Understanding the Nature of Psychokinesis

Fotini Pallikari[1]

Abstract – This paper is the extended transcript of a lecture of November 2, 2021, presented online at the Colloquia of the Institut für Grenzgebiete der Psychologie und Psychohygiene (IGPP).[2] It concerns a novel type of analysis of the micro-psychokinesis (MicroPK) meta-analysis data, BSB-MA, of carefully selected studies (Bösch et al., 2006a). The current paper introduced scientifically recognized data analyses other than the usual statistical approaches that yielded controversially debated conclusions. The method of Rescaled Range Analysis and the Markov model revealed correlations in the BSB-MA database introduced by three biases acknowledged in experimental science that altered some of the data: The Experimenter Expectancy Effect, the Conformity, and the Publication biases. They shaped the scatter of the random BSB-MA scores on the funnel plot. Most errors the biases have introduced were unintentional. Two interpretations of the evidence in the BSB-MA database based on the scientific method are likely: the paranormal, which explains some of the evidence, and the non-paranormal, which accounts for all evidence the present analyses realized. The principle of parsimony favors the latter interpretation.

Keywords: mind-matter interaction – telekinesis – psychokinesis – psychical phenomena – funnel plot – two state Markov chains – rescaled range analysis – meta analysis – conformity bias – experimenter expectancy effect – publication bias – random number generators analysis – Occam's razor

Zusammenfassung – Zum Verständnis der Natur der Psychokinese. Dieser Beitrag ist die erweiterte Abschrift eines Vortrags vom 2. November 2021, der online beim Kolloquium des Instituts für Grenzgebiete der Psychologie und Psychohygiene (IGPP)[2] gehalten wurde. Es handelt sich um eine neuartige Analyse der Daten der Mikro-Psychokinese (MicroPK) Meta-Analyse, BSB-MA, von sorgfältig ausgewählten Studien (Bösch et al., 2006a). In der vorliegenden Arbeit wurden wissen-

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2 https://www.youtube.com/watch?v=VKlD_A3EM_U
https://www.youtube.com/watch?v=pF3ML_Dccck

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schaftlich anerkannte Datenanalysen eingeführt, die sich von den üblichen statistischen Ansätzen, die zu kontrovers diskutierten Schlussfolgerungen führten, unterscheiden. Die Methode der Rescaled Range Analysis und das Markov-Modell deckten Korrelationen in der BSB-MA-Datenbank auf, die durch drei in der experimentellen Wissenschaft anerkannte Verzerrungen (biases) verursacht wurden, die einige der Daten veränderten: Der „Versuchsleitererwartungseffekt", der „Konformitätsbias" und der „Publikationsbias". Sie formten die Streuung der zufälligen BSB-MA-Werte auf dem Funnel-Plot. Die meisten Fehler, die durch die Verzerrungen verursacht wurden, waren unbeabsichtigt. Zwei Interpretationen der Befunde in der BSB-MA-Datenbank, die auf der wissenschaftlichen Methode basieren, sind möglich: die paranormale, die einige der Befunde erklärt, und die nicht-paranormale, die alle Befunde erklärt, die in den derzeitigen Analysen gefunden wurden. Das Sparsamkeitsprinzip begünstigt die letztere Interpretation.

Schlüsselbegriffe: Geist-Materie-Interaktion – Telekinese – Psychokinese – Psi-Phänomene – Funnel-Plot – Markov-Ketten mit zwei Zuständen – reskalierte Bereichsanalyse – Meta-Analyse – Konformitätsbias – Versuchsleitererwartungseffekt – Publikationsbias – Analyse mit Zufallszahlengeneratoren – Ockhams Rasiermesser

Introduction

The term Psychokinesis, PK, suggests that the mind directly influences matter. That the mind, psyche, or consciousness directly modulates physical reality. Experiments to test psychokinesis may involve electronic random number generators (RNGs), like the RNG machine of Figure 1 built by Helmut Schmidt (Millar, 2022), with which I experimented in the early 1990s. During the tests, the mind attempts to influence the probabilities of random processes. In the case of the RNG of Figure 1, the mental effort aims to influence the flashing of the 31 LED lamps driven by the electronic noise in the machine's circuitry (Pallikari, 1998). At the end of one trial, the digital display indicates the result by a number corresponding to the hits during the test. Statistical analysis of such numbers determines the magnitude of the possible mental effect on the random process (Pallikari-Viras, 1997).

In experiments where the mind attempts to influence the probabilities of the random process, the test is called micro-psychokinesis, or MicroPK. The testing hypothesis in MicroPK experiments with RNGs states:

> The statistical average of numbers generated by Random Number Generators shifts in the desired direction by thought processes alone without the mediation of a brain-machine interface device.[3]

A scientifically investigated hypothesis must be testable and falsifiable, both fulfilled in the case of MicroPK.

3 For more information on brain-machine, neuroprosthetic, interference devices, see Serruya (2002).

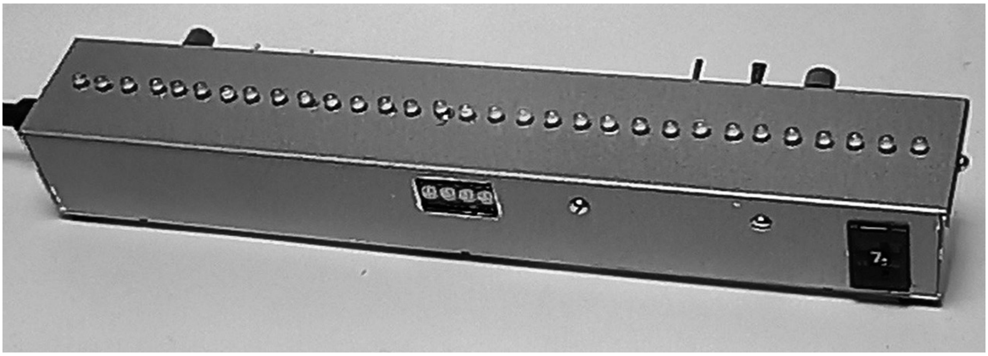

Figure 1. An electronic Random Number Generator built by German Physicist Dr. Helmut Schmidt (1928–2011). An array of 31 LED lamps on the upper face of a parallelepiped metal case featuring a digital display and a mode-regulating counter on its front face.

The BSB MicroPK Meta-Analysis

A large-scale MicroPK experiment took place in the late 1990s. Three experimental groups joined forces to replicate the MicroPK database produced by the PEAR[4] lab at Princeton University, USA. One was the PEAR lab itself. The other two groups were in Germany. One at the University of Giessen and the other at the IGPP in Freiburg. At the end of this experiment, none of the three groups of this consortium provided scientific evidence to support the MicroPK hypothesis (Jahn et al., 2000).

Psychologists Holger Bösch and Emil Boller, already part of the Freiburg leg in the large-scale MicroPK consortium, decided to look into the puzzling MicroPK hypothesis. Joined by psychologist Fiona Steinkamp, they designed a new meta-analysis of MicroPK studies, the Bösch-Steinkamp-Boller Meta-Analysis, referred to as the BSB-MA. They aimed "to examine the correlation between direct human intention and the concurrent output of true RNGs."

The BSB-MA database adopted strict inclusion/exclusion criteria to meet their goal (Bösch et al., 2006a, p. 501). The first criterion of inclusion allowed only psychokinesis studies, excluding, for instance, telepathy. Their second criterion selected studies that employed only proper random processes, excluding pseudo-random ones.

