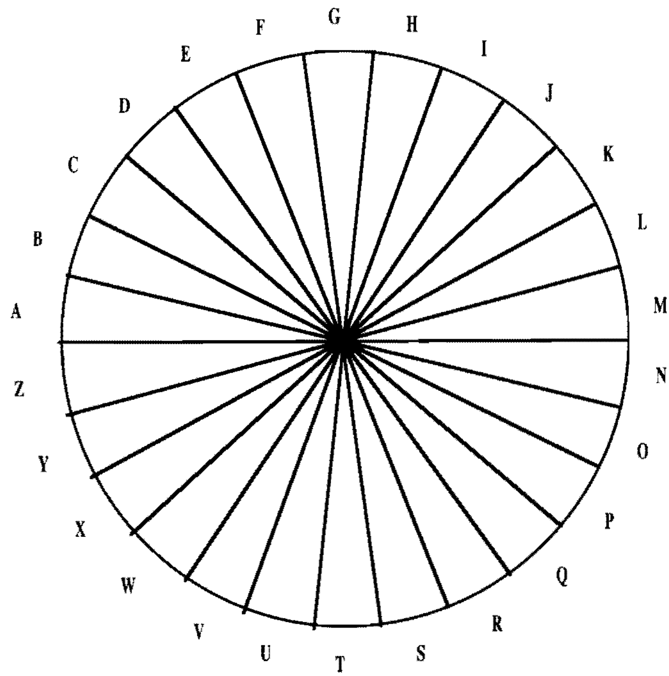

Figure 1. Psychic Reward wheel display.

to 4 percent. Audio feedback plays a different tune for each trial score, except 13 off, which, as the 4 percent negative feedback, gives no sound and a zero score. The mean chance expected (MCE) score is $1,000 when there are 600 or more trials.

One test consists of 30 trials. There are three series of 20 tests, a total of 1,800 trials for one experiment. Subjects type in a letter guess for each trial; the random target is indicated by an arrow, which disappears before the next trial. The trial score is shown, along with the total score so far and the average score. For faster play (if trial-by-trial feedback is not desired), guess letters may be entered before the arrow disappears, or up to 30 at the beginning of a test. The Macintosh edition provides an option of using the mouse to click on the target segment or letter.

STATISTICAL SUMMARY

SERIES = 1
TEST = 1
TRIAL = 30

PSYCHIC GENIUS [1000:1]: $2454+
EXCELLENT [100:1]: $2045 - $2453
VERY GOOD [20:1]: $1702 - $2044
ABOVE CHANCE: $962 - $1701
BELOW CHANCE: BELOW $962

YOUR AVERAGE SCORE = $1956
YOUR EXACT ODDS AGAINST CHANCE ARE 64 TO 1.
HIT ENTER WHEN READY TO PROCEED.

Figure 2. Example Statistical Summary of 30 Trials.

Entering the guess letter triggers the computer's internal clock (a minimum of 8 MHz or one cycle per 1.25 x 10^{-7} sec.) to freshly seed the random number generator using the RND function for a random number each trial. Scores are automatically recorded two ways. Experimenters who run experiments with other subjects should maintain control over the disks to ensure that all data are recorded, as with any computer program.

A chart showing subjects' progress appears after each test and can be viewed at any time. A running statistical summary appears after each test and can be viewed at any time to give subjects their exact odds against chance and their scoring category (see Figure 2 as shown on the computer monitor). If less than 30 trials are completed, a note indicates that there are not enough trials to produce valid statistics.

An analysis summary, which can be viewed at any time, gives the test scores for three series of 20 tests. The program calculates the *z*-scores (see section on Statistical Formulas) for each series (600 trials), and at the finish of 1,800 trials, gives the percentage increase, the *z*-score, the one-tailed probability and odds against chance of subjects' increase in scoring from first to third series. The *z*-score is also given for overall scoring. The analysis summary can be printed out as a data sheet.

