Abstract

In studies on micro-psychokinesis (micro-PK), in which intentional observer effects on results of quantum generators (tRNG) are investigated, Maier, Dechamps and Pflitsch (2018) and Maier and Dechamps (2018) have discovered a remarkable pattern in post-hoc analyses that resembles a damped harmonic oscillation. The micropsychokinetic effect seems to increase and decrease alternately several times during the data collection time. Furthermore, Maier et al. (2018) found a higher oscillation frequency of the micropsychokinetic effect compared to the course of the effect of simulated data. In this work, these observations are tested and the data is examined for a systematic decline of the effect over time. To investigate this, an online experiment on micro-PK was conducted and micropsychokinetic effects on erotic images were tested in male participants (n = 387). The Bayesian analysis showed anecdotal evidence for H_0 (BF_{01} = 1.3). However, in the sequential analysis a systematic decline of the micropsychokinetic effect was found and the results of the nonlinear regression analyses also confirmed the findings of Maier et al. (2018): The oscillation frequency of the effect in the course of data collection in the male sample data is clearly higher than in the simulated data. The role of the systematic decline of the micropsychokinetic effects is discussed with regard to the replication crisis.

Keywords: systematic decline effects, micro-psychokinesis, quantum observation, Bayesian statistics, replication

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Evidence for micro-psychokinetic effects in erotic visual material? An analysis using the Bayesian method and investigation of a systematic decrease of the effect over time of data collection

"Real new territory in a science can only be gained if one is prepared at a decisive point to leave the ground on which the previous science rests" (Werner Heisenberg, 1932 Nobel Prize, Physics).

In 2011, the well-known researcher Daryl J. Bem triggered a replication crisis in psychological research with the publication of his study results on psi effects (Bem, 2011), which showed empirical evidence for these effects and which continues to this day (Benedictus, Miedema & Ferguson, 2016; Loeb, 2016; McNutt, 2014; Munafò et al., 2017; Wagenmakers, Wetzels, Borsboom & van der Maas, 2011). Since then, psychological science has been experiencing a credibility crisis, and to this day there are still discussions about possible reasons and measures to increase the replicability of studies (e.g. Schönbrodt, Maier, Heene & Bühner, 2018). Using Bayesian statistics, which has become increasingly important in psychological science in the course of the replication crisis (Etz, Gronau, Dablander, Edelsbrunner & Baribault, 2018; Etz & Vandekerckhove, 2016; Wagenmakers et al, 2011), Maier, Dechamps and Pflitsch (2018) discovered a conspicuous pattern in exploratory data analysis in a study on micro-psychokinesis (micro-PK) that resembles a damped harmonic oscillation. The micro-psychokinetic effect appears to alternately increase and decrease several times during the data collection period. This observation is remarkable, as so-called *decline effects* also occurred in similar studies (Jahn et al., 2000; Maier & Dechamps, 2018; Radin, 2006). In addition, Maier et al. (2018) found a significantly higher oscillation frequency of the micropsychokinetic effect compared to the course of the effect of simulated data. Theoretically, Maier et al. (2018) underpin the systematic pattern of the effect as well as the clear difference in frequency with the quantum physical *model of pragmatic information* by von Lucadou (2015) and extend it with the possible role of entropy. According to Maier et al. (2018), this phenomenon, if it can be confirmed, could be partly responsible for the replication crisis and suggest a possible alternative review of the evidence for micro-PK, among others.

In the online study created, the observations of Maier et al. (2018) are to be reviewed and the data examined for a systematic decrease in the effect over the course of the data collection. The data analysis is carried out using the Bayesian method. The research question is to be answered with an experiment on micro-PK, as on the one hand the search for psi effects was the starting point of the replication crisis and triggered the discussion on how data should be collected and analyzed, and on the other hand the systematic pattern in the data set was discovered in a study on micro-PK. The aim of the experiment is to investigate the influence of micro-psychokinetic effects, which are triggered by the unconscious needs of a person addicted to pornography when observing erotic image material, on quantum-based results. Pornography because Bem (2011) obtained the strongest effects in his study on erotic stimuli. Finally, a statement should be made as to whether there might be evidence for micro-PK after all.