Finally, to combine the reported scores of various MicroPK tests, for instance, tests using electronic RNGs and tests using dice, they converted the score of each study into binary form according to the information published in each study. Therefore, their third inclusion/exclusion

4 PEAR is the acronym for Princeton Engineering Anomalies Research.

criterion involved studies that allowed for the conversion of scores into hit-and-miss trials, a condition available from most of the existing MicroPK studies with true RNGs. Their final total was 380 MicroPK studies performed by 62 principle experimenters over 35 years. For academic transparency, the authors made their meta-analysis files available, including all relevant information.

Like the three creators of the BSB-MA MicroPK database, other parapsychologists have also examined it by applying methods of statistical decision theory (Kugel, 2011; Radin et al., 2006; von Stillfried et al., 2009). They could not reach a consensus on the interpretation of results. Has human intention shifted the percentage of hits, *p*, in MicroPK tests to a statistical average above chance expectation in the 380 studies of variable size *N*? Or, was the recorded mean shift the outcome of biases?

This article offers a fresh look into the BSB-MA MicroPK database by avoiding typical statistical approaches that have not provided conclusive answers. Data analysis methods available to scientists for over fifty years will attempt to answer the critical question. The new tools are the *Rescaled Range Analysis* of time series (R/S) and the *Markov model of correlated binary data*. The distribution of scores on the funnel plot of the BSB-MA database will also contribute to the investigation.

The Funnel Plot of MicroPK Data in BSB-MA

To observe the quality of the MicroPK database, the BSB-MA authors plotted the size of studies, *N*, against the proportion of hits in each study, *pi* (π). For example, if a study consists of N=100 trials, of which 55 are hits, then the size of the study *N* is 100, and the proportion of hits in the study, the effect size *pi* is 55%. Figure 2 shows *N* against *pi* from data in the available BSB meta-analysis files. The dotted curves represent the 95% confidence interval curves for random binary data, equation (1)[5] in the appendix. The solid curves are the new position of the dotted curves for correlated data according to the Markov model. With the support of the Rescaled Range Analysis of time series, both methods adequately describe the scatter of MicroPK scores (Pallikari, 2015a; Pallikari & Papasimakis, 2008) to be discussed in separate sections.

The law of large numbers[6] gives a characteristic shape to the graph of Figure 2. As the sample size of studies increases, the precision in estimating the underlying MicroPK effect increases.

5 Derived from the statistical theory treating the distribution of the proportion of hits *pi* $(= 0.5 \pm 0.98/\sqrt{N})$ in samples of size *N* taken from a binomial population of the proper statistical average of 50% (Spiegel, 1961, p. 158).

6 The law of large numbers in probability and statistics states that as the size of a random sample of the population grows, its mean converges to the population mean.

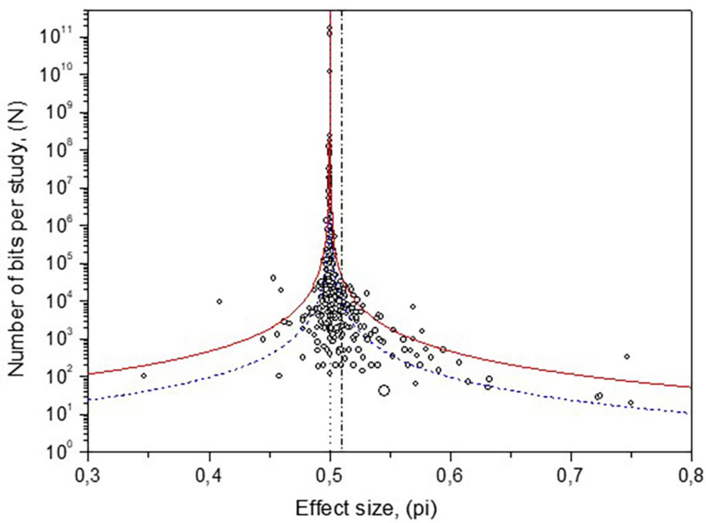

Figure 2. Funnel plot of BSB-MA MicroPK data presented as open circles. The dotted curves represent the 95% confidence interval curves of random data. See text. The solid curves are the 95% confidence interval curves of correlated data. The vertical dash-dotted line is at the statistical average pi = 0.510 (rounded st. error. 0.002) of the 380 MicroPK data. The vertical dash line is at the effect size where the funnel plot converges, 50%.

Therefore, the effect size *pi* scatters widely in small studies, while its scatter decreases with increasing *N*, converging to the effect size characterizing the entire database. The above attributes make the graph of *N* vs. *pi* of Figure 2 look like an inverted funnel, naming it the "funnel plot."

Three features characterize the funnel plot of BSB-MA MicroPK scores. The scatter of scores around chance effect size 50% is broader than expected for random data in studies of sizes up to about 100,000 trials. It converges to a 50% proportion of hits, which is a chance result. The scores do not spread symmetrically about 50%, as expected in a large enough database of random data.

The Broadening of the MicroPK Data Scatter

The funnel plot of a database offers visual evidence of presence of biases. Poorly overlapping confidence intervals of individual scores when data scatter farther than statistically expected implies the studies are statistically incompatible, marked by statistical heterogeneity (Walker et al., 1988). The criteria in the inclusion or exclusion of BSB-MA studies were adopted to make the MicroPK scores compatible.

The MicroPK funnel plot displays the scores of 380 independent studies expected to scatter randomly about their point of convergence. The 95% confidence interval curves for random data should envelop 95% of them. The total number of MicroPK scores located beyond the dotted curves of Figure 2 is 82, more than the expected 19 for random data. This broadening of data scatter on the funnel plot suggests a possible correlation between the MicroPK scores, as will be explained below. It needs corrected confidence interval curves that envelop the 95% of MicroPK scores by arbitrarily modifying equation (1)[7] or pursuing another approach, such as the Markov model of correlated binary data. The Markov model discussed in the respective paragraph of this paper provides a plausible data-broadening mechanism.

MicroPK Data scatter incompatibly on the MicroPK funnel plot compared with statistical expectation. It occurs in studies of size up to approximately 100,000 trials. Studies of size from about 100,000 up to 100,000,000,000 trials appear to scatter about 50% as expected for random data. This feature provides an essential evidence to assist the interpretation of the MicroPK mechanism.

The Markov model of correlated binary scores mathematically identifies the origin of the observed broadening of MicroPK scores to arise from a frequency of binary dyads in the studies, hit-hit, and miss-miss, higher than expected in random data.

The MicroPK Scores Converge to a 50% Effect Size

The MicroPK scores of size varying approximately from 100,000 up to 100,000,000,000 trials not only scatter as expected for random data but also converge to a 50% proportion of hits as expected in random data.

The Markov model mathematically shows the observed convergence of scores to 50% to arise from equal frequencies of binary dyads in the MicroPK studies, hit-hit, and miss-miss above 50%. More precisely, the graphically estimated probability of a hit-hit and a miss-miss MicroPK score dyad is approximately 88% across all studies. The binary-score-correlating frequency conveys

7 Increasing the nominator of equation (1) approximately five times.

the average strength of a MicroPK mechanism underway for all scores on the funnel plot, or the average power of biasing mechanisms introduced by the experimenters.

