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Operator-Related Anomalies in a Random Mechanical Cascade

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Abstract—Experiments with a "Random Mechanical Cascade" (RMC) apparatus have yielded anomalous results correlated with pre-stated intentions of human operators. Based upon a common statistical demonstration device, this machine allows 9000 polystyrene balls to drop through a matrix of 330 pegs, scattering them into 19 collecting bins with a population distribution that is approximately Gaussian. As the balls enter the bins, exact counts are accumulated photoelectrically, displayed as feedback for the operator, and recorded on-line. Operators attempt to shift the mean of the developing distributions to the right or left, relative to a concurrently generated baseline distribution. Of the 25 operators who have completed one or more experimental series with this device, four have achieved anomalous separations of their right and left efforts, and two others have displayed significant separations of either their right or left efforts from their baselines. The overall mean difference of right versus left efforts concatenated across the total data base of 87 series (3393 runs), has a probability against chance of $<10^{-4}$, with 15% of the individual series significant at $p < .05$, and 63% conforming to the intended directions.

The concatenated results display a stark and curious asymmetry, in that virtually all of the right vs. left separation is provided by the left vs. baseline separation. This pattern also appears in the data of several individual operators, and is not attributable to any known physical asymmetry in the experimental system. In addition to the systematic asymmetric deviation of the distribution means, cumulative excesses in the variances of the left and right distributions relative to baseline are also observed, progressing to statistical probabilities of .003 in the left efforts, but only .2 in the right. More detailed study of the individual bin population patterns reveals that while most of the bins contribute to the overall mean shifts and variance changes, those on the outer portions are more influential than those near the center.

Operator achievements tend to compound marginally but systematically in cumulative deviation patterns characteristic of the particular individuals and, in several cases, similar to those produced by the same operators in microelectronic Random Event Generator (REG) experiments. Within these characteristic patterns of achievement, some operators also show sensitivities to secondary experimental parameters, such as instructed vs. volitional establishment of the intended directions, or the presence or absence of feedback displays. Other successful operators seem insensitive to such options.

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Two major protocol variations have been explored, one employing remote operators, the other, multiple operators. In the former, operators with well-established performance in local experiments attempt to influence the bin distributions from remote locations up to several thousand miles from the laboratory. Significant results are again obtained that are quite similar to those of the local experiments, with the exception that the overall right and left distribution variances are smaller than those of the baseline. In the multiple operator experiments, early results show little resemblance to those achieved by the participating individuals alone.

Introduction

Through an extensive program of experiments previously reported in this Journal and elsewhere (Jahn & Dunne, 1986; Jahn, Dunne, & Nelson, 1987; Nelson, Dunne, & Jahn, 1984), it has been established that human operators can systematically influence the output of various microelectronic random event generators (REGs) to a marginal, but statistically significant extent, in accordance with pre-stated intentions. Specifically, the results have been found to correlate strongly with the individual operators and their intended directions of effort, and in some cases with certain secondary parameters such as whether the effort is volitionally chosen or randomly assigned, or whether the sequencing of trials is manual or automatic. Curiously, however, the performance seems less dependent on the details of the microelectronic noise source and processing circuitry, including various hard-wired or programmed pseudo-random systems.

The demonstrated insensitivity of these microscopic experiments to their interior details suggests broader exploration of the response of other classes of random physical processes to operator intention. In particular, it seems important to ascertain whether similar anomalies can be demonstrated on macroscopic systems employing other than electronic interactions. For this purpose, we have developed and applied a device termed a "Random Mechanical Cascade," which is a large-scale variant on the prototypical "Galtons Desk."

In 1894, the British eugenicist Francis Galton described a mechanical apparatus to illustrate certain statistical aspects of natural evolution. His description and interpretation are sufficiently relevant and ingenuous to bear repetition:

> It is a frame glazed in front, leaving a depth of about a quarter of an inch behind the glass. Strips are placed in the upper part to act as a funnel. Below the outlet of the funnel stand a succession of rows of pins stuck squarely into the backboard, and below these again are a series of vertical compartments. A charge of small shot is inclosed. When the frame is held topsy-turvy, all the shot runs to the upper end; then, when it is turned back into its working position, the desired action commences. . . . The shot passes through the funnel and issuing from its narrow end, scampers deviously down through the pins in a curious and interesting way; each of them darting a step to the right or left, as the case may be, every time it strikes a pin. The

pins are disposed in a quincunx fashion, so that every descending shot strikes against a pin in each successive row. The cascade issuing from the funnel broadens as it descends, and, at length, every shot finds itself caught in a compartment immediately after freeing itself from the last row of pins. The outline of the columns of shot that accumulate in the successive compartments approximates to the Curve of Frequency, and is closely of the same shape however often the experiment is repeated.

The principle on which the action of the apparatus depends is, that a number of small and independent accidents befall each shot in its career. In rare cases, a long run of luck continues to favour the course of a particular shot towards either outside place, but in the large majority of instances the number of accidents that cause Deviation to the right, balance in a greater or less degree those that cause Deviation to the left. Therefore most of the shot finds its way into the compartments that are situated near to a perpendicular line drawn from the outlet of the funnel, and the Frequency with which shots stray to different distances to the right or left of that line diminishes in a much faster ratio than those distances increase. This illustrates and explains the reason why mediocrity is so common. (Galton, 1894, pp. 63–65)

Galton's concept of demonstrating the development of Gaussian distributions by the compounding of a multitude of random binary events has since been extended into numerous other sectors, and various versions of his machine may be seen in science museums and instructional laboratories throughout the world. Our particular interest here is as a target for anomalous man/machine interactions.

Equipment and Protocol

Our RMC machine is roughly $10' \times 6'$ in size, and employs 9000 polystyrene spheres $\frac{3}{4}''$ in diameter, cascading through a quincunx array of 330 $\frac{3}{4}''$ nylon pins on $3\frac{1}{4}''$ centers, in much the same fashion as Galton described (Figure 1). A belt and bucket conveyor transports the balls from a plenum at the bottom to a funnel at the top, from which they bounce down through the matrix of pins in complex stochastic paths, accumulating finally in 19 parallel vertical collecting bins arranged across the bottom. The front of the pin chamber and collecting bins is clear acrylic, so that both the active cascade of the balls and their disposition into the developing distribution of bin populations are visible as feedback to the operator. By appropriate combinations of peg spacings, ball inlet configuration, and ball and peg material properties, the resulting distribution of ball populations in the collecting bins can be brought to a good approximation of a normal Gaussian distribution.

The entrance to each collecting bin is equipped with an optoelectronic counter. All 19 counters are scanned on-line by a microprocessor which transmits in real time the ordered accumulation of counts in each bin to LED displays at the bottom, and to a microcomputer where the complete sequence is registered on disk as a file of 9000 characters. Each file is indexed by file number, direction of effort, operator, date, time, humidity and temperature within the pin cavity, and various other experimental parameters.