In the following, after an insight into the replication crisis, the Bayesian method is briefly described. This is followed by a description of the data analysis by Maier et al. (2018) and Maier and Dechamps (2018) and possible quantum-theoretical explanations are given. An overview of micro-PK research is then given, followed by a description of pornography addiction and its methodological relevance in the present study.

Replication crisis in psychological research

In 2011, Bem (2011) published study results in the *Journal of Personality and Social Psychology* that were intended to show empirical evidence for psi effects in 8 of 9 experiments with over 1000 test subjects. The term *psi* refers to an unusual transfer of information or energy that cannot yet be fully explained by physical or biological mechanisms (Bem, 2011). Phenomena such as telepathy, clairvoyance, micro-PK or precognition are subsumed under this term. Psi has long been a fascinating phenomenon and there has been a tradition of research for many decades (see Radin, 2006; Varvoglis & Bancel, 2015). In science, the phenomenon of psi is very controversial and there is great doubt about its existence, especially among psychologists Bem (2011), not least for the reason that no robust effect proving the evidence of psi phenomena could be found so far. Despite high-powered studies, replication attempts have failed (Jahn et al., 2000; Maier & Dechamps, 2018; Maier et al., 2018). Bem's aim was therefore to make the experiments and statistical analyses on psi as simple, transparent and known as possible. Nevertheless, other researchers pointed out inadequate methods and flawed analyses by Bem and numerous failed replication attempts supported their criticism (Francis, 2012; Galak, LeBoeuf, Nelson & Simmons, 2012; Wagenmakers et al., 2011). Wagenmakers et al. (2011), for example, reanalyzed Bem's data with Bayesian statistics and found only a weak to no existing effect. According to Wagenmakers et al. (2011), Bem's study has shown that psychologists should change the way they analyze their data. "The field of psychology currently uses methodological and statistical strategies that are too weak, too malleable, and offer far too many opportunities for researchers to befuddle themselves and their peers" (Wagenmakers et al., 2011, p. 426). Many researchers in psychological science collect and evaluate the data in their experimental studies in the same way as Bem and, according to Wagenmakers et al. (2011), therefore produce the same methodological errors. The question therefore arose as to how credible other study results in psychological research are (Pashler & Wagenmakers, 2012). In a large-scale replication attempt by the Open Science Collaboration (2015) led by Brian Nosek, the assumption of Wagenmakers et al. (2011) was confirmed. Only 39% of the study results published in 2008 in three renowned journals (*Journal of Experimental Psychology: Learning, Memory, and Cognition, Journal of Personality and Social Psychology, Psychological Science*) could be successfully replicated (see Figure 1).

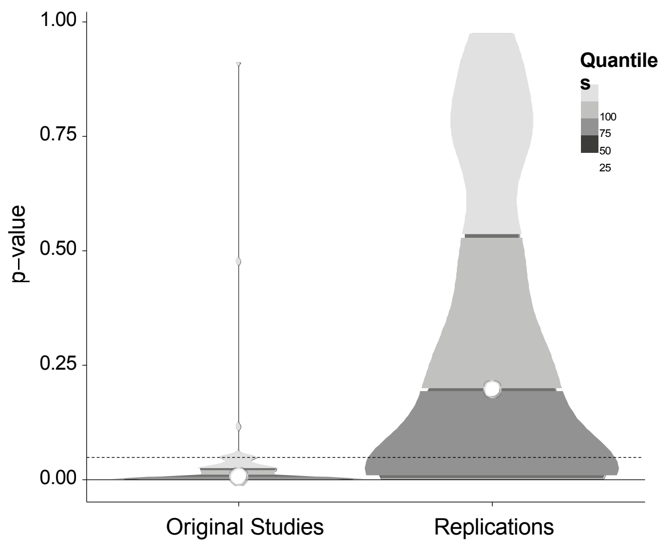

Figure 1: Density plot of original and replicated p-values (Open Science Collaboration, 2015)

However, the percentage figure of the Open Science Collaboration is controversial (Gilbert, King, Pettigrew & Wilson, 2016). But other large-scale replication projects have also shown that the majority of published study results cannot b e replicated (Klein et al., 2014; Nosek & Lakens, 2014). As a consequence, an international discussion about the replicability of scientific results has been sparked (Benedictus et al., 2016; Loeb, 2016; McNutt, 2014; Munafò et al., 2017). Scientific disciplines such as economics or medical research are also affected by the replicability problem (Begley & Ellis, 2012; Camerer et al., 2016).