There is no way of identifying which MicroPK scores have the introduced biases affected. Some scores, located outside the 95% confidence interval curves,[8] could have occurred by chance of very low likelihood, the same as any other score under these curves. The potential bias in the database manifests collectively in the bulk of the 380 MicroPK scores. Another mechanism for biasing the database is not reporting studies introducing an asymmetry in the data scatter.

The Scatter of MicroPK Scores is not Symmetrical

The law of large numbers dictates that the independent scores in a large enough database scatter symmetrically on the funnel plot about its point of convergence. Its effect size should statistically coincide with the mean of all scores. In the funnel plot of Figure 2, the dispersion asymmetry of MicroPK data is evident.

Of the 82 data points outside the 95% MicroPK confidence interval curves for random data, a majority of 63 is on the right-hand side of the funnel plot supporting its hypothesis. The proportion of hits in these studies statistically deviates from chance in the direction of intention. Surprisingly, there exist 19 MicroPK scores overpopulating the left-hand side of the funnel plot beyond the 95% confidence interval curves, refuting the MicroPK hypothesis. The scores of these studies statistically deviate from chance against intention. A viable mechanism of MicroPK needs to accommodate this last feature in data, as reasoned in the "Discussion" and "Epilogue".

MicroPK data scatter on the funnel plot asymmetrically also in areas located under the 95% confidence interval curves, for instance, around coordinates pi=45%, N=100. The data-dispersion asymmetry extends to studies as large as approximately 1,000,000 trials. A direct consequence of the apparent scatter asymmetry is that the mean of MicroPK scores, 51%, does not coincide with the score to which the funnel plot converges, 50%. Within rounded standard error,[9] it provides a statistically significant deviation from chance in the direction of intention, whereas by the law of large numbers, the expected average would be 50%. The unnatural asymmetry in the MicroPK funnel plot suggests that either the experimenters or the journals were not motivated to publish studies that did not support the tested hypothesis (Sterne et al., 2005, p. 76).

8 For instance, around pi=45% for $N=10^4–10^5$, or pi=65% for $N=10^4$.

9 It is the standard error of the mean, rounded to one closest significant digit. For instance, the error for the 380 MicroPK scores 0.00176 becomes 0.002 (0.510 ± 0.002).

A proportion of hits in a MicroPK study as high as 57% or as low as 42% in 100 trials can still occur by chance in a random process. Although the high score will be an acceptable result worth reporting as it supports the tested hypothesis, the low score might threaten it. Generally, the randomly occurring low MicroPK scores had fewer chances to appear in a publication, left forgotten in a file drawer, see also paragraph "The Asymmetrical Scatter of Control Data" and "Discussion".

The Funnel Plot of Control Data in BSB-MA

The authors of the MicroPK meta-analysis also shared the files of 137 control tests performed alongside the MicroPK tests. The experimenters did them to assess the randomness of the processes with which they tested the MicroPK hypothesis. The study of control data enables a better understanding of the MicroPK mechanism.

Three features characterize the funnel plot of the BSB-MA control scores, Figure 3: Its convergence to a proportion of hits 50%, a chance result. Its asymmetrically scattered scores around 50%. Its dispersion of scores is close to the expected from random data.

Control Data Converge to 50% Effect Size

Just as in the case of the MicroPK, the funnel plot of the 137 control data converges to 50%, confirming that the processes the experimenters have used in their MicroPK tests were indeed random. The largest study in the database is of the order of 100,000,000 trials, much smaller in comparison with the largest MicroPK BSB-MA study.

The Asymmetrical Scatter of Control Data

The asymmetry of data scatter on the MicroPK funnel plot is also present in the funnel plot of control data with an essential difference. It is the mirror opposite to that observed in the case of MicroPK scores. Areas void of control data are on the right-hand side of the funnel plot, the side of psi hitting, especially for studies of smaller size ($N < 10{,}000$).

The experimenters investigating the level of randomness of their devices avoided reporting scores that appeared to contradict the tested hypothesis. Unreported control scores could have occurred, however, randomly by chance. For instance, a 52% proportion of hits in a test of 1,000 trials would not have disqualified the random process the experimenters were testing.

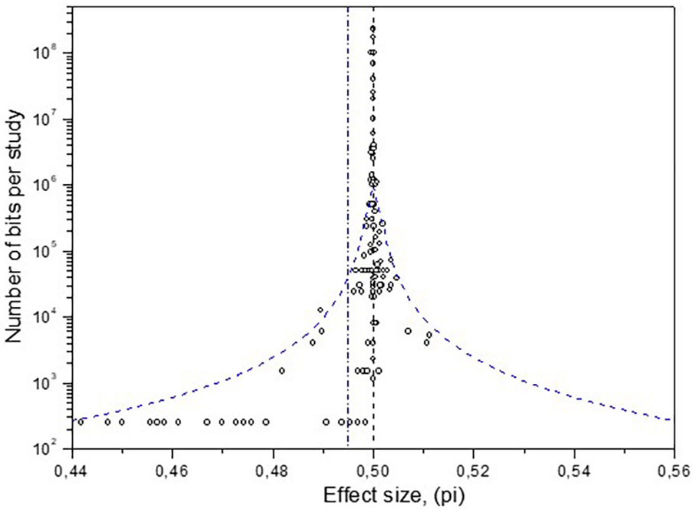

Figure 3. Funnel plot of control data in the BSB-MA. The dotted curves represent the 95% confidence interval curves of random data. The vertical dash-dotted line is placed at the effect size *pi* = 0.495 (rounded st. error = 0.001) corresponding to the statistical average of the 137 control data-points (see text). The vertical dash line is at the effect size where the funnel plot converges, 50%.

The direct consequence of this asymmetry in data scatter is that the overall statistical average of control scores is 0.495 (rounded st. error 0.001),[10] as displayed in Figure 3 by the vertical dash-dotted line. It falsely presents a statistically significant shift of mean from the expected 50% to which the funnel plot converges. It furthermore contradicts the assumed random nature of the testing devices.

The mirroring asymmetry in data scatter observed on the MicroPK and control funnel plots strongly indicates that the average experimenter avoids reporting some scores that do not support the tested hypothesis.

10 Rounded from 0.0011.

The Tightened Scatter of Control Data

The 95% confidence interval curves on the 137 control data in Figure 3 should leave outside by chance about six scores. This statistical rule is marginally satisfied, as control scores tend to cluster near the center of the funnel plot. Just one score wanders outside the 95% confidence interval curves for random data, with a few others lying on them. The weakness of the control database is its smaller size, ruling such questionable imperfections acceptable.

The Markov Model of Correlated Binary States

The first-order Markov model (von Mises, 1964, p. 221–223) mathematically describes the two MicroPK funnel plot features: the broadened scatter of scores and its convergence to 50%. It does it, assuming correlated scores of trials in each MicroPK study in detailed way. The score of each MicroPK trial depends on the previous one and determines the score of the next. Two self-transition probabilities describe the generation of each score: the probability p_{11} for a hit trial to follow another hit trial and the probability p_{00} for a miss trial[11] to follow a miss trial. The self-transition probabilities for the BSB-MA database were graphically estimated by fitting the confidence interval curves described by equation 2 (through equ. 3 and 4)[12] on the funnel plot so that they envelop 95% of the MicroPK scores. The Markov model thus reproduces the broadened confidence interval curves of MicroPK scores for $p_{11}= p_{00}=$ 83% (Pallikari, 2015a; Pallikari & Papasimakis, 2008).