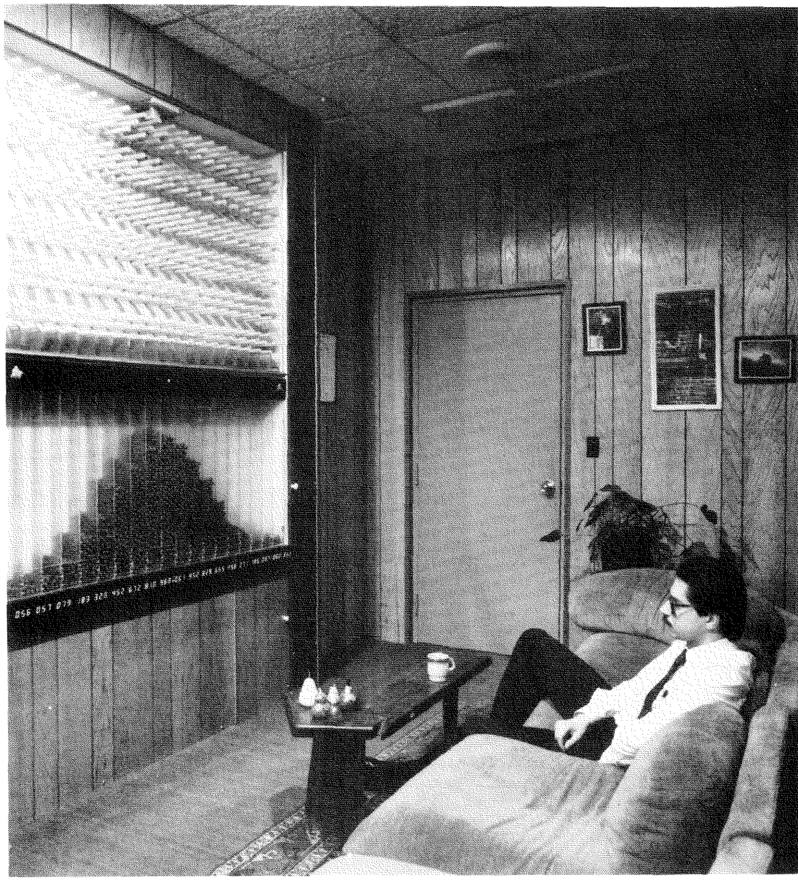

Fig. 1. Random Mechanical Cascade apparatus (RMC).

A logbook is also maintained with the same indexing information, a photograph of each completed run distribution showing the bin totals displayed on the LED's, the bin totals registered by the computer other summary information including total populations right and left of the center bin, a right-left ratio, the distribution mean and standard deviation, and any appropriate comments.

The standard experimental protocol calls for the operator, seated on a couch about eight feet from the machine, to attempt to distort the distribution of balls to the right or higher numbered bins (RT), or to the left or lower numbered bins (LT), or to generate a baseline (BL). These intentions are interspersed in concomitant sets of three runs, each of which lasts about 12 minutes. The sequence of each tripolar set of runs may be chosen by the operator (volitional assignment), or may be defined by some pre-established recipe (instructed assignment). Each set must be completed in one session, lasting about one hour. The operator has the choice of lighted or blank LED feedback displays, and employs his own subjective strategies. Operators schedule their own sessions, and are encouraged to generate large data bases, usually divided into independent experimental series of 10 tripolar sets of 3 runs.* Secondary parameters are fixed within a given series, but the operator's subjective strategy is not controlled. All operators are uncompensated anonymous volunteers who are willing to provide the requisite large data bases. None claims special abilities, and no screening or training of operators is attempted. (Although generic pronouns are used throughout this text, roughly equal numbers of male and female operators have contributed to the data base.)

The primary purpose of the tripolar experimental format is to mitigate any possible biasing effects of physical or environmental changes in the operation of the machine, such as long-term drift resulting from pin or ball wear, or the shorter-term influences of temperature or humidity. Variation of humidity, for example, has been found to correlate with small changes in the distribution variance, and very slightly with changes in the mean. (A detailed assessment of long-term drift of the distribution mean, including contributions from wear and mechanical factors, vibration, humidity, temperature, gravitational and tidal effects, and operator position is available in Nelson, Dunne, & Jahn, 1988a, which also includes a description of qualification and calibration procedures and the treatment of any technical problems that may arise in a given run.)

The machine, its counting and data recording systems, and the experimental protocol just described have evolved over the course of the program (Nelson, Dunne, & Jahn, 1983). In the earliest exploratory experiments, data were manually recorded as mechanically measured bin fill heights, but it soon became clear that these were compromised by differential stacking patterns of the balls, so that the much more precise photoelectronic counting system was devised. Similarly, early attempts to establish a universal baseline distribution by copius calibration data had to be abandoned once the effects of temporally varying physical conditions, such as temperature, humidity, pin and ball wear became apparent. At that point, it was decided to include only differential data generated in matched tripolar runs in the formal data base. All preceding runs, and any subsequent runs deviating from that protocol, are now regarded as exploratory, and indexed as such in a separate data file. Also included in the exploratory data are several series in which operators attempted to influence the accumulations in particular individual bins. Although interesting results were obtained in these experi-

*** Prior to October, 1983, 20 sets constituted a series. In a few cases, operators have completed slightly less or more than the prescribed number of sets per series due to technical malfunction, record-keeping errors, or unavoidable departure from the laboratory. Rather than exclude such data, they have been included as odd-size series. If less than 7 sets have been generated, however, the series has been voided and the data retained in a separate file.**

ments, this paper is confined to tripolar protocols addressing the shift of the distribution mean.

Statistical Treatment

Given the three-dimensional complexity of the individual ball collisions with the pegs, the complicating effects of ball-ball collisions, and the irregularities of the inlet flow, any deterministic dynamical modeling of the flux of balls through the pin matrix is unattainable. In this respect, the RMC experiment differs substantially from the strictly binary **REGs**, where precise theoretical expectations are derivable. However, a rudimentary quasi-binary model of the RMC statistical process, analogous to that more rigorously employed for the REG experiments, can be heuristically based on the virtually Gaussian character of the data distributions. As shown in Figure 2, a histogram of the 19 bin populations for the 1131 baseline runs of the formal data base is nicely fit by a Gaussian curve normalized to the distribution mean and standard deviation. To be sure, there is a slight excess population of the end bins by balls reflected from the side walls of the machine, and of the center bins by balls falling directly through the finite pin matrix, but these do not compromise the gross utility of the Gaussian model.

Such a quasi-binary approach can illustrate the immense statistical leverage of this kind of experiment. For example, using bin number as the statistical variable, the mean of this quasi-Gaussian distribution, μ, is found to be approximately 10.023 and the standard deviation, ***a,*** about 3.27 bins. Although this distribution derives from a very complex ensemble of collisional events, it can be modeled, for statistical purposes, as if it were the result of N simple binary events for each ball, in each of which it is deflected

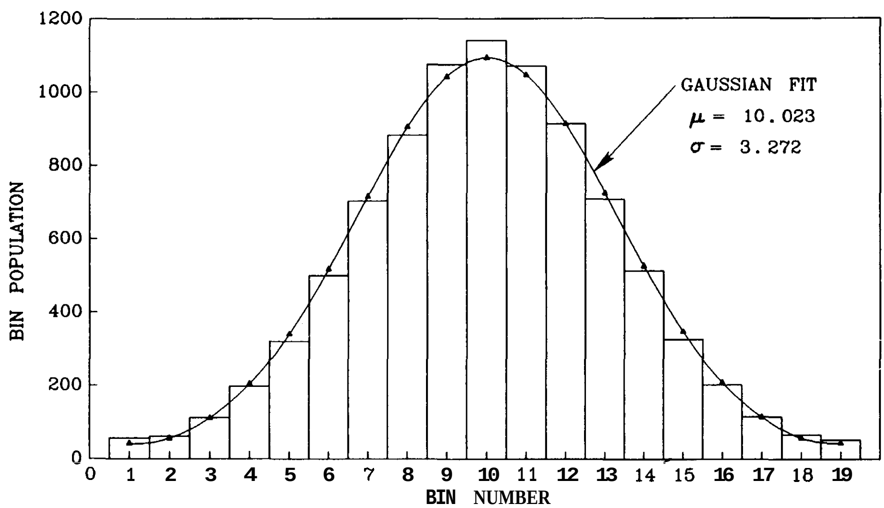

Fig. 2. RMC: Baseline mean bin populations on theoretical Gaussian (1131 runs).

either to the right or to the left by some uniform distance, $D = 0.5$ bin. If the probabilities for deflection in either direction are equal, binomial statistics requires a distribution variance of $\sigma^2 = D^2N$. Hence, the complex physical process actually experienced by a single ball is equivalent to $N \approx 43$ elementary binary choices, which may be regarded as a minimum estimate of the information content of a single ball's trajectory. Since there are 9000 such "ball-trials" in a single run, the statistical power of each run consists of approximately 387,000 binary equivalent bits. (By comparison, a typical REG run of 50 trials yields 10,000 bits.)