There are numerous reasons for the lack of replicability of study results. From an evolutionary perspective, the "why" question can be answered on two levels (Tinbergen, 1963, cited in Schönbrodt et al., 2018): The effect causes and the purpose causes.

With regard to the cause of purpose, the "misguided scientific culture" (Fecher, Fräßdorf, Hebing & Wagner, 2017, p. 156) plays a decisive role. The existing incentive structures in science favor an "inflation of false-positive results" (Schönbrodt et al., 2018, p. 38). Due to high publication pressure, quantity rather than quality is strengthened (Baker, 2016) and an unrealistically high number of significant results is rewarded (Gervais, Jewell, Najle & Ng, 2015). As a result, often only significant results are published and often with low power.

According to Schönbrodt et al. (2018), the causes of impact are unintentional errors, flexibility in data analysis and so-called *questionable research practices* (QRPs), which include publication bias (Pashler & Wagenmakers, 2012), p-hacking (Ioannidis,

2005) and *HARKing* (Hypothesizing After the Results are Known; Kerr, 1998). QRPs are regularly and widely used by researchers (Fiedler & Schwarz, 2016). When multiple QRPs are used simultaneously, the probability of a false-positive result can increase from the 5% level to over 50% (Simmons, Nelson & Simonsohn, 2011).

The replication crisis is a complex problem and parallel reforms are needed across the entire breadth of academic practice (Pashler & Wagenmakers, 2012). One solution to the replication crisis is to "strengthen research transparency as a valuable scientific asset" (Schönbrodt et al., 2018, p. 37). With the help of *open science*, many of the causes just described can be remedied.

In addition to the methodological causes, there is another possible cause of the replication problem that could be partly responsible. Maier et al. (2018) and Maier and Dechamps (2018) investigated whether the cause of the replication problem could also be partly related to quantum physical phenomena. They observed so-called systematic "decline effects" (Maier et al., 2018, p. 9) in studies on micro-PK. Decline effects are defined as a strong decrease in the effect over time after clear evidence for the alternative hypothesis was available. The decline effects show a so-called "appearance-disappearance pattern" (Maier et al., 2018, p. 7), which resembles a damped harmonic oscillation. Maier and colleagues (2018) discuss possible reasons (e.g. entropy) and the question of whether such systematic patterns also occur in other studies in which unconscious processes are involved (Maier & Dechamps, 2018; Maier et al., 2018). However, this assumption is still speculative and studies are needed to verify it. If the assumptions made by Maier et al. (2018) and

Maier and Dechamps (2018) should be confirmed in the future, the findings should be taken into account in research.

Another consequence of the replication crisis is the discussion about alternative research methods, as the common evaluation methods, the frequentist significance tests, have been criticized in the course of the replication crisis (Etz et al., 2018; Wagenmakers et al., 2011). The probabilistic approach using Bayesian statistics is recommended by some researchers as an alternative (Etz et al., 2018; Etz & Vandekerckhove, 2016; Wagenmakers et al., 2011).

Inferential statistical analysis with Bayesian statistics

Bayes' theorem was discovered in the mid-18th century by the English mathematician and clergyman Thomas Bayes (Bayes, 1763, cited in Etz, 2018). In the history of Bayesian statistics, the work of Harold Jeffrey and Dorothy Wrinch is significant, as they laid "the conceptual groundwork for the development of the Bayes factor" (Etz & Wagenmakers, 2017, p. 313) and are considered the inventors of the Bayesian significance test. Bayes' theorem has been criticized by many theorists and yet it has been successfully applied in practice for many decades (McGrayne, 2014). A famous example is the success of the Englishman Alan Turing in World War II, who used Bayes' theorem to solve the Enigma secret code of the German navy. However, Bayes' theorem also has numerous applications today, such as recognizing spam emails (Kruschke, 2015).