If a mind-matter biasing mechanism was underway during each MicroPK test of N trials, it introduced correlations between adjacent scores. On average, across studies, it generated a line of N binary scores where the hit-hit and miss-miss dyads occurred at 83% frequency. The Markov model imitates the combined effect of whatever biasing mechanism(s) produced the broadening of MicroPK data scatter and its convergence to 50%.

Based on the Markov model, mathematical expressions of the confidence interval curves that fit the MicroPK BSB-MA database were estimated and represented by equations 2 (through 3 and 4). They envelop 95% of MicroPK data shown in Figure 2 as solid curves. Fitting equation 2 on the MicroPK funnel plot enabled the estimation of the two self-transition probabilities $p_{11}= p_{00}=$ 83%, implying 83% frequency of binary score dyads. The self-transition probabilities illustrate the average strength of the not yet determined underlying MicroPK biasing mechanisms.

11 A hit trial generates a score in the direction of intention. $0 < p_{11}, p_{00} < 1$.

12 A short mathematical description of the Markovian model for the MicroPK database is in the Appendix.

Four Examples of Correlated Binary Scores

Three steps validate the appropriateness of equation 2 to describe the MicroPK confidence interval curves: first, by writing a computer program to generate Markov binary data according to probabilities p_{11} and p_{00} of our choice. Second, by generating enough data to build respective funnel plots. Third, by fitting equation 2 on the funnel plot for the chosen self-transition probabilities and confirming that they successfully enclose as many scores as expected. This test was applied to four cases presented in Figure 4.

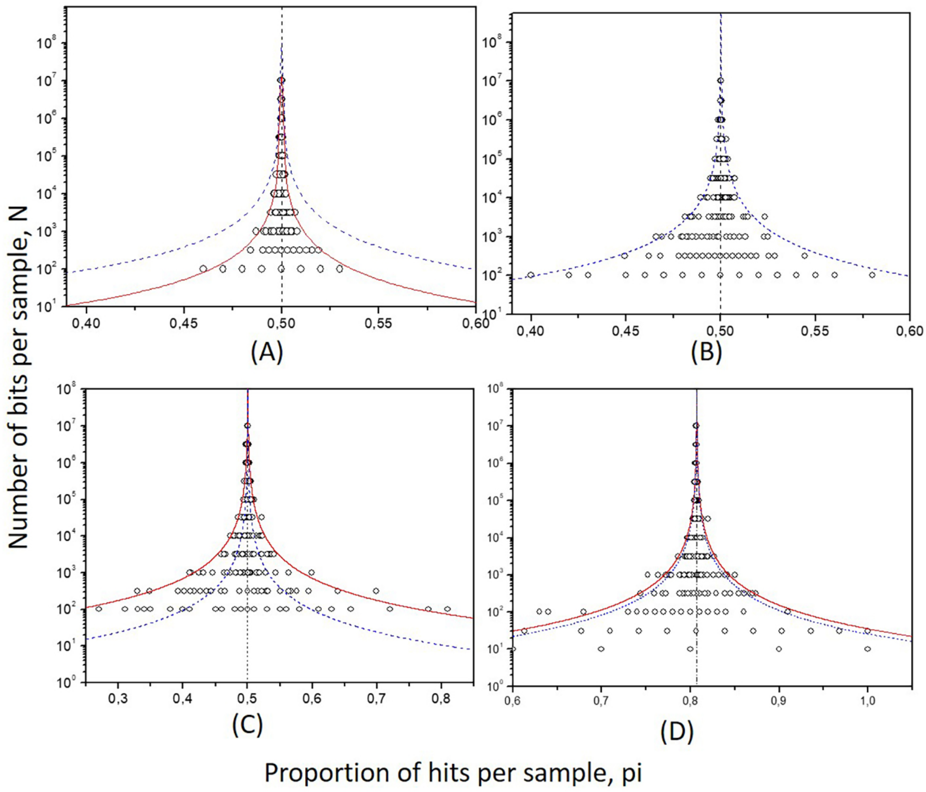

Figure 4. Examples of four funnel plots of Markov correlated binary data for self-transition probabilities, p_{11} & p_{00}. *Circles*: computer-generated data according to (A) $p_{11}=p_{00}=12\%$. (B) $p_{11}=p_{00}=50\%$. (C) $p_{11}=p_{00}=88\%$. (D) $p_{11}=88\%$, $p_{00}=50\%$. *Solid curves*: 95% confidence interval curves of correlated data following Equ. 2 for the same-transition probabilities in each separate case. *Dotted curves*: 95% confidence interval curves of random binary data ($p_{11}=p_{00}=50\%$) added for comparison (Papasimakis & Pallikari, 2006b).

In cases (A), (B), and (C), the probabilities $p_{11}$and p_{00} are equal. In all three cases, the funnel plot converges to 50%, predicted by equation 3. Case (B) displays the funnel plot of random data p_{11}=p_{00}= 0.5. When p_{11} and p_{00} are below 50% in case (A), the funnel plot shrinks its data scatter compared to case (B).

When p_{11} and p_{00} are above 50%, in case (C), the funnel plot broadens its data scatter. Such a case is (C) where p_{11}=p_{00}= 88%, a near simulation of the MicroPK BSB-MA database. In all four examples, the confidence interval curves, drawn according to the Markov model for the same set of self-transition probabilities in each case, adequately envelop the statistically expected number of computer-generated data, solid curves. In all four cases, the computer-generated data notably scatter symmetrically about the peak of their funnel plot. All dotted 95% confidence interval curves in Figure 4 refer to random data.

In case (D), the probabilities p_{11} and p_{00} are unequal. The self-transition probability p_{11}= 0,88 favors the generation of hit-dyads while p_{00}= 0.50 induces the generation of miss-dyads randomly. Now, the peak of the funnel plot is at an effect size above 50%. If the funnel plot of the MicroPK BSB-MA database had such characteristics, it would have confirmed the MicroPK hypothesis.

Runs of Correlated Binary MicroPK Scores

The Markov model has successfully simulated the confidence interval curves for the MicroPK BSB-MA database for self-transition probabilities equal to 83%. How do these correlations operate inside a MicroPK test shaping the sequence of binary scores? Von Mises mathematically estimated that it affects the frequency of runs of binary scores (von Mises, 1964, pp. 184–188). Binary data from a true RNG during MicroPK tests cluster naturally, forming the so-called runs.[13] Figure 5 demonstrates the effect of Markov self-transition probabilities displaying the expected frequency a_m of runs of length m occurring in one sequence of 10,000 trials plotted against the length of run, equation 5. The graph shows that in the case of random binary data, p_{11}=p_{00}= 50%, it is likely to find one run of length 12 every time 10,000 trials are collected, a_m=1, m=12. It could mean 12 hits or 12 misses in a row. Naturally, a run of a shorter length will occur more than once in such a long sequence.

Markov bias characterized by equal self-transition probabilities above 50% will increase the length of the runs compared to the random case. It is likely to find one run of length 51 when generating 10,000 trials under a biased process where the self-transition probabilities are 83% (a_m = 1, m = 51). The mathematical prediction suggests that a MicroPK study of 10,000 trials biased by Markov self-transition probabilities of 83% likely contains a run of 51 hits or misses.

13 A run of length m is a sequence of m equal binary scores immediately preceded and followed by one opposite binary score.