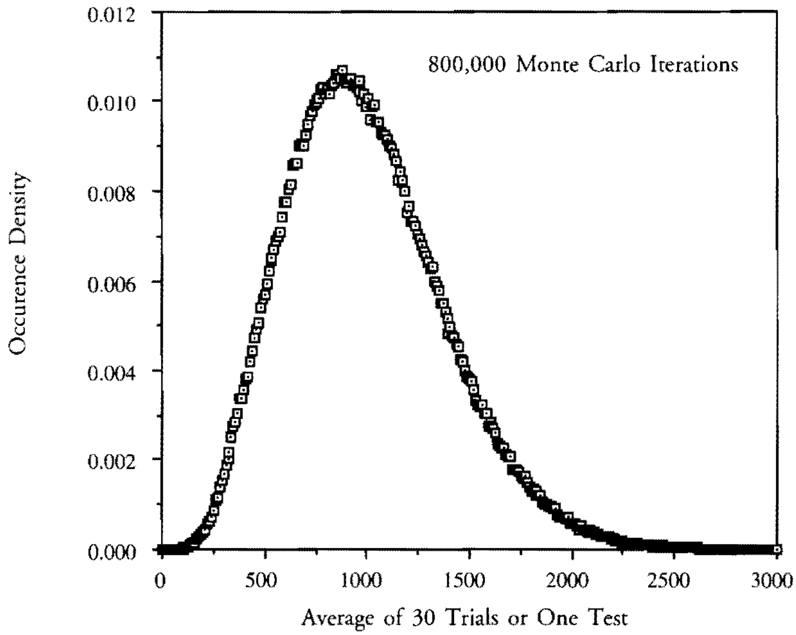

Figure 3. Chance Distribution of Average Scores for 30 Trials.

A random version of the program (PSYRND) operates by itself with the computer simulating a user. The random program can be used to generate control experiments, as we did with 24 control experiments (9 by JH and 15 by AV) and determined that chance results are obtained between first and third series (z = .38), as well as for overall scoring (z = .19). Twelve of the control experiments showed an incline between first and third series and 12 showed a decline, as expected by chance.

DISTRIBUTION CURVES

The chance distribution of average scores of 30 trials is quite skewed, as shown in Figure 3, which shows data from 800,000 Monte Carlo 30-trial iterations. The peak of the distribution, also called the mode, is an average score of 962 when 30 trials have been completed.

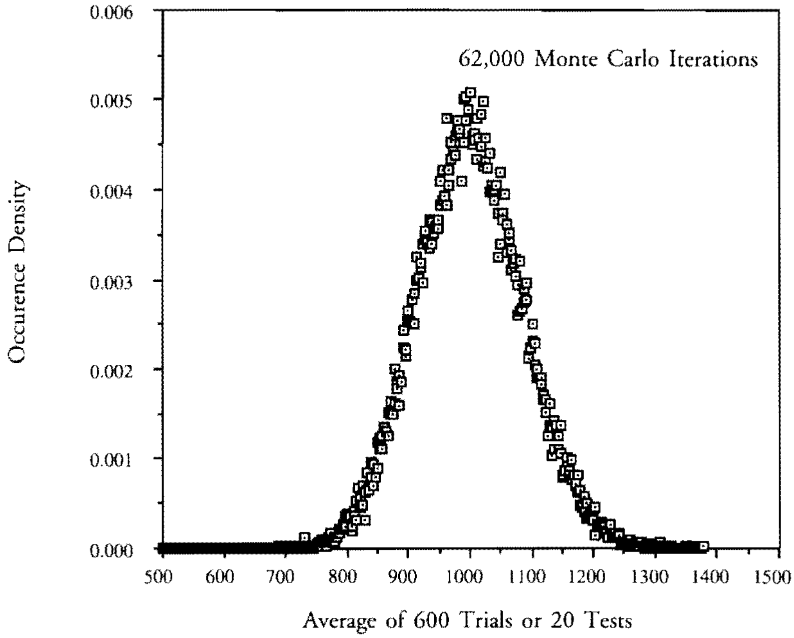

Figure 4. Chance Distribution of Average Scores for 600 Trials.

Originally the statistics of Psychic Reward were predicated on the use of the Central Limit Theorem, which assumes that the results will behave as a "normal" distribution after about 30 trials. James Spottiswoode did a Monte Carlo simulation of 30-trials tests to show that this was an incorrect assumption; the distribution is still skewed when the number of trials is 30. Subsequently it was determined that for 600 trials or greater, the distribution becomes fairly normal and the Central Limit Theorem may be used. The chance distribution of average scores (62,000 Monte Carlo iterations) when the number of trials is 600 is shown in Figure 4.

The new curve fit for 600 trials is compared with Monte Carlo results and the Central Limit Theorem in Figure 5. (Additional curve fit data for 5, 30, 60, 90, 120, 150, 210, 300, 400, and 500 trials are given by Houck.[13] These curve fits for less than 600 trials are used in a statistics program to calculate exact probabilities for scores.)