In the 1940s, the frequentist method of both Fisher and Neyman and Pearson prevailed over Bayesian statistics. The reason for this, in addition to criticism of the subjectivity of Bayes' theorem, was that frequentist statistics led to the had far more practical applications at the time (Dienes, 2011). However, as a result of the replication crisis and advances in computer technology, a renewed debate has arisen as to which statistical method is more suitable for drawing correct conclusions from data (Etz et al., 2018; van de Schoot, Winter, Ryan, Zondervan-Zwijnenburg & Depaoli, 2017). The increasing use of the Bayesian method in psychological research is also due to the criticism of *p-values* and classical statistics in general (Dienes, 2011; Trafimow & Marks, 2015; Wagenmakers et al., 2011; Wetzels et al., 2011).

The essence of Bayesian inference is the possibility of constantly updating the credibility of a statement by incorporating the available information, from the number 0 (false, untrustworthy) to 1 (true, trustworthy) (Kruschke, 2015). Probability in Bayesian statistics is defined as the *degree of belief* (Etz & Vandekerckhove, 2018) and "the Bayesian approach to statistics is fundamentally about making use of all available information when drawing inferences in the face of uncertainty" (Etz, 2018, p. 65). Prior knowledge at the beginning of the study is quantified and taken into account using a priori probability. At the beginning of the data analysis, the probability that the hypothesis p(H) is true, the so-called a priori probability, is subjectively determined with the help of prior knowledge or empirical data (Etz, 2018). The a priori probability therefore indicates which hypothesis is more or less likely if all known information is included in advance. If no prior knowledge is available, the hypotheses can also be given the same probability (for a detailed explanation, see Rouder, Speckman, Sun, Morey and Iverson, 2009).

The probability *p* that the data occur under the validity of the hypothesis (D|H) is called *likelihood* and is a key factor in Bayesian inference (Etz, 2018). The likelihood function is used to update the a priori probability to the a posteriori probability *p*(H|D), i.e. the probability that the hypothesis is valid under the data obtained:

$$p(H|D) = p(D|H) \cdot p(H)/p(D) \quad (1)$$

The likelihood contains all relevant information contained in the data (Birnbaum, 1962, cited in Dienes, 2011). In order to decide which of two hypotheses is more probable for an experimental result, the ratio of their likelihoods is considered:

$$BF_{10} = p(D|H_1) \cdot / \, p(D|H)_0 \quad (2)$$

This final result is called *Bayes Factor* (BF) and is equal to the relative amount of evidence of the data for or against a postulated effect (Berger & Pericchi, 1996). Thus, the existence or non-existence of an effect can be tested against each other in the same data. For example, a BF_{10} greater than 1 supports the evidence for the alternative hypothesis, a BF_{10} less than 1 supports the null hypothesis and a BF_{10} of 1 indicates that the data are not informative enough (Dienes, 2011). The BF_{01} is the reciprocal of the BF_{10} and a value greater than 1 indicates evidence for the null hypothesis, analogous to the explanation above. Table 1 contains a

Classification scheme as an aid to interpretation for categorizing the level of BF into categories ranging from *anecdotal evidence* to *extreme evidence* (Jeffreys, 1961, cited in Wetzels & Wagenmakers, 2012).

Table 1

Classification scheme for the Bayes factor

Bayes factor, BF_{10}	Interpretation
≥100	Extreme evidence for H_1
30-100	Very strong evidence for H_1
10-30	Strong evidence for H_1
3-10	Considerable evidence for H_1
1-3	Anecdotal evidence for H_1
1	No evidence
1/3-1	Anecdotal evidence for H_0
1/10-1/3	Considerable evidence for H_0
1/30-1/10	Strong evidence for H_0
1/100-1/30	Very strong evidence for H_0
1/100	Extreme evidence for H_0

Annotation. Translated into German by the author.

For example, a BF_{10} of 40 indicates very strong evidence and means that the alternative hypothesis is 40 times more likely than the null hypothesis in the data obtained. A detailed introduction to Bayesian statistics can be found in Etz and Vandekerckhove (2018) or in Etz and colleagues (2018).