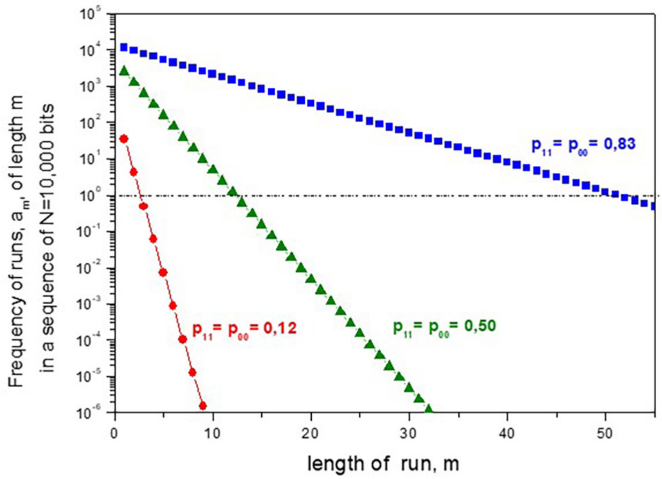

Figure 5. Frequency of runs of length m in a Markovian sequence consisting of 10,000 binary states vs. the length of run for three self-transition probabilities, $p_{11}=p_{00}=p$: Squares, $p=83\%$. Triangles, $p=50\%$. Circles, $p=12\%$, equation 5.

The Markov bias acts as if a gluing-like mechanism operates on the generation of each score per trial to enhance its persistence (Pallikari, 2003, p. 206).

Finally, the length of runs shrinks compared to the random case when the self-transition probabilities of the Markov bias are below 50%. In such a case, it shall take 120 efforts of sampling each time 10,000 trials to observe just one run of length five ($a_m \cong 0.008$, $m \cong 5$).

The Markov simulation of the BSB-MA data yielding $p_{11}=p_{00}=83\%$ indicated that the overall bias had introduced a persistence in the same binary states, hits, and misses alike, enhancing their natural clustering.

Here are the puzzling questions:

> Why was the generation of hit and miss scores promoted alike ($p_{11}=p_{00}>50\%$) in MicroPK tests and not only the hit scores ($p_{11}>50\%$, $p_{00}=50\%$) if the test aimed at supporting the MicroPK hypothesis?
>
> Why were MicroPK scores found on the funnel plot beyond the left-hand side confidence interval curve against intention refuting the MicroPK hypothesis?

The interpretation of the BSB-MA database needs to provide an answer to these two questions.

The Rescale Range Analysis of BSB-MA Data

The Rescaled Range Analysis (R/S) performed on the 380 MicroPK and 137 control time series attempts to answer the above puzzle. A time series is a sequence of records arranged according to their date of registration or publication, from the oldest study of 1969 to the more recent one of 2004. The applied R/S analysis uses a computer program following the related theory (Pallikari & Boller, 1999) to identify whether the time series consists of randomly aligned scores or connected ones through long-range correlations.

Long-range correlations characterize the presence of trends throughout the whole length of the time series. Two kinds of such correlations or trends exist, indicating persistence of variability about the mean of scores or anti-persistence. The first type of persistent deviation from the mean is often represented by the biblical seven years of abundance followed by seven years of famine in Egypt. A person asked to write down a random sequence of bits will write a series exhibiting anti-persistence. It is a human trait to alternate the numbers too much to display randomness (Schroeder, 1951, p. 359).

The measure identified by the R/S analysis that estimates the type of correlations in the time series is the so-called Hurst exponent, H. In case of persistent long-range correlations $H > 0.5$. In the case of anti-persistent long-range correlations $H < 0.5$. The R/S analysis performed on a time series of random data will yield $H = 0.5$ within statistical error.

Some MicroPK and control studies were published simultaneously, for instance, in the same conference proceedings, prohibiting an ideal arrangement of each score according to individual dates of publication.

Applying the R/S Analysis to Time Series of Small Length

Investigating the presence of long-range correlations by the R/S analysis requires a long enough time series to provide accurate results. The MicroPK and control time series fall within the category of relatively short sequences. Their Hurst exponents were therefore assessed compared to random sequences of bits of similar length that formed a new baseline, the dotted curve in Figure 6. Ten random binary data sequences generated online[14] of size ranging between 100 to 1500 bits created the new reference baseline.

MicroPK and control time series exhibit H values well above the baseline, indicating the presence in them of persistent long-range correlations, $H > 50\%$, Table 1.

14 From the online application at random.org.

Rescaled Range Analysis of BSB-MA Data

	MicroPK		Control	
	Raw	Randomized	Raw	Randomized
H (δH)	0,70 (0,05)	0,55 (0,02)	0,68 (0,03)	0,57 (0,05)
N	380		137	
$Z_{\delta H}$	2,79		1,89	

Table 1. Parameters characterizing the rescaled range analysis R/S of MicroPK and control time series in the BSB-MA. *N*: length of time series. *H*: Hurst exponent. In brackets is the associated standard error, δ*H* of *H*. $Z_{\delta H}$, is the *z* score of the difference in *H* between raw and randomized sequences with respect of their standard errors.

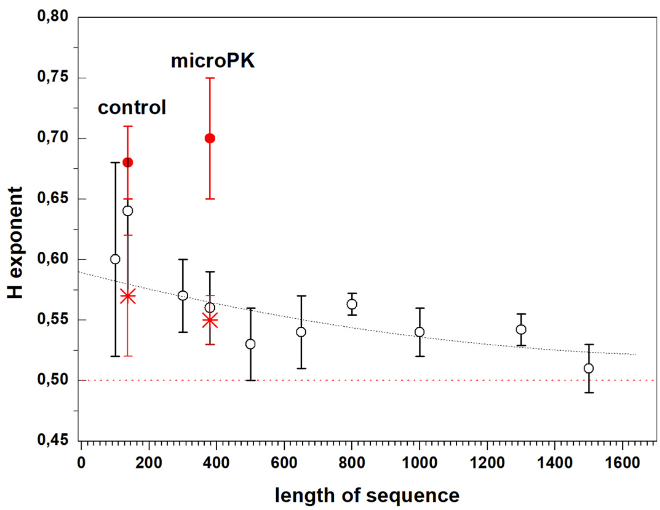

Figure 6. Hurst exponents, *H*, and their associated error, δ*H*, estimated through the Rescaled Range Analysis (Pallikari & Boller, 1999) performed on time-series of binary data, versus the length of the sequence. Open circles: Random sequences generated online (random.org). Solid circles: BSB-MA control and MicroPK time series, as indicated. Crosshair: randomized BSB-MA control and MicroPK time series, see Table 1. Dotted curve: second-order polynomial fit (Origin 7 software) on *H* exponents from online time series. Dash-dotted horizontal line: theoretical baseline for sequences of random data at *H* = 50%.

To ensure that the long-range correlations in MicroPK and control time series were the result of an arrangement according to the date of publication, the sequences were randomized[15] and then subjected to the R/S analysis. The approach was repeated ten times. The estimated average Hurst exponent of the randomized time series is marked in Figure 6 with a crosshair symbol and reported in Table 1. The statistical significance of the difference between the two Hurst exponents, H_{raw} of the original time series and the average $H_{\mathrm{randomized}}$ after randomization, is conveyed by the z-score of their difference, $Z_{\delta\mathrm{H}}$ Table 1. The result shows that we can be 99.5% confident that randomization has destroyed the persistent long-range correlations in the MicroPK time series.