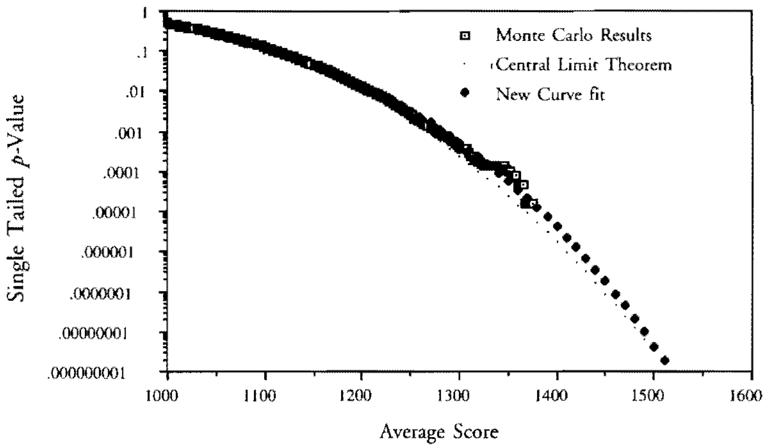

Figure 5. p-Value Comparison for 600 Trials.

The resulting curve fit for all the data sets for different numbers of trials is shown in Figure 6. This data provides a representation of the correct statistics for the Psychic Reward program.

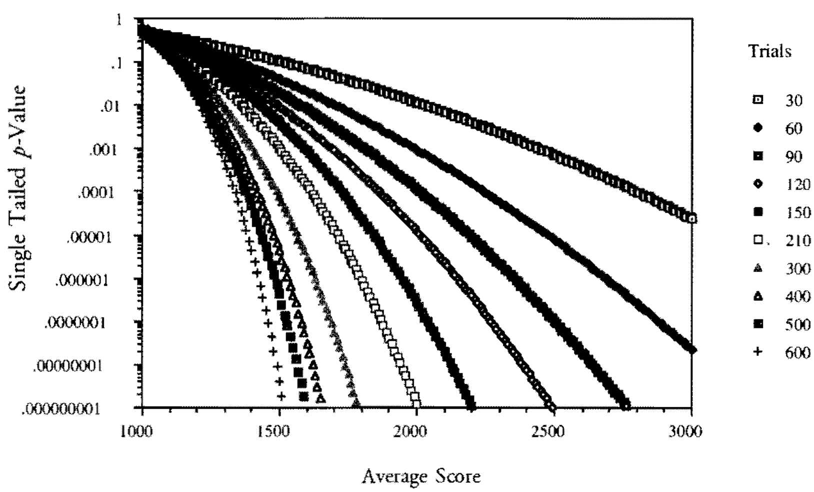

Figure 6. Combined Curve Fit Results.

Statistical Formulas

The standard deviation was calculated by Houck (see Table I) as 2110.35 and confirmed in Monte Carlo iterations. The resulting formula for calculating the *z*-score by the Central Limit Theorem, for some number of trials N, is:

$$Z = \frac{(\text{Average Score} - 1000)\sqrt{N}}{2110.345} \tag{1}$$

When determining if learning has occurred between the first and third series, the *z*-score is determined by comparing average scores from the third series and the first series. There are 600 trials in both series so the use of the Central Limit Theorem is justified. Following Spiegel:[14]

$$Z = \frac{\overline{X}_3 - \overline{X}_1}{\sigma_{1-3}} \tag{2}$$

where:

$$\begin{array}{ll} \overline{X}_1 & \text{is the average score from the first series} \\ \overline{X}_3 & \text{is the average score from the third series} \\ \sigma_{1-3} & \text{is the combined standard deviation} \end{array} \tag{3}$$

and:

$$\sigma_{1-3} = \sqrt{\left(\frac{\sigma_1^{\,2}}{N_1}\right) + \left(\frac{\sigma_3^{\,2}}{N_3}\right)} \tag{4}$$

For our problem $N = N_1 = N_3$ = total number of samples from the first series and

$$\sigma = \sigma_1 = \sigma_3 = 2110.35 \tag{5}$$

Table I
Calculation of Standard Deviation for Psychic Reward

Number of Occurrences	Value (X)	X - m	$(X - m)^2$		
1	10,000	9,000	81.0	x	10^6
2	4,000	3,000	9.0	x	10^6
2	2,000	1,000	1.0	x	10^6
2	750	-250	.0625	x	10^6
2	500	-500	.25	x	10^6
2	200	-800	.64	x	10^6
2	100	-900	0.81	x	10^6
12	75	-925	0.855625	x	10^6
1	0	-1000	1.0	x	10^6
N = 26	26,000				

$$\mu = \frac{26{,}000}{26} = 1{,}000 \tag{T1}$$

$$\sigma^2 = \frac{\sum_{j=1}^{N}(X_j - \mu)^2}{N} \tag{T2}$$

$$\sigma^2 = \frac{\sum \#\ \text{Occ.}(X - \mu)^2}{N} \tag{T3}$$

$$\sigma^2 = \frac{115.79 \times 10^6}{26} = 4.453 \times 10^6 \tag{T4}$$

$$\sigma = 2110.345$$

therefore:

$$\sigma_{1-3} = \frac{2110.35\sqrt{2}}{\sqrt{N}} = \frac{2984.48}{\sqrt{N}} \tag{6}$$