The stochastic dynamical behavior of this quasi-binary system is found empirically to converge to a stable statistical ensemble with a well-bounded mean after roughly one-third of the 9000 balls have been processed. In similar fashion, the optimum number of runs per experimental series, which must be a trade-off between operator comfort and statistical confidence, can be assessed in terms of the standard error of the estimates of the series mean. For example, the earliest series lengths were arbitrarily set at 20 runs per intention, for which the standard error corresponding to a 95% confidence interval around the grand baseline mean was found to be .0078 bins. But for the first 10 runs of these series, the standard error was only .0111 bins, still adequately small to allow any systematic anomalies to cumulate rapidly to significant deviations from expected values. Thus, we were able to respond to operator complaints that the 20-run series were too long by reducing the protocol to 10 runs per intention, and the series data accumulation rate increased accordingly.

The absence of any precise theoretical expectations, combined with the long-term variations in the calibration data mentioned earlier, force any search for distribution anomalies correlated with operator intention to proceed on a local differential basis. That is, only the cumulative systematic differences among the right, left, and baseline efforts within a given tripolar set can profitably be assessed. The most appropriate statistical tool for this purpose is Student's t-test for paired observations, supplemented by a conventional one-way analysis of variance (ANOVA). More specifically, the primary assessment of the effect of operator intention on the distributions employs correlated t-tests to compare differences within the tripolar data sets for each series, or for larger concatenations, taking into account the small, but occasionally significant correlations among the three strings of data due to common influences of machine wear, humidity, and other possible but unidentified effects.

The difference between the right and left efforts (RT–LT) is regarded as the primary indicator of an effect of operator intention. It is then possible to perform only one other fully orthogonal comparison, namely that between the baseline and the algebraic average of the right and left efforts. However, since interpretation of this latter quantity is somewhat complex, we have chosen to present the conceptually simpler paired t-tests for both RT–BL and LT–BL differences, supplemented by various graphic displays. While these tests are not fully independent of the primary RT–LT comparison, they are instructive in locating the three intentions relative to each other, and, of course, any one of the three tests constitutes a coherent, standardized measure across series.

Even in this local differential treatment, the raw data show correlations among the three data strings, perhaps attributable to shorter-term vagaries of machine operation. These are assessed by Pearson product-moment coefficients, which are helpful in explaining the considerable range of the standard deviation of the differences, and thus the variations in the size of the mean shifts that may be regarded as significant. For example, as the correlation between RT and LT data increases, the standard error of the differences decreases, yielding a larger t-score for a given mean difference.

For a supplementary perspective, the three conditions, RT, LT, BL, can be considered as three treatments in a conventional one-way analysis of variance. This approach can establish an overall estimate of unexplained, or error, variance appropriate for the comparisons, and it can explore covariates such as humidity and temperature, but it cannot incorporate any of the secondary experimental parameters, such as feedback mode or instructional/volitional options, since only a few operators have explored these systematically.

Consonant with the earlier REG experiments, it proves instructive to display the primary indicator of the effect of operator intention on the RMC, that is, the RT-LT difference, as a graph of cumulative deviation from the expected difference, given no effect, of zero. Likewise, the separate behaviors of RT and LT may be graphed as cumulative differences from the local BL values. To establish the scale of the cumulative deviations, envelopes of the t-scores corresponding to given probabilities against chance may be superimposed on these graphs.

Overall Results

Mean Shifts Correlated With Intention

The primary RMC data base consists of 87 series (3393 runs) generated by 25 individual operators. The overall results are shown in Figure 3, and in Table 1.* For the grand concatenation of these data, the paired t-test for RT–LT yields $t = 3.89$, $p < 10^{-4}$, one-tailed in direction of intention, with 15% of the series and 24% of the individual operator data bases beyond the 5% chance probability level and 63% splitting RT–LT in the intended direction. The one-way ANOVA yields a comparably significant departure from chance expectation ($F = 8.13$, with 2 and 3390 *df*, $p = 3 \times 10^{-4}$). The

* All tables are in the Appendix. Much more detailed results of all RMC experiments performed to date are presented in two PEAR Technical Reports (Nelson, Dunne, & Jahn, 1988a and 1988b). Many of the summary conclusions of this paper are supported by data displayed there, but not included here.

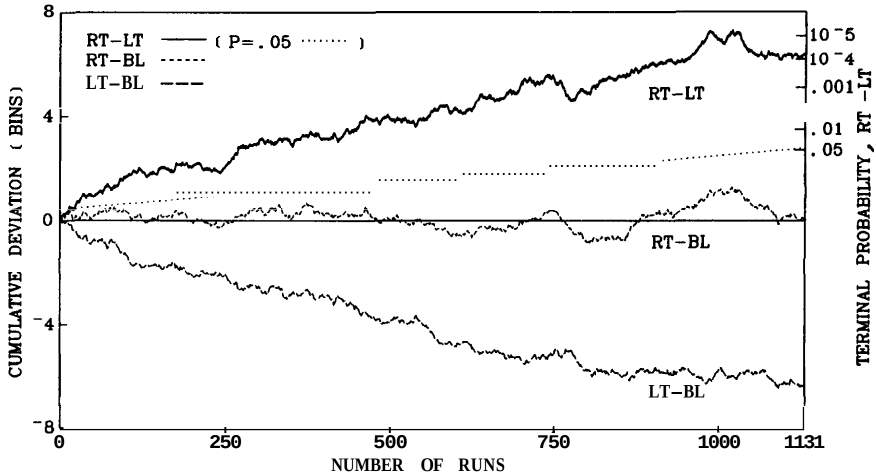

Fig. 3. RMC cumulative deviations: all data.

cumulative deviation graphs that trace the progress of these mean shifts through the various operators and series display notable consistencies of linear trends superimposed on backgrounds of stochastic variations. Thus, by any of the statistical criteria employed, there is clear evidence of a significant anomaly compounding from the gradual accumulation of small but consistent shifts in the distribution means, in a fashion quite similar to that found in the microelectronic REG and pseudo-REG experiments.