Due to the shorter length of the control time series, we are slightly less confident (94%) that randomization destroyed the long-range correlations in it. Overall, it seems safe to conclude that the arrangement of scores according to their publication date has introduced persistent correlations in the MicroPK time series. How can we interpret such trends in the MicroPK time series?

Estimating the correlation coefficient between first neighbors C_1 in the sequence of MicroPK scores arranged per date of publication assists the understanding of the origin of such trends. The correlation coefficient of first neighbors is 66%.[16] MicroPK studies published on neighboring dates tend to produce similar scores. It is more likely that following the publication of a positive MicroPK score will follow another publication presenting a positive MicroPK score. Similarly, a negative MicroPK score will follow another published negative MicroPK score, and so on. A tendency for the persistent continuation of the result or trend. The observation suggests the presence of bias in the scores of the BSB-MA database.

> The average experimenter testing the MicroPK hypothesis has biased some scores to mimic the previously published MicroPK study regardless of whether it was a failure or a successful result.

The result of the R/S analysis on the MicroPK time series answers the puzzle: "Why were so many MicroPK scores found on the funnel plot beyond the left-hand side 95% confidence interval curve, indicating that the mind influenced the random process against intention, thus refuting the MicroPK hypothesis?"

"Why did the Markov model interpret the broadening of the scatter of MicroPK data by the equal promotion of the hit and miss score (p_{11}=p_{00}>50%) and not only by the promotion of hit scores (p_{11}> 50%, p_{00}= 50%) if the test aimed at supporting the MicroPK hypothesis?"

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15 Sequences were randomized using Microsoft Excel's RAND function.

16 Equation (6) in the appendix.

In other words, the social pressure of *conformity bias* (Padalia, 2014) led the average experimenter to introduce errors unintentionally so that their score mimicked previous reports. This is the *conformity* or social pressure bias. Under the social impact, the average experimental scientist feels comfortable mimicking the paradigm set by their peers. It is an aspect of the more general *Experimenter Expectancy Effect* bias defined as the unintentional biasing of research results to fulfill the experimenter's hypotheses or expectations (Rosenthal, 2014).

Errors in Scientific Investigation

To err is human. In scientific investigation, experimenters may unintentionally introduce incorrect records for several reasons like the types of bias observed in the BSB-MA database.

There is a lot in print on the problem of biases or errors in a scientific investigation. It made headlines in several scientific magazines during 2015–16 (Gobry, 2016; Nuzzo, 2015; Wilson, 2016). There are also many books written on how experimenters bias their research results through negligence, unintended error, and fraud (Broad & Wade, 1982; Chevassus-au-Louis, 2019; Grant, 2007; Kohn, 1997; Ritchie, 2020).

Discussion

Processes that passed the test of randomness operated by independent experimenters have produced the *p* scores of the BSB-MA database. These BSB-MA data of independent MicroPK studies appear to defy statistical expectations unexpectedly. MicroPK scores amass on the funnel plot in areas located beyond the 95% confidence interval curves making their dispersion broader than expected for independent data. The broadening of MicroPK scores on the funnel plot confirms the outcome of the R/S analysis. In essence, the assumed independent scores of MicroPK studies depend on each other. The MicroPK research should aim to identify the mechanism that has biased the random binary data. The Markov model suggests a probable data-correlating mechanism.

The unexpected finding is that the MicroPK scores accumulate beyond the 95% confidence interval curves of random data against intention, in other words, against the tested hypothesis. As demonstrated by the R/S analysis, conformity and experimenter expectancy effect biases modulating the database can explain the odd occurrence. After all, the random process in a MicroPK test can generate a moderate number of binary scores that fall in the region beyond the 95% confidence interval curves by sheer chance. In those cases, social pressure may take over, influencing the experimenter to unintentionally introduce errors while recording data that causes the overpopulation of the left-hand side of the funnel plot beyond statistical expectation. Cramming MicroPK scores on the extreme left-hand side of the funnel plot beyond the 95% confidence interval curve challenges the MicroPK hypothesis. The conformity bias mechanism will also cluster scores on the outer right-hand side of the funnel plot.

Prominent on the funnel plot is the lack of symmetry in the scatter of MicroPK and control scores. We understand that *publication bias* is the cause of it (Thornton & Lee, 2000). Scores missing below effect size 50% in the MicroPK funnel plot (Figure 2) and absent records above chance in the funnel plot of control data (Figure 3) reinforce the conclusion for an inherent *file drawer* or *publication bias* tainting the BSB-MA database. The proof is in the mean of scores. Although both funnel plots converge to 50%, the statistical averages of their scores in each funnel plot deviate from 50% significantly (Franco et al., 2014).

There is a third most intriguing observation regarding the scatter of data on the funnel plot. The broadening and asymmetry of data scatter are limited to small studies of size up to approximately N=100,000 trials. Studies of size above 100,000 trials scatter symmetrically about 50%, nicely converging to it as expected by the proportion of binary scores generated by a random process.

What kind of data biasing process shifted the average proportion of hits in MicroPK tests with random number generators both in favor and against intention, depending on the size of the study? Why does the biasing process cease to affect the scores of studies larger than about 100,000 trials? The BSB-MA authors have reported it as a small-size studies problem. This explanation is sensible in studies monitoring the response of human subjects to medical treatments. Medical progress may positively depend on the closer relationship between the doctor and patient developed in smaller groups (Sterne et al., 2011, p. 2).[17]

Data Biasing is Mostly Unintentional

We propose that this last peculiarity offers evidence that most errors that have shaped the MicroPK and control databases due to conformity and experimenter expectancy effect biases are unintentional. Such unintentional errors should be present in studies of all sizes, large and small (Ioannidis, 2005).[18] They introduce visible distortion in the location of small studies scores on the funnel plot. Their presence becomes, however, statistically undetectable in studies of larger size. The following example can better illustrate this scenario.

17 Quote from Sterne et al. (2011, p. 2): “Medical intervention may have been implemented less thoroughly in larger studies, resulting in smaller effect estimates compared with smaller studies.”

18 Quote from Ioannidis (2005): “for many current scientific fields, claimed research findings may often be simply accurate measures of the prevailing bias.”

Let us assume that the average experimenter in their study of $N = 1000$ MicroPK trials unintentionally introduces about 60 erroneous scores due to conformity bias aiming to reproduce a previously published high MicroPK score. Consider that the error disturbs an ideal balance between 500 hits and 500 misses. Consequently, these 60 trials will erroneously replace 60 misses with 60 hits. The proportion of hits will change from the initial 0.5 to the false 0.56, equivalent to a statistically significant mean shift ($z \cong 3.79$).[19] The error will propel the naturally occurring score from the center of the funnel plot to the region beyond the 95% confidence interval curves of random data (the blue dotted curves in Figure 2). Such errors added to the few naturally occurring extreme scores would cause the observed overpopulation of the area beyond statistical expectations.