A disadvantage of Bayesian analysis is that the calculation of the BF depends on the answer to a question about which there may be disagreement (Dienes, 2011): Which way of assigning probability distributions of effect sizes determined by theories receives the most support as a default setting? Answering this question requires an intensive examination of the respective data and theories. This can be seen as a weakness, as answering the question is time-consuming and subjective. But this weakness is

This is also seen as a strength, as more careful thought is given to theoretical mechanisms and experiments are linked to past research in order to best predict the effect sizes (Dienes, 2011). Another weakness is that the control of type 1 and type 2 error probabilities is not guaranteed. The Neyman Pearson statistic would have to be used to control for this, which in turn would violate the likelihood principle (Dienes, 2011). Dienes (2011) concludes:

> Ultimately, the issue is about what is more important to us: using a procedure with known long term error rates or knowing the degree of support for our theory (the amount by which we should change our conviction in a theory). If we want to know the degree of evidence or support for our theory, then our reliance on orthodox statistics is irrational.

Bayesian statistics have further advantages over frequentist statistics (Etz et al., 2018; Wagenmakers et al., 2018; Wagenmakers et al., 2011). On the one hand, the BF, which is considered a measure of the evidence available in the data, contains information about the power of the sample size in addition to information about the strength of the effect. A high BF can only be achieved if sufficient power is given by the sample size, whereas with the frequentist approach an effect can also be discovered by chance if the power is weak. Accordingly, optional stopping is possible with the Bayesian method during data accumulation if, for example, the previously defined BF has been reached. Furthermore, in contrast to the *p-values*, the BF can be used to make a statement about the strength of the effect (Wagenmakers et al., 2018). The Bayesian method also allows the evidence to be quantified in favor of the null hypothesis, which is not possible with traditional *p-values* is not possible (Wagenmakers et al., 2011). Furthermore, Bayesian statistics enable the effect to be tracked during data collection by means of sequential data analysis (Rouder, 2014). In this way, a conspicuous systematic pattern was discovered in studies on micro-PK in exploratory data analysis (Maier & Dechamps, 2018; Maier et al., 2018), which is described in more detail below.

Systematic decrease in the effect over the course of data collection

In studies on micro-PK, Maier and colleagues (2018) discovered a systematic decrease in the effect over the course of data collection when looking more closely at the effect. The micro-psychokinetic effect appears to alternately increase and decrease several times (Maier et al., 2018). This observation of the so-called appearance-disappearance pattern is remarkable, as the same pattern was observed in other studies on micro-PK (Jahn et al., 2000; Radin, 2006).

In the research by Maier and Dechamps (2018), the influence of smokers on a *true random number generator* (tRNG), which randomly generates neutral or cigarette images, was investigated. The tRNG's are generators that produce numerical results based on quantum sources and are considered an optimal source of randomness. The assumption was that smokers induce a non-random deviation of the mean of the smoking images. In the first study, bayesian analysis revealed strong evidence for the existence of micro-psychokinetic effects (BF_{10} of 66.7 for the H_1). This result was to be replicated in a second preregistered study. However, the BF at the end of the study clearly pointed to evidence of the H_0 (BF_{01} = 11.07). As the two BFs in the studies have a high value of over 10, these cannot be random fluctuations, as a BF of 10 indicates strong evidence (Jeffreys, 1961, cited in Wetzels &

Wagenmakers, 2012). In contrast, neither in the control group, the non-smokers, nor in the simulated data, which were created for comparison with the same experimental conditions but without any observation of a human being, was a BF greater than 10 present in these groups during the entire data collection period of both studies.

In another online study with 12,571 subjects, Maier and colleagues (2018) aimed to show clear evidence either for or against micro-PK. They investigated whether there were intentional observer effects on quantum randomness. The assumption was that subjects would see more positive than negative stimuli generated by a tRNG and that there would be a non-random deviation from the mean. Before the image presentation, the subjects were exposed to a relaxation exercise to put them in a relaxed and optimistic mood. The bayesian analysis showed strong evidence for the H_0 (BF_{01} = 10.07), which means that there is no micro-psychokinetic effect in the data obtained. However, in the exploratory data analysis, Maier et al. (2018) also observed an appearance-disappearance pattern here. It appears that "the effect in its temporal development across participants behaved like a dampened harmonic oscillation" (Maier et al., 2018, p. 10; see Figure 2).