Asymmetry Effect

Beyond its existence and magnitude, the overall RMC anomaly entails an additional curiosity not found in the REG experiments. Namely, the concatenated results shown in Figure 3 display a stark left-going asymmetry. In fact, the right and baseline efforts are statistically indistinguishable over the full course of these experiments, so that the entire RT–LT effect is contained in the systematic separation of the left efforts from both of the others. This asymmetry is not explainable in terms of any known physical bias in the experimental system, especially given the tripolar protocol and differential data reduction process, and hence can be correlated only with operator intention, suggesting that it may have some psychological or neurological implication. Examination of the individual operator data bases might tempt the assignment of much of this effect to one or two of the most prolific operators, who individually show strong left-going asymmetries. However, removal of their contributions fails to symmetrize the remaining data. Alternately, the influences of every operator on the total data base may be balanced by concatenating equal subsets of the individual data, for example the first 10 runs only of each of the 25 operators (Figure 4). Again the traces proceed steadily toward significant terminal values for RT–LT and LT–BL

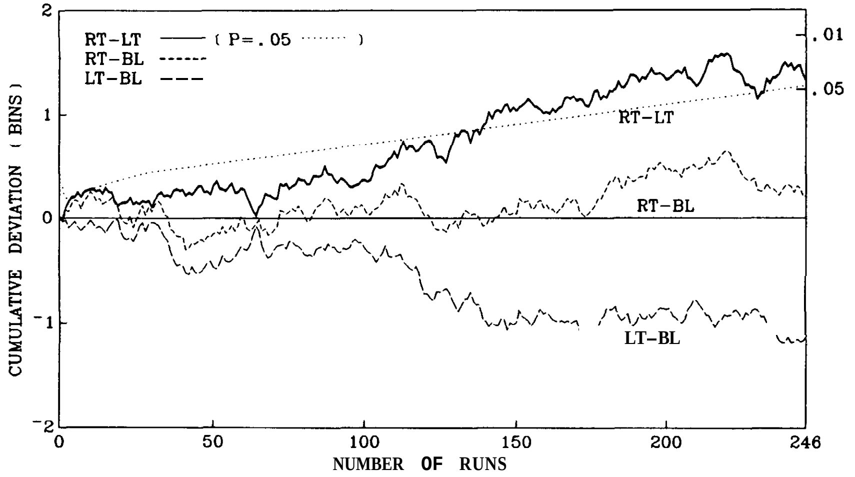

Fig. 4. RMC cumulative deviations: all operators, first 10 runs.

and show the same asymmetry, indicating that the overall effect reflects contributions from all operators in the group.

Secondary Parameters

Analysis of the composite data base for correlations with secondary parameters is necessarily limited since all operators have not contributed equally to the various categories. The mode of instruction, that is, whether the order of intentions in each tripolar set is chosen by the operator at the time of the session (volitional), or is prespecified for the entire series (instructed) has been varied in six operator data bases, and across these, the qualitative results seem to indicate a preference for the volitional mode; although the difference is not statistically significant ($t = 0.895$, $p = .371$, 2-tailed, $df = 779$). Similarly, the feedback has been varied for three operators by having the LED counter displays on or off, and here even less difference is found, although the results of each mode remain individually significant (LED on: $t = 1.829$, $p = .034$, 1-tailed, $df = 359$; LED off: $t = 2.845$, $p = .002$, 1-tailed, $df = 249$; At on/off $= 0.878$, $p = .379$, 2-tailed, $df = 608$). Less well defined parameters, such as date or time of day, have also been examined and show no clear influences across the total data. However, when these various parameters are analyzed on an individual operator basis, some correlations can be quite strong, indicating important operator-specific sensitivities. For example, with the LED display off, one operator (55) achieves a RT−LT t-score of 1.915 ($p = .029$), but with the display lit, performs at chance ($t = 0.294$, $p = .385$). Similarly, in the Volitional mode, another operator (70) obtains a RT−LT t-score of 2.143 ($p = .019$), but in the Instructed mode produces results slightly opposite to intention (t

$= -0.693$, $p = .253$). Several other examples are displayed in Nelson, Dunne, and Jahn, 1988b.

Variance and Goodness-of-Fit *Effects*

In the REG experiments, it was found instructive to array all terminal series scores as frequency distribution histograms (Jahn, Dunne, & Nelson, 1987; Jahn, Nelson, & Dunne, 1985). To pursue similar displays of the RMC results, we must again utilize the differential treatments, RT–LT, RT–BL, and LT–BL, comparing the distribution of series t-scores against a theoretical t-distribution for the nine degrees of freedom appropriate to a ten-run series. The results in Figures 5a, b, c confirm the shift of the distribution in the direction of intention for RT–LT and LT–BL, and in addition show an increase in the distribution variance in all three cases.

Similar frequency histograms for the run means, show little effect on the variance of the distributions, but the BL data are found to fit the expected Gaussian better than expected by chance ($\chi^2_{BL} = 7.75$, 17 *df,* $p = .97$) while both the RT and LT distributions are relatively rough, ($\chi^2_{RT} = 21.63$, $p = .21$ and $\chi^2_{LT} = 35.05$, $p = .0065$).

It next seems reasonable to inquire whether the individual run bin population distributions might themselves display variance changes as ancillary effects of operator intention. In the REG studies, no such effects were observed at the trial or run levels, but the situation appears to be quite different for the RMC. Figure 6 displays the cumulative differences in the standard deviations of the RT and LT runs compared to the BL run of the same set. The generally positive trends culminate as a highly significant increase in the LT run variances relative to the BL, and a non-significant increase in the RT run variances. This effect is more pronounced for some individual operators than others, but the concatenated data suggest that, on balance, both LT and RT efforts to shift the mean also entail a broadening of the bin population distributions in some fashion.

Individual Bin Populations

To pursue such goodness-of-fit issues in yet more detail, the response of all 19 individual bin populations to operator intention may be extracted from the data base management system. Over a sufficiently large number of runs, each of these bin populations should, by chance, distribute normally about some mean, with some standard deviation, in terms of which parameters any given population anomaly may be statistically quantified. Immediately instructive is a graphic display of the differences in individual bin populations between the RT, LT, and BL run sets over the entire data base, that highlights the major contributions to the overall distribution mean shifts (Figures 7a,b,c). On these histograms the significances of each of these differences is indicated by a .05 probability envelope, computed on the basis of the individual bin population standard deviations. Consistent with the

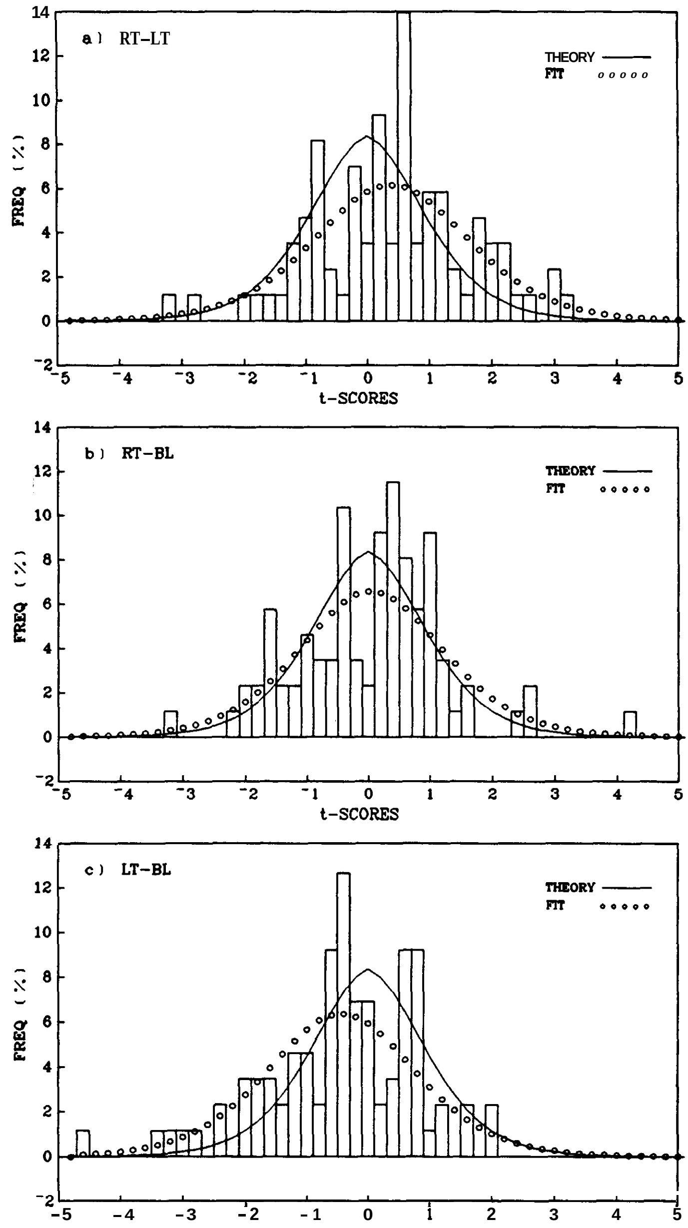

Fig. 5. RMC series *t*-score histograms: a) RT–LT; b) RT–BL; c) LT–BL.