For one person using the Psychic Reward Program:

$$N = 600 \text{ which corresponds to } 30 \text{ trials x } 20 \text{ tests} \tag{7}$$

When comparing the first and last series for several people:

$$N = 600 \text{ times the number of people} \tag{8}$$

The resulting formula to determine the *z*-score

$$Z = \frac{(\text{Avg. score from third series} - \text{Avg. score from first series})\sqrt{\#\text{ of people}}}{121.84} \tag{9}$$

PARTICIPANTS

A total of 23 adults (17 women, 6 men) participated in the pilot study as experimenter/subjects. We term them "experimenter/subjects" because they took full responsibility for their own experiments, which were done on their own computers at home. Most subjects submitted data sheets after responding to a magazine article[15] that compared data from Targ's ESP Teaching Machine and Tart's Ten-Choice-Trainer with that of the first five Psychic Reward subjects. Readers who purchased the software were asked to complete 1,800 trials, send us the data sheets (whether the results were "good, bad, or indifferent"), and sign a form that stated: "As an experimenter/subject with Psychic Reward, I hereby swear that my data are mine alone, that they faithfully represent my ESP experiment, that all my data are included, and that my data have not been altered or manipulated in any way." We can give no guarantee, of course, that these statements are true. However, since subjects had to pay a software purchase fee to be included in the study, and were not promised any financial reward, any motive to lie on a sworn statement seems obscure. We cannot completely rule out that skeptics posing as subjects might risk exposing themselves as liars in order to ridicule such experiments.

JH was acquainted with Subjects 2 and 3, and AV was acquainted with Subject 1. The remaining subjects corresponded with AV from around the U.S. and Canada. Two of the subjects (1 and 23) have professional credentials in psychology. The remaining subjects were lay people. None, except AV, had previously undergone AC testing.

ANALYSIS

A meta-analysis of all experimental data uses the Stouffer method.[16] Because each target is independently produced by a pseudo-random number generator, information about past performance cannot aid subjects for future trials.

RESULTS

ANOMALOUS COGNITION EXPERIMENTS

A total of 21 experimenter/subjects completed one AC experiment of 1,800 trials. Table II gives a *z*-score summary for first, second, and third series of 600 trials, the increase from first to third series, and overall scoring for 1,800 trials. A significant percentage (71% or 15/21, $p_0 = .5$, binomial $p = .039$, one-tailed) improved their scoring from first to third series.

Subject No. 2 (HW) showed the most significant increase in scoring ($z = 2.32$, $p \leq .01$, one-tailed). Subject 18 (TW) also showed a significant increase in scoring ($z = 2.06$, $p \leq .02$, one-tailed).

Table II
z-Score Summary of 21 AC Experiments

Subject	1st Ser. Z	2nd Ser. Z	3rd Ser. Z	1st to 3rd Z	Overall Z
1. RH	- .66	-.06	-.02	.46	-.43
2. HW	-2.11	-.92	1.18	2.32*	-1.06
3. GD	-1.31	-.14	.50	1.28	-.55
4. CM	.02	.95	1.14	.78	1.22
5. AV	-.91	.98	-.17	.53	-.05
6. RK	-1.00	.19	-.73	.19	-.89
7. BM	-.21	.91	-1.27	-.76	-.32
8. MP	-1.44	-.80	-.82	.43	-1.76
9. CE	-2.36	-.34	-1.67	.48	-2.52
10. EO	- .67	-1.01	- .16	.36	-1.07
11. MG	.94	-1.08	1.02	.06	.51
12. MB	1.77*	.59	.86	-.64	1.86*
13. DB	4.20*	1.40	.20	-2.84	3.35*
14. AK	.48	-.38	.56	.06	.38
15. BR	-.82	2.07*	-1.44	-.44	-.10
16. LT	-1.24	-1.51	.57	1.27	-1.25
17. LM	- .94	.06	.36	.92	-.29
18. TW	- .84	-.98	2.08*	2.06*	.15
19. RL	.71	-.24	-.55	-.89	-.04
20. DM	- .06	.04	.67	.51	.38
21. FS	.17	1.07	-.29	-.33	.54
Total	-1.37	.17	.44	1.27	-.42

*Significant at .05 level, one-tailed.