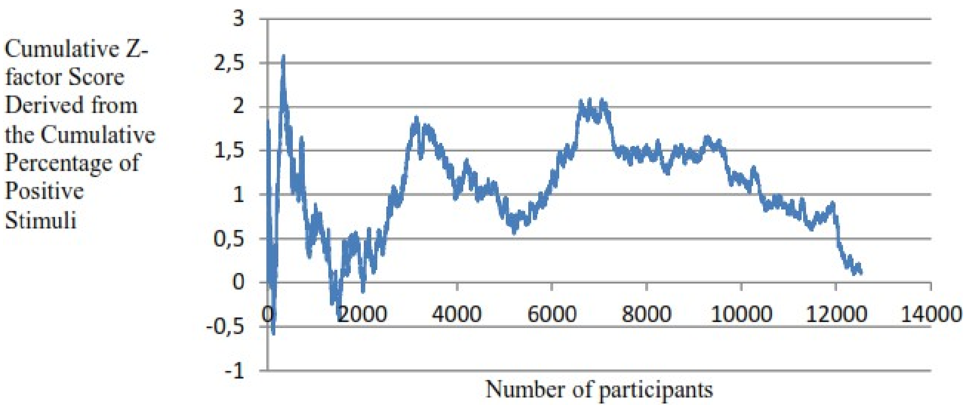

Figure 2 Sequential analysis of the data by calculating the cumulative *Z-scores* of the positive stimuli received after each participant (Maier et al., 2018, p. 6)

Theoretical models have been used to understand this appearance-disappearance pattern in micro-PK. A model that attempts to describe the systematic nature of this empirical phenomenon was proposed by von Lucadou (2006, 2015). The pragmatic information model refers to the observer-dependent quantum effects and states that the quantum effects present in micro-PK violate *the no-signal theorem* (von Lucadou, 2006, 2015). This theorem states that communication in quantum mechanics must not be faster than the speed of light. This means that in an entangled, separated system, any measurement performed on one side of the system must not affect the probability of obtaining similar results in the other system (Ghirardi, Grassi, Rimini & Weber, 1988). To address this violation, subsequent confirmation of the effect must be prevented so that the effect disappears with additional data collection, such as in a replication experiment. The novelty and strength of the effect is complementary to the probability that this effect will be replicated. The more novel or stronger a quantum effect, the lower the probability of successful replication (von Lucadou, 2006, 2015). Maier and Dechamps (2018) go further and suggest that micropsychokinetic effects might have to decrease in a systematic way due to an interplay between micro-PK effects and entropy in order to avoid the violation of the law of conservation of energy. This would mean that mentally induced deviation from quantum randomness causes entropy to counteract this violation. "The weaker the quantum effect becomes by this intervention, the quicker the entropic counter-process decreases. This would allow the deviation effect to re-establish itself although with a lowered effect size than initially shown" (Maier et al., 2018, p. 7). The interplay between effect and entropy therefore leads to a systematic decrease in the effect over time and is similar to a damped harmonic oscillation (Maier & Dechamps, 2018; Maier et al., 2018). This interaction persists until the quantum effect disappears. The formula of the damped harmonic oscillation is as follows:

$$y(t) = a e^{-\beta t} \cos(\omega t + \varphi) + mt + h \tag{3}$$

The meaning of the individual parameters is described in Table 2.

Table 2

Parameter description of the damped harmonic oscillation

Parameters	Meaning
a	Amplitude
β	Damping coefficient
ω	Circular frequency
φ	Phase shift
m	Slope of the linear component
h	Displacement along the y-axis

Both Maier et al. (2018) and Maier and Dechamps (2018) applied this formula to their data set by estimating the parameters of the mathematical formula using regression analysis. A graphical representation of the obtained mathematical oscillation function over time together with the cumulative Z-values can be seen in Figure 3. An explanation of the calculation of the cumulative *Z-values* can be found in Appendix B.