overall behavior of the run means, the RT-BL bin population differences appear quite randomly distributed, whereas a majority of the LT–BL and RT–LT differences are supportive of the mean shifts. Because of their larger

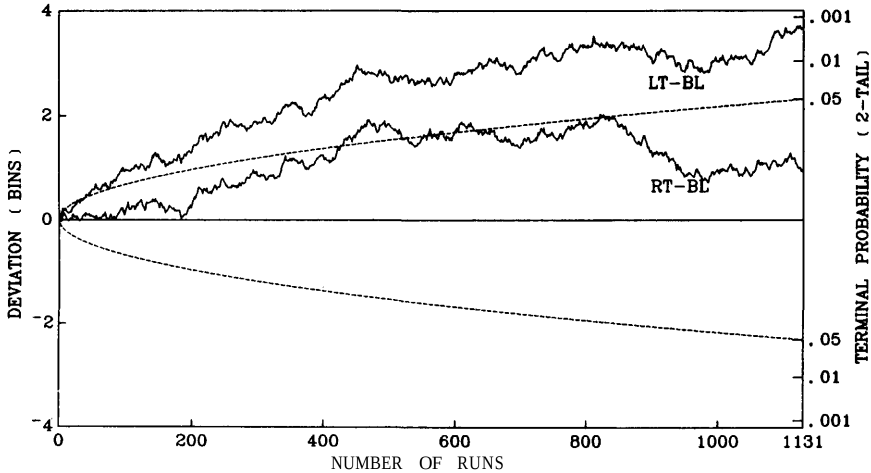

Fig. 6. RMC cumulative deviations of standard deviations: all data.

"leverage," outer bins contribute more heavily to the shifts than inner bins.

The data base management system also allows assessment of the temporal evolution of the bin-filling patterns. Although this has not yet been pursued systematically, cursory examination of these and of the progress of the overall mean of the developing distributions has not indicated any strong pattern of localization of the anomalous effects in any given portion of the 12-minute experimental period. Rather, like the REG effects, these seem statistically well distributed throughout the entire run.

Individual Operator Results

As found in our REG experiments, many of the RMC cumulative deviation graphs for individual operators are sufficiently replicable and internally consistent to be regarded as characteristic "signatures" of achievement by those particular operators. These signatures vary considerably from one operator to another and, in some cases, are found to be quite sensitive to the secondary experimental parameters. The grand concatenations of results across operators presented above, although reinforcing the credibility of the phenomenon, tend to obscure these important, potentially instructive, individual differences. Hence, the balance of this article will address individual operator performance.

Correlations With Intention

Four of the 25 operators have achieved statistically significant overall RT–LT separations positively correlated with their directional intentions, based on t-tests for paired data. Two show significant overall results in

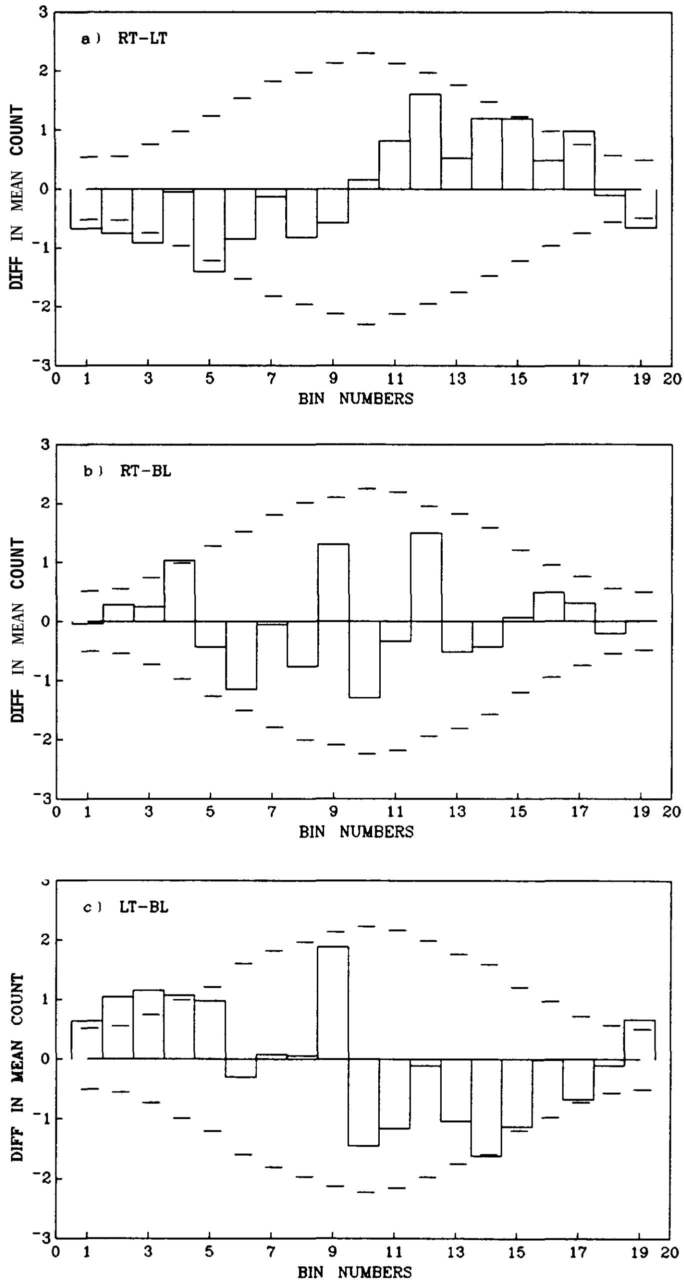

Fig. 7. RMC bin population differences: a) RT–LT; b) RT–BL; c) LT–BL.

RT–BL and two others have significant LT–BL achievements. Three operators' results are opposite to their intentions to a degree unlikely by chance, one each in RT–BL, LT–BL, and RT–LT (Table 1). Detailed statistical analyses for all the individual and compounded series are available (Nelson, Dunne, & Jahn, 1988b).

More informative than these summary results, however, is the internal consistency of many of the individual cumulative deviation graphs, wherein the characteristic signatures of performance become apparent. Several of these cases display virtually linear slopes of effect superimposed on the background of statistical fluctuations, reflecting individual preferences for a particular direction of intention, and establishing individual scales of achievement. In a few cases, the RMC signatures are qualitatively similar to those achieved by the same operators on the REG experiment, suggesting that the overall phenomenon may be less device-specific than operator-specific.

Secondary Parameters

Individual operator sensitivities to secondary parameters, such as the mode of instruction, or the feedback display being on or off, are also characteristically varied. In some cases, an operator's performance may be categorically different in the volitional protocol than in the instructed, or when live feedback is provided or denied. Yet other operators seem insensitive to these options. As mentioned, the tendency toward larger variances in the RT and LT data is not uniformly shared by all operators, and the individual bin population patterns vary considerably from one operator to another (Nelson, Dunne, & Jahn, 1988b). All of this is consistent with the individual operator variations found in the REG studies, and suggests that performance is in some way related to characteristics of personal consciousness, as well as to physical aspects of the devices and processes with which they are interacting.