The highest above-chance scoring subject (No. 13, DB), although showing a large decline, achieved an overall significant z of 3.35, $p \leq .0004$, one-tailed. The president of her own successful consulting company, she complained that she became too busy to continue "playing a game." She attributed her success to "good instincts."

The next highest above-chance scoring subject (No. 12, MB) showed a decline but attained an overall significant z of 1.86, $p \leq .03$, one-tailed.

Of 21 subjects who did one AC experiment, two (HW and TW) achieved significant increases in scoring and two (DB and MB) achieved significant above-chance scoring.

Table III
z-Score Summary of 25 Additional AC Experiments

Subject	1st Ser. Z	2nd Ser. Z	3rd Ser. Z	1st to 3rd Z	Overall Z
4. CM-2	.74	.94	2.54*	1.26	2.44*
5. AV-2	-1.77	.22	.95	1.92*	-.35
AV-3	-.36	1.20	.07	.30	.53
AV-4	-2.22	1.00	2.08*	3.03*	.50
8. MP-2	-.59	.92	-1.44	-.60	-.63
10. EO-2	-2.40	-.15	-1.15	.89	-2.13
12. MB-2	1.45	.78	-.54	-1.41	.99
14. AK-2	1.08	-.24	1.13	.03	1.13
AK-3	-.13	-.90	-1.72	-1.12	-1.59
AK-4	.12	.86	-.10	-.16	.50
AK-5	.63	-.38	1.67*	.74	1.11
18. TW-2	-.99	-1.24	.32	.93	-1.10
TW-3	-.18	.69	-.16	.01	.20
TW-4	-.26	-1.16	-.27	-.01	-.97
20. DM-2	-.29	1.09	-.44	-.11	.22
DM-3	.14	-.09	1.92*	1.26	1.14
DM-4	.69	.60	2.48*	1.26	2.18*
DM-5	-.50	-.96	-.46	.02	-1.11
DM-6	.68	-.21	.47	-.15	.54
DM-7	1.21	-.86	.49	-.51	.49
DM-8	-.55	-.93	.13	.47	-.78
DM-9	.06	1.18	.32	.18	.90
DM-10	-1.08	-.05	-.41	.47	-.89
DM-11	-.17	.56	-.53	-.25	-.08
DM-12	.11	-.42	-1.03	-.81	-.77
Total	**-.92**	**.49**	**1.26**	**1.53**	**.49**

*Significant at .05 level, one-tailed.

ADDITIONAL AC EXPERIMENTS

Eight of the 21 subjects sent in data sheets for additional AC experiments. (This option was not open to the first three subjects, who used an early version of the software that had only one data file.) Table III gives a z-score summary of their total of 25 experiments.

Subject 4 (CM), did a second experiment, which, when combined with the first experiment, gives significant overall scoring ($z = 2.59$, $p \leq .005$, one-tailed). She also showed a significant increase ($z = 1.78$, $p \leq .04$, one-tailed) from the first series of her first experiment to the third series of the second experiment. Subject 4 issued her own report on her experiments, which she kindly sent us. Her data are the model of the results we hoped Psychic Reward would produce.

Over a period of two years co-author AV (Subject 5) did three additional AC experiments. He showed a significant increase ($z = 2.11$) from the first series of the first experiment to the third series of the fourth experiment. His combined z from first series to third series of all four experiments was significant ($z = 2.89$, $p \leq .002$, one-tailed). His scoring pattern resembles that of Tart's star subject, who showed significant increases within sessions but declines between sessions—which Tart interpreted as "learning" and "forgetting."

Subject 12 (MB) did a second experiment, which when combined with the first experiment, yields a significant overall z of 2.02, $p \leq .02$, one-tailed.

Subject 14 (AK) did four additional experiments. She showed a nonsignificant increase from the first series of the first experiment to the third series of her fifth experiment.

Subject 18 (TW) did three additional experiments. The combined z from her first series to third series of all four experiments reduces the significance of her increase ($z = 2.06$) in the first experiment to a nonsignificant z of 1.50.

Subject 20 (DM) did eleven additional experiments. She showed an initial significant ($z = 1.80$) increase over the first four experiments, from the first series of her first experiment to the third series of her fourth experiment. Thereafter she declined over the last eight experiments. A note on her seventh data sheet says, "very discouraged."

Additional experiments by subjects 8 (MP) and 10 (EO) gave nonsignificant results.

Of eight subjects who did additional AC experiments, two (CM and AV) achieved significant increases in scoring and two (CM and MB) achieved significant above-chance scoring. One subject (TW) lost her status of significant increase.