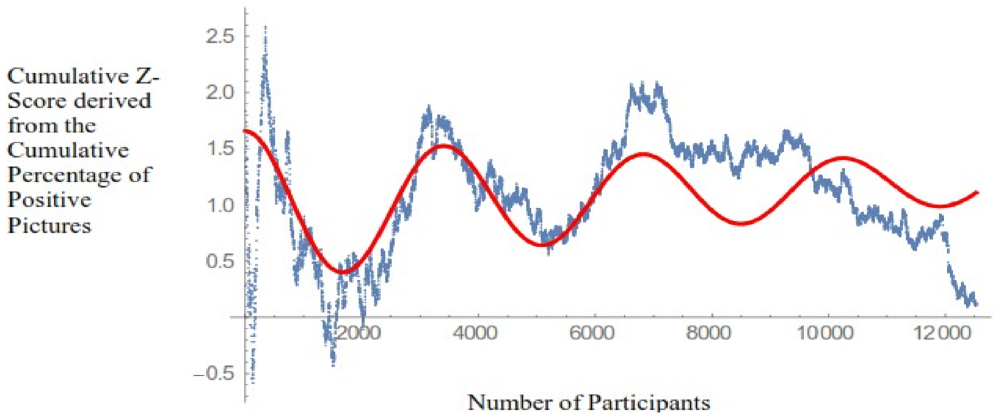

Figure 3: Damped harmonic oscillation function (Maier et al., 2018, p. 8)

However, the assumption that the micro-psychokinetic effect decreases systematically poses a major theoretical problem. According to this theory, how can a true null effect be distinguished from decline effects? Maier and Dechamps conclude: "The consequence is that with the standard scientific replication approach micro-psychokinesis effects cannot be scientifically studied" (2018, p. 32). To solve this problem, Maier et al. (2018) compared the results of the parameter estimation based on the described human data set with the results of the parameter estimation of a simulated data set containing data from 12,571 simulated subjects. To generate this dataset, a program loop was created that replicated the experimental program with the same experimental design, course and material, etc.

automatically started 12,571 times without human observation and stored the number of positive stimuli shown. The strength of the effect in the simulated data also behaves like a damped harmonic oscillation, as random effects asymptotically approach zero with increasing data accumulation. When comparing the effect over time of the data collection of the human data set with that of the simulated data set, the oscillation frequencies in particular should differ, provided that the assumption that the micropsychokinetic effect resembles a systematic appearance-disappearance pattern is correct (Maier et al., 2018). Real effects should cause higher frequency oscillations than those seen in artificial data (Maier et al., 2018). In a comparison of the 95 % confidence intervals of both frequencies, Maier et al. (2018) found a deviation: "the amount of oscillations found with human compared to simulated data clearly differed" (Maier et al., 2018, p. 10). This frequency difference can be clearly seen in Figure 4 below.

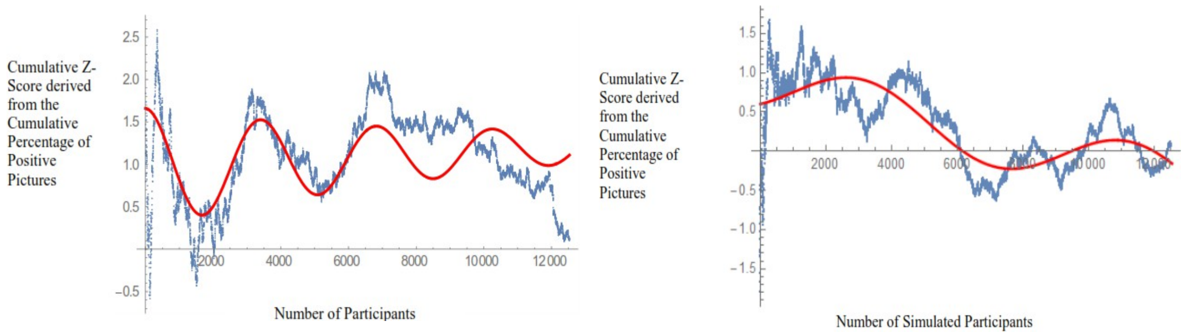

Figure 4: Illustration of the oscillation of the effect in human data (left) and simulated data (right) (Maier et al., 2018, p. 8)