One other finding of the REG studies that seems to carry over to the RMC results is the departure of some baseline data from fully chance behavior (Jahn, Dunne, & Nelson, 1987; Jahn, Nelson, & Dunne, 1985). Although, for all the reasons mentioned earlier, RMC data processing is restricted to differential criteria, examination of the individual operator raw data nonetheless suggests that in several cases the RT–BL or LT–BL differences may be attributable to unusually high or low baseline trends. As one example, the right-going efforts of operator 42 have a grand mean of 10.017, which is actually *below* the grand baseline mean for all operators of 10.023, yet is still highly significant relative to the baseline mean of 9.997. Other cases of this sort are included in Table 1.

Remote Protocol

All of the data reported and discussed above have been obtained with the operators seated on a couch a few feet before the machine, with its operation clearly visible to them. Again in parallel to our REG research, a complementary program of experiments has been undertaken wherein operators who have already generated data in this "local" protocol, attempt the same influence on the RMC performance from remote locations. In this remote protocol, the operator arranges in advance a specific time during which a set of three runs will be initiated by members of the laboratory staff, who remain blind to the sequence of intentions. The order is chosen by the operator, who communicates this information by telephone or letter after the results are recorded, but before any feedback is given. Ten operators have so far completed 26 such series, again of 10 tripolar sets each, over distances ranging up to several thousand miles.

Of these completed series, four have shown cumulative deviations beyond the .05 chance expectation for the RT–LT difference. The concatenated results, presented in Figure 8, show remarkably similar characteristics to the local data, including the strong left-going asymmetry, and the average magnitude of the RT–LT split (.0064 bins, compared to .0057 local). The only overall distinction in the remote data is in the standard deviations of the runs, which are consistently, though not significantly smaller in the right and left conditions than in the baselines, compared to the reverse for the local runs. The individual bin populations are consistent with this feature, in the sense that a greater portion of the mean shift burden seems to be borne by the inner bins. These data are summarized in Table 2 and presented in detail in Nelson, Dunne and Jahn, 1988a, b.

Multiple Operator Protocol

A second major protocol variation has been undertaken to explore the effect of more than one operator simultaneously attempting to influence the

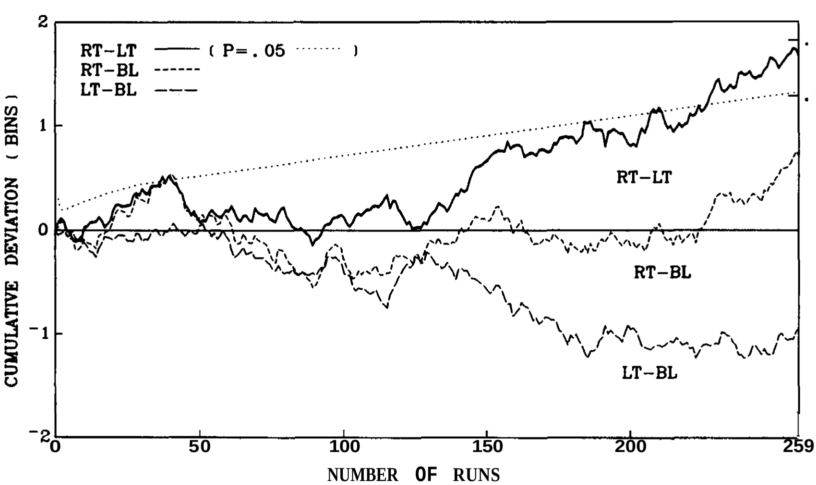

Fig. 8. Remote RMC cumulative deviations: all data.

distribution. Nine local series by seven co-operator pairs, along with two remote series by two, and one remote series by seven cooperating individuals have been performed, following the same technical procedures as for single operators. So far, these results show no overall RT–LT separation, although in contrast to the single operator local and remote patterns, both the LT- and RT-going efforts display strong right-going trends relative to BL, with the RT–BL values significant at the $p = .044$ level and the LT–BL opposite to intention at $p = .055$ (Figure 9). These results are summarized in Table 3 and detailed in Nelson, Dunne and Jahn, 1988a, b. Although this data base is far from sufficient to distinguish replicable patterns for given operator pairs to compare with the individual results, it already appears that no simple linear combination of the operators' influences obtains. Rather, consistent with the predictions of our theoretical model, a more complex superposition seems to be involved (Jahn & Dunne, 1986; Jahn & Dunne, 1987).

Summary

The RMC has proven to be an effective and efficient experiment for exploring the interaction of human operators with random physical systems, but in several respects the results are quite complex and will require much more study to comprehend fully. At this juncture, the findings may be summarized in the following categories:

1. There is clear evidence of a significant anomalous separation of the means of the overall right- and left-intended experimental distributions, correlated with the pre-stated goals of the human operators.
2. Compared to the concurrently generated baseline data, there is a stark and unexplained asymmetry in the directional results: Namely, the

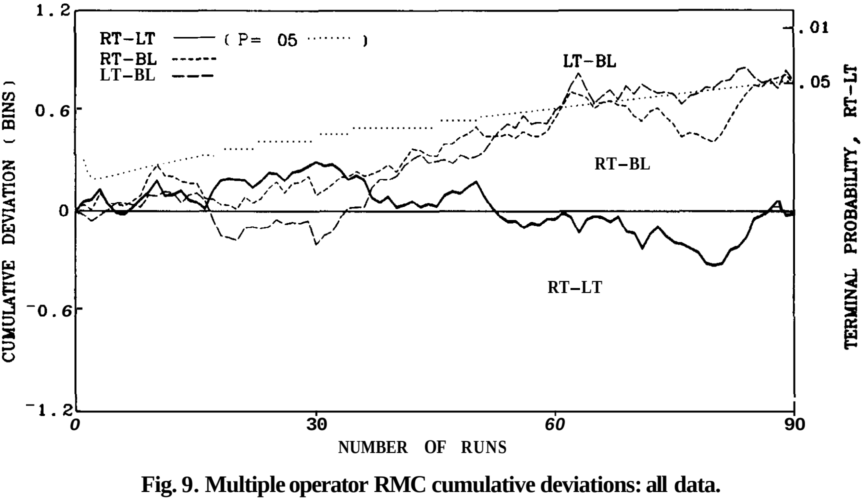

Fig. 9. Multiple operator RMC cumulative deviations: all data.

RT–LT separation resides almost totally in the LT–BL disparity; the RT and BL data are statistically indistinguishable.

3. The overall effects reflect the integration of very small shifts that compound with some regularity as the data base increases, and cannot be attributed to large contributions from any one operator.
4. Concatenation of individual bin population data indicates that the majority of bins contribute to the overall mean shift trends, but that the outer bins are more effective than those near the center.
5. Preliminary examination of the evolution of the distribution means over the course of individual runs indicates no clear pattern of concentration of effects in any particular portion of the 12-minute experimental periods.
6. The standard deviations of the experimental distributions tend to be larger for the right and left-intentioned runs than for the baselines. The LT–BL excess compounds to a highly significant value over the full data concatenation.
7. Results are clearly operator-specific, often displaying statistically repeatable characteristic trends that differ from one operator to another.
8. In several cases the individual operator performances are sensitive to secondary parameters of the experimental protocol; in other cases, they are not.
9. Operator signatures on RMC often show similarities to effects obtained by the same individuals on the micro-electronic REG and pseudo-REG experiments, implying that while the results are operator-specific, and in some cases condition-specific, they may not be so device-specific.
10. Although RMC data must be processed on a differential basis, there is good indication that for some operators the differential effects are driven as much by anomalies in the baseline as by those of the right and left efforts.
11. Separation of operator and machine by distances up to several thousand miles does not appear to inhibit the effect, or to alter its primary characteristics, except for a narrowing of the right and left run distribution variances, relative to baseline.
12. On the basis of very limited data, the cooperative efforts of two or more operators simultaneously interacting with the device appear to produce radically different results from the individual influences.