Alternatively, if the same small-size error occurred in a study of 100,000 trials, where 50,000 were initially hits, their new number will become 50,060, and their proportion will change from 0.5 to 0.5006. The reported score containing this unintentional error would be hardly visible on the funnel plot. It is a score that could occur by chance in random data ($z \cong 0.38$).[20]

Consider the opposite case where the experimenter introduced a small number of miss scores influenced by a prior study that had reported a shift from chance against intention. Replacing hit with miss scores will introduce analogous changes to the mean, like in the last example, only in the opposite direction. The biased RNG score will appear on the funnel plot of small studies significantly shifted beyond the left 95% confidence interval curve of random data. The change will be, however, diluted and invisible on the funnel plot of the sizable studies. Thus, some unintentional errors can stretch the scatter of scores on the funnel plot of smaller studies leaving their effect in the larger ones undetected. Scores of size approximately above 100,000 trials will scatter on the funnel plot like true random data, converging symmetrically to 50%. The BSB statistical analysis of MicroPK data has recognized the stretching or broadening of data scatter in the smaller studies as "extreme heterogeneity" of unknown origin. The above rough examples describe the simple mechanism that introduced the heterogeneity in the database or the broadening of data scatter due to unintended errors introduced through the conformity bias already identified by the R/S analysis.

If the majority of falsely reported scores were intentional, on the other hand, their number would not be small but just adequately large to yield the intended fraudulent result. It would introduce significant mean shifts below and above 50%, even in studies of size above 100,000 trials. The distribution of scores on the MicroPK funnel plot testifies that this is not the case.

19 $z = (0.56 - 0.5)/[0.5/\sqrt{1000}] \cong 3.79$

20 $z = (0.5006 - 0.5)/[0.5/\sqrt{100,000}] \cong 0.38$

Combining the Evidence to Explain MicroPK

The MicroPK hypothesis asks for a clarification of its mechanism to manage the ample evidence in the BSB-MA database provided by the R/S analysis, the Markov model, and the configuration of scores' scatter on the funnel plot. The scientific method in testing a hypothesis follows the five steps of observation-research-experiment-data analysis-conclusions.

We can attempt two descriptions of the MicroPK evidence that differ in the last stage of the scientific method. The first explanation will assume the paranormal human capacity, accommodating most evidence. The second will introduce all evidence replacing the mind-over-matter element with well-known attitudes for biasing experimental data. The principle of parsimony will finally compare the two likely descriptions of the MicroPK hypothesis.

A Paranormal Explanation of the Evidence

Micro-psychokinetic ability characterizes exceptionally gifted individuals who can directly affect random processes through intention. The strength of the PK effect is irregular, weak, and undisciplined. The Greek parapsychologist Dr. A. Tanagras also described it in his theory of Psychobolia as uncontrollable in individuals who lack appropriate training (Pallikari, 2019, 2020a, 2020b, p. 340).[21] Consequently, its nature prohibits scientists from replicating it in the lab. As the evidence on the BSB-MA funnel plot shows, PK-gifted individuals cannot always affect physical reality in line with their wishes or intention. The direct psychokinetic influence on a random process may come even against their intent. This bidirectional feature of the micro-psychokinetic skill bestows it a new characteristic not previously recognized.

Due to its weak, uncontrollable, bidirectional, and rare nature, the psychokinetic effect can modulate only a small number of scores in a MicroPK study, increasing the length of runs of the favorite binary outcome in them. It, therefore, generates sizable mean shifts in small studies above and below chance broadening the scatter of scores on the funnel plot. Its finite effect, however, becomes diluted and invisible in studies of larger size. The widening of data scatter at smaller studies combined with their discarding due to publication bias creates the false impression that the statistical average of scores is not stationary. It falsely indicates the collapse of the law of large numbers. On the other hand, the limited MicroPK effect will be 'diluted' in studies with about 100,000 trials and more whose scores will behave on the funnel plot like random data. They will scatter as expected under the confidence interval curves and converge to a 50% proportion of hits.

21 This was the view of the Greek parapsychologist Dr. A. Tanagras in his theory of Psychobolia. Gifted PK mediums require training before they can control the effect at will.

The Non-Paranormal Explanation of the Evidence

Three well-known biases in experimental research have shaped the MicroPK and control BSB-MA databases; the experimenter expectancy effect, the conformity, and the publication bias. They worked as follows.

The experimenter-expectancy effect bias introduced some false scores that overpopulated the right-hand side of the MicroPK funnel plot beyond the 95% confidence interval limit for random data. The purpose was to fulfill the MicroPK hypothesis that expected significant mean shifts from chance in the direction of intention. Its involvement emerges again in the restricted scatter of control scores that remain close to the 50% proportion of hits to support the hypothesis for random processes employed in the tests.

The conformity bias, the attitude a new study to mimic previous experimental results, introduced some false scores that overpopulated the left-hand side of the funnel plot beyond the 95% confidence interval limit for random data. The drive was to reproduce and outdo the score of a preceding study that had occurred by sheer chance against the direction of intention. In addition to the experimenter expectancy effect bias, it also contributed scores to overpopulate the right-hand side of the funnel plot beyond the 95% confidence interval limit for random data. Both biases have contributed to the observed broadening of scores scatter on the funnel plot.

The publication bias introduced the visible asymmetry in the spread of scores on the MicroPK and the control funnel plots. It is the main reason the statistical average of scores in each of the two databases significantly deviates from the value to which their funnel plots converge. Publication bias upon conformity bias affected the overpopulated regions on the far left-hand side of the MicroPK funnel plot, making it less dense in scores compared to the symmetrically opposite right-hand side beyond the 95% confidence interval curves of random data.

The number of falsely introduced errors by the three biases was limited and unintentional in the majority. Their modest presence disturbs the scatter of scores significantly in studies of small size. Their impact weakens in studies larger than about 100,000 trials where their scores appear to act randomly: properly confined between the 95% confidence interval curves for random data and properly converging to the expected 50% proportion of hits.

Between Two Interpretations of the Evidence for Micro-Psychokinesis – Occam's Razor

The non-paranormal interpretation of the MicroPK hypothesis covered all evidence from the BSB-MA database examined by recognized scientific methods. The paranormal portrayal falls short of accommodating some of the evidence. For instance, it did not account for the slight confinement of the scatter of control scores and the mimicking pattern between subsequently published scores revealed by the R/S analysis. It was also the overpopulation of the funnel plot at the far left-hand side against intention, where the invented bi-directional characteristic of the psychokinetic ability is absent from its definition.

To examine debatable hypotheses, scientists often embrace the principle of Occam's razor (Heylighen, 1997), also called the principle of parsimony or intellectual elegance (Walsh, 1979). The principle of parsimony rejects complicated explanations that introduce unrecognized parameters, maintaining a simple description of the studied phenomenon that adequately accounts for all evidence utilizing already confirmed scientific knowledge. The paranormal description of the MicroPK mechanism, as presented here, does not meet the requirements of Occam's razor. The non-paranormal explanation of the evidence in the BSB-MA database prevails with the following description of the evidence about MicroPK.

> The MicroPK BSB-MA database consists of random binary scores generated by true RNGs. Three acknowledged biases in experimental research meddled with some of the data: experimenter expectancy effect, conformity, and publication bias. The evidence following the scientific method of inquiry invalidates the hypothesis that intention directly influences a random process by an intangible mind-matter mechanism.

The study of the MicroPK phenomenon and the usefulness of belief in it requires further investigation by the field of psychology (Cardeña, 2014).

The Usefulness of Belief in the Paranormal

Despite the lack of scientific evidence, claims for experimental proof supporting mental influence on physical reality keep being published (Pallikari, 2015b). How are we to understand such a contradiction?