Of the total of 21 subjects who did AC experiments, five (HW, MB, DB, CM, AV) achieved significant increases or above-chance scoring. Combined data of all 46 AC experiments show a significant rise (z = 1.98, $p \leq .024$) from first to third series, with overall scoring at chance (z = .08).

CIES Experiments

Three subjects, including two new ones, completed experiments in consciousness interaction with electronic systems (CIES). This is an experimental paradigm in which subjects attempt to influence the computer to give positive results when the same letter is used for all guesses or random letters are used. The manual accompanying the software gives directions for doing CIES experiments but we had not anticipated that any subjects would choose to do them. Hence, we made no formal prediction about the outcome of CIES experiments. Table IV gives a z-score summary of six CIES experiments. The combined overall scoring for all six experiments is significant (z = 2.05, $p \leq .02$, one-tailed).

Subject 10 (EO) did two CIES experiments by using the same guess letter for all targets. Comparing the results from EO's first two AC experiments from Tables II and III (combined overall z = -2.26) to her two CIES experiments in Table IV (combined overall z = 1.63) gives a significant increase (z = 2.75, p $\leq$ .003, one-tailed).

Subject 22 (ET) used the same guess letter for all targets and showed a decline, with overall above-chance scoring.

Subject 23 (MK), used a random number table to generate random letter guesses in three experiments. His use of a fast (33 MHz) computer (four times the speed of 8 MHz machines) enabled him to do 1,800 trials in a single

Table IV

z -Score Summary of 6 CIES Experiments

	Subject	1st Ser. Z	2nd Ser. Z	3rd Ser. Z	1st to 3rd Z	Overall Z
10.	EO-1	.26	2.25*	-1.53	-1.27	.5
	EO-2	1.54	1.04	.39	-.81	1.73*
22.	ET	2.89*	-.05	-.40	-2.33	1.41
23.	MK-1	-1.51	.49	-.22	.90	-.71
	MK-2	.45	1.68*	-3.19	-2.58	-.61
	MK-3	3.44*	-.86	2.00*	-1.02	2.65*
	Total	**2.89***	**1.86***	**-1.20**	**-2.90**	**2.05***

*Significant at .05 level, one-tailed.

session. His increase in scoring from the first to third experiment was significant (z = 2.38, $p \leq .009$, one-tailed). MK also achieved the highest 30-trial test score of the study: $2,714 (odds of 5,500 to 1). MK commented, "I was so surprised by what was happening that I could hardly believe it myself while I was doing it."[17]

Of three subjects who did CIES experiments, one (MK) showed a significant increase in scoring and one (EO) showed a significant increase from earlier AC experiments. Together the three subjects scored at an overall significant level. They tended to show declines in scoring within an experiment, but, when repeating the experiment, achieved an increase in overall scoring.

It should be noted that there is no generally accepted theory or model of any known mechanism by which CIES or AC experiments succeed, which is why they are termed "anomalous." Over the years attempts have been made to explain one anomalous phenomenon by another, depending on the researcher's point of view. One proposed model, for instance, E. C. May's "Intuitive Data Sorting"[18] was used in an experiment by Dean Radin and May[19] to explain anomalous CIES by anomalous cognition. They hypothesized that subjects were intuitively cognizing sequences of random numbers in a binary random generator and were able to sort the significant and nonsignificant sequences into different bins with an accuracy of .02 second per item when pushing the generator button. That model, at least, can be excluded in the CIES experiments cited here, since the speed needed to control the seeding of each random target is a minimum of 1.25×10^{-7} second, which is beyond human reaction time. In the case of MK, whose results were the most significant, the reaction time would need to be 3×10^{-8} second.

DROP-OUT SUBJECTS

Numerous unmotivated subjects dropped out before completing 1,800 AC trials. We were able to obtain partial data from 11 drop-out subjects who had completed at least 12 tests. We compared the average scores of the first six tests (180 trials) with those of the last six tests. They showed a substantial increase ($z = 1.34$) from first ($z = -1.51$) to last 180 trials ($z = .40$). Six out of 11 showed improvement. Their overall scoring pattern resembles that of the motivated subjects who completed their AC experiments. In spite of the small number of trials, one subject achieved a significant rise in scoring ($z = 1.88$, $p \leq .03$, one-tailed) from first ($z = -1.04$) to last 180 trials ($z = 1.62$) of 900 trials. This subject worked under the supervision of AV.