Again, more detailed substantiation of these conclusions may be found in the two Technical Reports (Nelson, Dunne, & Jahn, 1988a and 1988b).

In summary, the Random Mechanical Cascade has become an important tool in the ongoing study of the interactions of human consciousness with random physical systems. Taken in conjunction with the findings of our other experiments, the RMC results have confirmed the active role of human intention in the establishment of physical reality, and have provided additional insights to guide the evolution of a more incisive theoretical model of the underlying processes.

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Appendix

TABLE 1A
Local, RT–LT

Opr.	# Series	# Pairs	RT Mean	LT Mean	RT–LT S.D.Diff.	RT–LT t-score	RT–LT Prob.	#Series p < .05	#Series p < .5	t-score Corr.
10	17	270	10.0297	10.0195	.0521	3.233	7×10^{-4}	7 (1)	11	1.659
14	1	19	10.0273	10.0278	.0417	−0.053	(.479)	—	—	1.059
16	4	37	10.0208	10.0035	.0509	2.067	.023	1	3	0.966
17	1	10	9.9968	9.9994	.0534	−0.157	(.440)	—	—	−1.895
20	2	20	10.0222	10.0228	.0339	−0.076	(.470)	—	1	2.553
21	1	10	9.9781	10.0124	.0388	−2.799	(.010)	— (1)	—	2.327
41	7	91	10.0242	10.0243	.0527	−0.013	(.495)	— (1)	3	0.605
42	3	30	10.0165	9.9990	.0426	2.250	.016	1	3	−0.317
44	1	20	10.0362	10.0343	.0531	0.162	.436	—	1	0.437
49	1	10	10.0291	10.0212	.0375	0.659	.263	—	1	0.091
51	1	10	10.0066	10.0002	.0307	0.655	.264	—	1	2.260
53	2	20	10.0064	10.0134	.0400	−0.782	(.222)	—	1	0.519
55	20	300	10.0283	10.0244	.0490	1.373	.085	2	13	2.994
63	1	7	10.0342	10.0126	.0358	1.600	.080	—	1	1.750
64	1	10	10.0219	10.0241	.0523	−0.135	(.448)	—	—	−0.817
66	1	10	9.9907	10.0017	.0478	−0.728	(.243)	—	—	0.034
68	2	40	10.0180	10.0221	.0508	−0.511	(.306)	—	1	0.233
69	1	11	10.0253	10.0121	.0359	1.219	.126	—	1	1.019
70	5	50	10.0206	10.0107	.0499	1.412	.082	2	3	−0.039
78	4	40	9.9919	9.9910	.0529	0.111	.456	—	2	0.550
79	1	9	10.0448	10.0329	.0666	0.535	.304	—	1	−0.072
84	3	30	10.0138	10.0058	.0549	0.799	.215	—	2	−0.316
91	1	16	10.0325	10.0395	.0383	−0.729	(.239)	—	—	1.394
93	3	31	10.0219	10.0045	.0466	2.075	.023	—	3	1.078
94	3	30	9.9977	9.9841	.0462	1.605	.060	—	3	0.550
All	87	1131	10.0229	10.0172	.0493	3.891	5×10^{-5}	13 (3)	55	6.301

TABLE 1B
Local, RT–BL

Opr.	# Series	# Pairs	BL Mean	RT Mean	RT–BL S.D. Diff.	RT–BL t-score	RT–BL Prob.	# Series p < .05	# Series $p < .5$
10	17	270	10.0328	10.0297	.0508	−0.990	(.162)	— (2)	6
14	1	19	10.0322	10.0273	.0483	−0.440	(.333)	—	—
16	4	37	10.0145	10.0208	.0496	0.778	.221	—	3
17	1	10	10.0022	9.9968	.0471	−0.361	(.363)	—	—
20	2	20	10.0014	10.0222	.0471	1.977	.031	1	2
21	1	10	10.0000	9.9781	.0423	−1.644	(.067)	—	—
41	7	91	10.0211	10.0242	.0531	0.559	.289	—	4
42	3	30	9.9968	10.0165	.0449	2.410	.011	1	3
44	1	20	10.0420	10.0362	.0457	−0.566	(.289)	—	—
49	1	10	10.0219	10.0291	.0462	0.488	.319	—	1
51	1	10	10.0047	10.0066	.0456	0.133	.448	—	1
53	2	20	10.0173	10.0064	.0589	−0.830	(.209)	—	—
55	20	300	10.0272	10.0283	.0497	0.375	.354	2 (1)	11
63	1	7	10.0207	10.0342	.0458	0.782	.232	—	1
64	1	10	10.0164	10.0219	.0476	0.364	.362	—	1
66	1	10	10.0210	9.9907	.0306	−3.142	(.006)	— (1)	—
68	2	40	10.0224	10.0180	.0453	−0.604	(.275)	—	1
69	1	11	10.0463	10.0253	.0679	−1.023	(.165)	—	—
70	5	50	10.0185	10.0206	.0572	0.269	.394	— (1)	4
78	4	40	9.9979	9.9919	.0559	−0.683	(.249)	—	2
79	1	9	10.0214	10.0448	.0649	1.079	.156	—	1
84	3	30	10.0123	10.0138	.0425	0.189	.426	—	2
91	1	16	10.0290	10.0325	.0462	0.306	.382	—	1
93	3	31	10.0142	10.0219	.0492	0.875	.194	—	2
94	3	30	10.0041	9.9977	.0557	−0.636	(.265)	— (1)	2
All	87	1131	10.0229	10.0229	.0501	0.047	.481	4 (6)	48

TABLE 1C
Local, LT–BL

Opr.	# Series	# Pairs	BL Mean	LT Mean	LT–BL S.D. Diff.	LT–BL t-score	LT–BL Prob.	# Series p < .05	#Series p < .5
10	17	270	10.0328	10.0195	.0536	−4.077	2×10^{-5}	6	12
14	1	19	10.0322	10.0278	.0402	−0.474	.321	—	1
16	4	37	10.0145	10.0035	.0480	−1.389	.087	1	3
17	1	10	10.0022	9.9994	.0404	−0.213	.418	—	1
20	2	20	10.0014	10.0228	.0435	2.201	(.020)	— (1)	—
21	1	10	10.0000	10.0124	.0388	1.010	(.169)	—	—
41	7	91	10.0211	10.0243	.0487	0.624	(.267)	—	3
42	3	30	9.9968	9.9990	.0529	0.232	(.409)	—	1
44	1	20	10.0420	10.0343	.0483	−0.715	.242	—	1
49	1	10	10.0219	10.0212	.0369	−0.058	.478	—	1
51	1	10	10.0047	10.0002	.0322	−0.436	.337	—	1
53	2	20	10.0173	10.0134	.0528	−0.332	.372	—	1
55	20	300	10.0272	10.0244	.0494	−0.985	.163	1	13
63	1	7	10.0207	10.0126	.0391	−0.550	.301	—	1
64	1	10	10.0164	10.0241	.0506	0.482	(.321)	—	—
66	1	10	10.0210	10.0017	.0590	−1.038	.163	—	1
68	2	40	10.0224	10.0221	.0469	−0.031	.488	1 (1)	1
69	1	11	10.0463	10.0121	.0680	−1.664	.064	—	1
70	5	50	10.0185	10.0107	.0484	−1.136	.131	—	3
78	4	40	9.9979	9.9910	.0515	−0.856	.199	—	3
79	1	9	10.0214	10.0329	.0394	0.872	(.204)	—	—
84	3	30	10.0123	10.0058	.0435	−0.823	.209	1	2
91	1	16	10.0290	10.0395	.0566	0.743	(.235)	—	—
93	3	31	10.0142	10.0045	.0440	−1.221	.116	—	2
94	3	30	10.0041	9.9841	.0466	−2.349	.013	1	3
All	87	1131	10.0229	10.0172	.0500	−3.787	8×10^{-5}	11 (2)	55