Surveys show that belief in the paranormal is quite common (Salas, 2022; Wiseman & Watt, 2006). The public would favor efforts to validate psychokinesis rather than tolerate the scientific evidence that refutes it. Believing that we can act on the present to affect events through focused thought alone bestows tremendous confidence in us. Feeling powerful, we become more self-confident, focused, relaxed, and alert to opportunities, handling our actions with increased effectiveness. In such favorable mental state, we shall focus on appropriate opportunities when they happen to pass us by, and the chances of our desires to materialize will grow. We feel powerful and project our positive appearance to others.

Interestingly, the telekinetic movement of an object or the bending of a spoon with the supposed power of the mind still requires an unnecessary vicinity that invalidates its prefix 'tele'.[22]

If one wonders why we hang on to irrational views, as are those not based on scientific evidence, author Matthew Hutson has the answer. Such beliefs can keep us happy, healthy, and sane. He adds, magic can be good for you (Hutson, 2012). One may further add, for as long it does not exploit or harm others.

Epilogue

The authors of the BSB-MA recognized the problem the unreported research of predominantly small-size studies introduces to the statistical evaluation of the psychokinesis effect. Their statistical analysis of small studies encouraged the supporters of the mind-over-matter hypothesis to propose that the strength of psychokinesis depends on how many trials a study collects (Radin et al., 2006, p. 532). As it makes a likely argument, it prompted an interpretation of the MicroPK BSB-MA database in paragraph "The Non-Paranormal Explanation of Evidence" from the paranormal perspective. As already demonstrated, the metaphysical version of the evidence in the BSB-MA database falls short of scientific gravity.

The three authors further recognized the existing risk of the statistical evaluation of scientific evidence to arrive at debatable conclusions. Quote: "any conclusion about the evidence lies in the eye of the beholder. This situation is unlikely to change anytime soon" (Bösch et al., 2006b, p. 533). As presented in paragraph "Between Two Interpretations of the Evidence ...", there is an alternative non-paranormal scientific approach other than the statistical to analyze the evidence from the MicroPK BSB-MA database.

Arguments in support of the psychokinesis hypothesis may invoke aspects of quantum theory. One such instance summoned the collapse of the wave function of a quantum particle supposedly due to the measurement of its state by conscious observers through psi (Pallikari, 2015b, pp. 2, 5; Pallikari, 2022). A well-formulated answer to the case came from a German team at the Max Planck Institute for Brain Research and the Frankfurt Institute for Advanced Studies. The authors tested several consciousness-related predictions based on available experimental results and concluded: "Quantum mechanics needs no consciousness." They showed that the collapse-by-consciousness hypothesis in quantum measurement is redundant (Yu & Nikolić, 2011). It responds to the general question, "why some scientists refuse to consider the evidence for psi phenomena" (Taylor, 2022).

22 Telekinesis comes from the Greek word τηλεκίνησις. Tele (τηλε) means long distance, and kinesis (κίνησις) means movement: To move an object from a long distance. Similar words derived from the Greek are telescope, telephone, television, etc.

We can rest assured that science would not neglect to use a scientifically verified MicroPK effect, no matter how weak it may be. One related example is perhaps Casimir force,[23] the force from nothing (Lambrecht, 2002). Proposals exist for its application in science and engineering related to space propulsion.[24]

The methods applied here to investigate MicroPK, the Rescaled Range Analysis, and the Markov model are suitable for time series and funnel plots of other psi databases (Tressoldi & Storm, 2021). They can be adequate even if the databases may contain only small-size studies (Pallikari & Papasimakis, 2008, p. 7).

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The acute comments and productive critique of the two reviewers have significantly improved the content and presentation of this manuscript.

APPENDIX

This section concerns the readers who are comfortable with or curious about the mathematical equations describing the concepts discussed in this article.

The decision theory in statistics assesses the statistical average of a sample of collected random data and its confidence interval concerning population statistics. Less known is the alternative modification, which applies to correlated binary data. Here follows a short description[25] of the theory assuming the Markovian-type of correlations in data adapted to meet the requirements of the current article. The Markov process presupposes the presence of memory in the sequence of binary scores. The phenomenon is common in physical processes, such as in records of turbulence (Papasimakis & Pallikari, 2006a, p. 61; Papasimakis & Pallikari, 2006b), where the memory 'glues' similar binary states into longer sequences (Pallikari, 2003).

The confidence interval curves for randomly distributed binary data, equation 1, appear on the funnel plot presenting the size of the study, N, against the proportion of successes in the study (Pallikari, 2015a, p. 501), dotted curves in Figures 2 and 3.

$$N = \frac{0.96}{(\mathrm{pi} - 0.5)^2} \qquad (1)$$

23 The force of quantum vacuum between two plates. If the size of each plate is 1 x 1 cm^2 separated by 1/10,000 cm, the Casimir force is equal to the 1/10,000,000 of the weight of an apple.

24 https://patents.google.com/patent/US20080296437A1/en

25 A more extended discussion of the Markovian analysis was published elsewhere (Pallikari, 2015a).

The Markovian bias assumes that each binary state depends on the previous according to the self-transition probability p_{11}, the probability

$$N = \frac{z_0^2 \cdot V^2 \cdot [\wp \cdot (1 - \wp)]}{(pi - \wp)^2} \qquad (2)$$

for two successes in a row to occur and p_{00}, the probability for two failures in a row. Then, the probability of a failure to follow a success will be $1-p_{11}$, and $1-p_{00}$ of a success to follow a failure. The equation representing the new confidence interval curves of correlated data follows the general equation 2 (Pallikari, 2015a, p. 503).

The Markovian bias generally modulates the population statistical average and its variance according to the two self-transition probabilities. The parameter $\wp$, in equation 3 (equation 8a in Pallikari, 2015a, p. 503), represents the proportion of hits *pi* of the most representative study of the population, coinciding with the value to which the funnel plot of correlated data

$$\wp = \frac{1 - p_{00}}{2 - (p_{11} + p_{00})} \qquad (3)$$

converges. In other words, $\wp$ is the population statistical average:

The parameter *V*, the *variance factor* of equation 4, modulates the variance of the random data.

$$V = \sqrt{\frac{p_{11} + p_{00}}{2 - (p_{11} + p_{00})}} \qquad (4)$$

It describes how the correlated binary scores will scatter about the peak of the funnel plot, equation 8c in (Pallikari, 2015a, p. 503).

The desired level of statistical significance in the random process specifies the parameter z_0 in equation 2. It equals z_0=1.96 for the 95% confidence interval curves.

The frequency of runs of length *m*, a_m, in a sequence of *N* binary data that occur at frequencies p_{11} *and* p_{00} (von Mises, 1964, p. 188)[26] is

$$a_m = (N - m - 1) \cdot (p_{11}^2 p_{00}^m + p_{00}^2 p_{11}^m) \qquad (5)$$

If the binary data are random, $p_{11}=p_{00}=0.5$ and the study very large ($N >> m$), then equation 5 reduces to $a_m = N \cdot 0.5^{m+1}$. It estimates that by chance one run of *m*=twelve 0s (or twelve 1s) occurs in a sequence of *N*= 10,000 random binary scores.

26 Also in Pallikari & Papasimakis (2008, p. 5)

In a sequence of correlated binary scores where the Markov self-transition probabilities $p_{11}=p_{00}=p$ the correlation coefficient C_1 between first neighbors is, equation 6, according to Schroeder (1991, p. 359)

$$C_1 = 2p - 1 \qquad (6)$$

For the MicroPK BSB-MA database the estimated Markov self-transition probabilities $p_{11}=p_{00}=p\cong 0.83$ yield $C_1=0.66$.

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