DISCUSSION

In Table II, two thirds of the 21 subjects scored below chance in their first series, which is consistent with the hypothesis that they initially inhibited their AC abilities by using their left brains to try to logically predict the targets. Four (HW, AV, MK, EO) subjects who showed significant gains in scoring at the .01 level began below chance. (A fifth, CM, significant at the .05 level, began above chance.) Schmeidler[9] cautions that comparison of initial low scores with later scores that are at chance or slightly above will show an upward slope, but that this slope should not be considered evidence of learning. Four out of five of our significant subjects progressed to significant above-chance scoring. Figure 7 shows graphed comparisons of *z*-scores of the five subjects. To look at their overall pattern of scoring, we compared the first half of their data with the second half, omitting the middle series if there were an odd number (for

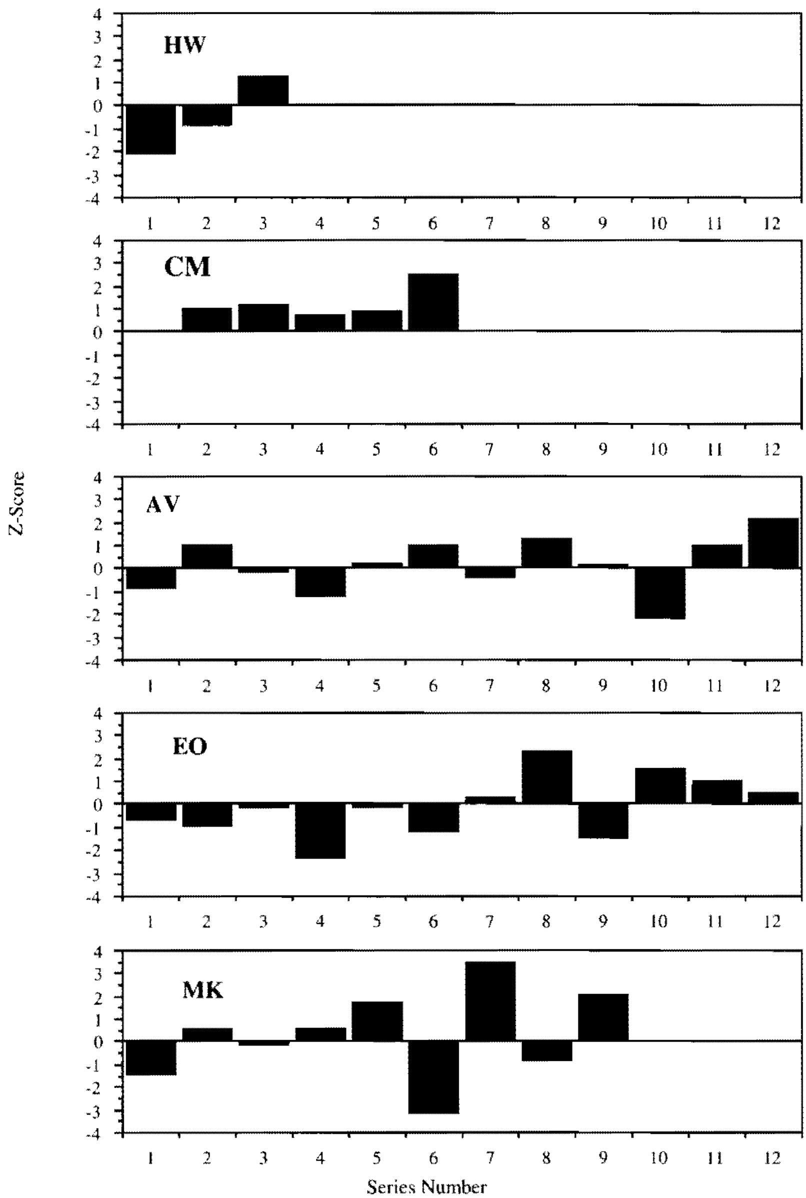

Figure 7. *Graphed Comparisons of Five Significant "Learning" Subjects.*

HW and MK). Combined data of the first half (20 series, combined $z = -1.57$) have 12 negative scores and 8 positive scores, with none being significant. Combined data of the second half ($z = 2.80$) have 5 negative scores and 15 positive scores, with 5 being significant. The significant increase ($z = 3.09$) from first to second half is due more to significant scoring in the second half ($z = 2.80$) than below-chance scoring in the first half ($z = -1.57$).

Consistent with the learning hypothesis, Table II shows that the 21 subjects progressed from below-chance scoring in the first series to above-chance second series scores to higher scores in the third series. Subject-by-subject, a significant percentage (71% or 15/21, $p_0 = .5$, binomial $p = .039$, one-tailed) show an increase from first to third series. Fifteen out of 25 ($p_0 = .5$, binomial $p = .2$, one-tailed) experiments in Table III show an increase from first to third series. Note that 64% of the 25 additional experiments show a decline (suggestive of forgetting) from the end of one experiment to the beginning of the next.