TABLE 2A
Remote, RT–LT

Opr.	# Series	# Pairs	RT Mean	LT Mean	RT–LT S.D. Diff.	RT–LT *t*-score	RT–LT Prob.	#Series p < .05	#Series p < .5	*t*-score Corr.
10	6	61	10.0171	10.0126	.0538	0.651	.259	—	4	−0.713
12	1	9	10.0020	9.9808	.0580	1.100	.152	—	1	−0.876
16	7	70	10.0047	9.9981	.0520	1.070	.144	2	4	0.260
41	1	10	10.0150	10.0126	.0262	0.288	.390	—	1	2.208
49	3	30	10.0076	9.9934	.0392	1.991	.028	1	3	1.958
68	2	20	9.9994	10.0108	.0386	−1.326	(.100)	— (1)	—	0.874
69	1	9	10.0318	10.0429	.0480	−0.691	(.255)	—	—	−2.092
78	1	10	10.0163	9.9944	.0449	1.538	.079	—	1	0.185
93	2	20	10.0258	10.0139	.0533	1.000	.165	—	2	−0.917
94	2	20	10.0075	10.0000	.0376	0.890	.192	1	1	0.368
All	26	259	10.0111	10.0047	.0482	2.139	.017	4 (1)	17	1.197

TABLE 2B
Remote, RT–BL

Opr.	# Series	# Pairs	BL Mean	RT Mean	RT–BL S.D. Diff.	RT–BL t-score	RT–BL Prob.	# Series $p < .05$	# Series $p < .5$
10	6	61	10.0159	10.0171	.0546	0.180	.429	—	3
12	1	9	9.9956	10.0020	.0439	0.443	.335	—	1
16	7	70	10.0013	10.0047	.0526	0.539	.296	1	3
41	1	10	10.0290	10.0150	.0491	−0.905	(.195)	—	—
49	3	30	10.0078	10.0076	.0564	−0.021	(.492)	1	1
68	2	20	10.0100	9.9994	.0545	−0.867	(.199)	— (1)	1
69	1	9	10.0488	10.0318	.0608	−0.834	(.214)	—	—
78	1	10	9.9797	10.0163	.0432	2.680	.013	1	1
93	2	20	10.0109	10.0258	.0488	1.367	.094	—	2
94	2	20	9.9984	10.0075	.0556	0.731	.237	—	1
All	26	259	10.0084	10.0111	.0533	0.826	.205	3 (1)	13

TABLE 2C
Remote, LT–BL

Opr.	# Series	# Pairs	BT Mean	LT Mean	S.D. Diff. LT–BL	LT–BL t-score	LT–BL Prob.	# Series $p < .05$	# Series $p < .5$
10	6	61	10.0159	10.0126	.0501	−0.503	.309	—	3
12	1	9	9.9956	9.9808	.0420	−1.057	.161	—	1
16	7	70	10.0013	9.9981	.0457	−0.597	.276	1	4
41	1	10	10.0290	10.0126	.0515	−1.011	.169	—	1
49	3	30	10.0078	9.9934	.0491	−1.610	.059	—	3
68	2	20	10.0100	10.0108	.0468	0.084	(.467)	—	1
69	1	9	10.0488	10.0429	.0395	−0.446	.334	—	1
78	1	10	9.9797	9.9944	.0516	0.904	(.195)	—	—
93	2	20	10.0109	10.0139	.0385	0.351	(.365)	—	1
94	2	20	9.9984	10.0000	.0405	0.177	(.431)	—	1
All	26	259	10.0084	10.0047	.0462	−1.278	.101	1	16

TABLE 3A
Multiple operators, RT–LT

Opr.	# Series	# Pairs	RT Mean	LT Mean	RT–LT S.D. Diff.	RT–LT t-score	RT–LT Prob.	# Series p < .05	# Series p < .5	t-score Corr.
220	2	20	10.0133	10.0190	.0446	−0.573	(.287)	—	1	1.115
244	1	10	10.0248	10.0170	.0483	0.511	.311	—	1	−1.442
251	1	10	10.0187	10.0079	.0343	0.994	.173	—	1	1.247
252	1	10	10.0168	10.0159	.0455	0.066	.474	—	1	−0.456
277	1	10	9.9923	10.0195	.0430	−2.001	(.038)	— (1)	—	0.091
284	2	20	10.0136	10.0041	.0544	0.775	.224	—	2	−0.401
299	1	10	10.0093	10.0106	.0647	−0.064	(.475)	—	—	−1.241
All	9	90	10.0128	10.0130	.0486	−0.034	(.487)	— (1)	6	−0.251
2 Operators, remote, RT–LT										
294	2	20	10.0006	10.0017	.0470	−0.098	(.462)	—	1	−0.881
7 Operators, remote, RT–LT										
750	1	10	10.0016	10.0001	.0479	0.101	.461	—	1	−0.361

TABLE 3B
Multiple operators, RT–BL

Opr.	# Series	# Pairs	BL Mean	RT Mean	RT–BL S.D. Diff.	RT–BL t-score	RT–BL Prob.	# Series p < .05	# Series p < .5
220	2	20	10.0011	10.0133	.0366	1.483	.077	1	1
244	1	10	10.0114	10.0248	.0499	0.849	.209	—	1
251	1	10	10.0102	10.0187	.0619	0.434	.337	—	1
252	1	10	10.0018	10.0168	.0501	0.947	.184	—	1
277	1	10	9.9785	9.9923	.0288	1.518	.082	—	1
284	2	20	10.0129	10.0136	.0515	0.057	.478	— (1)	1
299	1	10	10.0099	10.0093	.0525	−0.036	(.486)	—	—
All	9	90	10.0044	10.0128	.0463	1.723	.044	1 (1)	6
2 Operators, remote, RT–BL									
294	2	20	9.9958	10.0006	.0460	0.469	.322	—	2
7 Operators, remote, RT–BL									
750	1	10	10.0246	10.0016	.0272	−2.677	(.013)	— (1)	—

TABLE 3C
Multiple operators, RT–BL

Opr.	# Series	# Pairs	BL Mean	LT Mean	LT–BL S.D. Diff.	LT–BL *t*-score	LT–BL Prob.	#Series $p < .05$	#Series $p < .5$
220	2	20	10.0011	10.0190	.0421	1.896	(.037)	—	—
244	1	10	10.0114	10.0170	.0450	0.392	(.352)	—	—
251	1	10	10.0102	10.0079	.0562	−0.129	.450	—	1
252	1	10	10.0018	10.0159	.0678	0.656	(.264)	—	—
277	1	10	9.9785	10.0195	.0394	3.294	(.005)	— (1)	—
284	2	20	10.0129	10.0041	.0468	−0.838	.206	—	1
299	1	10	10.0099	10.0106	.0569	0.040	(.485)	—	—
All	9	90	10.0044	10.0130	.0505	1.613	(.055)	— (1)	2
2 Operators, remote, LT–BL									
294	2	20	9.9958	10.0017	.0504	0.520	(.305)	—	—
7 Operators, remote, LT–BL									
750	1	10	10.0246	10.0001	.0524	−1.480	.087	—	1