The progression of series is most clearly seen in the combined data for all 46 AC experiments: first series $z = -1.60$; second series $z = .48$; third series $z = 1.22$. A substantial rise in scoring ($z = 1.47$) from first to second series becomes significant ($z = 1.98$) from first to third series. A significant percentage of all AC experiments (65% or 30/46, $p_0 = .5$, binomial $p = .027$, one-tailed) show the rise in scoring from first to third series, as predicted by the learning hypothesis.

To investigate what role is played by the second series, we did an additional analysis to compare the first half of all data with the last half by splitting the second series. The first half of the second series for 46 experiments is below chance ($z = -.17$), while the last half is above chance ($z = .83$). The first half of all data gives a z of -1.39; the last half gives a z of 1.49. The increase ($z = 2.04$) is slightly greater than the increase from first to third series ($z = 1.98$). Thus including second series data in the analysis slightly increases support for the learning hypothesis.

Several subjects described the experience of making the transition from presumed left-brain to right-brain functioning as becoming more relaxed. They described their best scoring strategies as:

Being able to completely let go—a feeling of not caring.
Maintaining a relaxed, easy-going playful attitude.
Being relaxed, meditative, not allowing misses to bother me.
The harder I concentrated, the more I got wrong—
I tried to find a medium level of concentration.
Relax and go for it.

How important is AC talent? The significant AC scoring of two subjects in their first series (DB, $z = 4.20$; MB, $z = 1.77$) suggests that they have pre-existing AC talent. Yet AV, who has successfully demonstrated AC ability in numerous experiments[20,21] began below chance and did not attain significant scoring until his twelfth series ($z = 2.08$). We can only speculate that there is no "pure" type of AC talent, and that some individuals (such as DB and MB) quickly adapt to forced-choice testing, while others (such as AV) undergo a long process of trial and error.

If latent AC talent is distributed more or less normally throughout the human population, we would expect the most talented group on the right tail of the curve to show significant above-chance scoring or increases in scoring, and an equal-sized untalented group on the left tail to show chance results. Including the 11 drop-out subjects in our total population of 34 subjects, eight (24 per cent) attained significance. So we would expect another 24 per cent to give chance results, with the remaining 52 percent divided between the more talented and the less talented. In all, we would expect from 50 to 76 per cent of people (a mean of 63 per cent) to show some indication of success. Consistent with this hypothesis, 65 per cent of our 34 subjects showed improvement.

SUMMARY AND CONCLUSION

Pilot experiments by 23 Psychic Reward experimenter/subjects yielded four who achieved significant gains in scoring at the .01 level (4/23, $p_0 = .01$, binomial $p = .000076$, one-tailed), one who achieved both a significant increase and significant overall scoring, and two who showed significant overall scoring. A significant percentage (71%) of 21 subjects who did one AC experiment showed improvement. Eight of the subjects did 25 additional AC experiments, making a total of 46 experiments, of which a significant percentage (65%) showed a rise in scoring. Combined data of all 46 AC experiments showed a significant increase from first to third series, with overall chance scoring. Three subjects, including two new ones, did six CIES experiments, whose combined data showed overall significant scoring. Eleven dropout subjects showed a substantial increase in AC scoring, with one attaining a significant rise. Of the total of 34 subjects, a significant number (6/34, binomial p = .0063, one-tailed) achieved significant (p_0 = .05) rises in scoring. A comparison of the number of subjects achieving significant increases (p_0 = .05) in Tart's two studies (2/35, binomial p = .53, one-tailed, z = -.08) with ours (6/34, and z = 2.50) shows that Psychic Reward works significantly better (z = 1.82, and p = .034, one-tailed) than earlier devices in training AC.

The Null Hypothesis can be rejected. Our pilot data tentatively suggest that the weighted positive feedback provided by Psychic Reward enables motivated subjects to enhance their awareness of subtle internal signals or "intuitive hunches." The motivation of the subjects seems to outweigh pre-existing AC talent as a factor in achieving significant rises in scoring. Another factor may be that informal home testing enables subjects to enter into a relaxed state of mind conducive to AC success.

With our open design for pilot experiments we cannot control against additional unreported data. However, of nine subjects who did multiple experiments, 56 per cent achieved significance—a trend that should encourage replications.

It is our hope that formal replications will establish Psychic Reward as an effective instrument for testing and training anomalous cognition of the future and consciousness interaction with electronic systems. A theoretical question to be investigated is whether subjects are learning how to control their preexisting AC ability, or whether the training actually strengthens AC ability. A practical question to be investigated is what effect the training has on subjects' ability to make successful decisions.

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