If this assumption proves to be correct, Maier et al. (2018) suggest that future micro-PK research should focus on systematic decline studies to verify the evidence.

effects. The data should be examined specifically for oscillatory patterns of the effect over time and the results compared with patterns in simulated data. The frequency of the oscillation seems to be a good indicator for micro-PK research or psi research in general. However, frequency comparison could also replace significance tests in other psychological experiments involving unconscious processes. Since "from a physical point of view effects are produced automatically and should therefore also violate the laws of energy conservation and entropy" (Maier et al., 2018, p. 10), there should also be a decrease in the effect during replication experiments in these studies and an oscillating pattern of the effect should be observed over time.

Micro-psychokinesis

Micro-psychokinesis (micro-PK) research investigates mentally induced statistical variations in probabilistic systems such as coin tosses, dice rolls or random number generators (Varvoglis & Bancel, 2015). There is a long tradition of research and the first experiments date back to the late 19th and early 20th century (Crookes, Hursley, Bull & Myers, 1885, cited in Maier & Dechamps, 2018). The object of investigation in the first experiments on psychokinesis was initially the mental influence on the movement of objects (Varvoglis & Bancel, 2015), whereupon Rhine (1944) somewhat later conducted experiments on the mental influence on a probabilistic system such as dice rolling. From the 1960s onwards, quantum states were finally used in experiments to generate true randomness (Beloff & Evans, 1961, cited in Maier & Dechamps, 2018). The so-called tRNG's have since become a standard tool in micro-PK research (Jahn, Dunne & Nelson, 1987) and there have since been numerous studies that intended observer effects on random quantum generators (for an overview see Varvoglis & Bancel, 2015).

Evidence for micro-psychokinetic effects was shown in meta-analyses by Radin and Nelson (1989, 2003), whereby studies with random number generators based on algorithms (pseudoRNG) were included in the meta-analysis alongside studies with tRNG. A more recent meta-analysis only considered studies that used a tRNG (Bösch, Steinkamp & Boller, 2006). The analysis of 380 experimental studies from 1961 to 2004 revealed a significant, but very small and heterogeneous effect showing a significant random deviation. Due to a correlation between sample size and effect size as well as the heterogeneity and the merely small effect, the authors concluded that publication bias could have falsified the effect. This problem does not only apply to meta-analyses in micro-PK research, but meta-analyses across the entire spectrum of psychological research are criticized for the same reason (Ioannidis, 2016).

Large-scale replication studies have also been conducted (Jahn et al., 2000; Maier & Dechamps, 2018). Research groups from the PEARlab at Princeton University, the Grenzgebiete der Psychologie und Psychohygiene in Freiburg and the Institute of Behavioral Medicine at Justus Liebig University in Giessen have joined forces with the aim of replicating the study by Jahn et al. (1987). The replication study with 227 subjects and over two million test runs was unable to confirm the results (Jahn et al., 2000). In another replication attempt, two exactly identical micro-PK studies were conducted (Maier & Dechamps, 2018). In the first study, the bayesian analysis revealed a strong

Evidence for micro-PK (BF_{10} = 66.7), whereas in the second preregistered replication study strong evidence for the null hypothesis, i.e. no micro-psychokinetic effect, was found (BF_{01} = 11.07). The flawed meta-analyses and the failed replication attempts currently indicate that there is no evidence for micro-PK.

Parallel to the empirical studies, quantum theoretical explanations have emerged that attempt to describe the micro-psychokinetic effects (Atmanspacher, Römer & Walach, 2002; von Lucadou, 2006, 2015; Maier & Dechamps, 2018; Penrose & Hameroff, 2011).

Quantum physics explanatory models. Quantum theory was born when Max Planck discovered in 1900 that energy exists in the form of quanta. Since then, physicists such as Bohm, Bohr, Born, de Broglie, Dirac, Einstein, Feynman, Heisenberg, Pauli, Schrödinger, von Neumann, Wheeler and Wigner have produced groundbreaking findings that underpin the theory very well mathematically and explain many phenomena of the microworld (Byrne, 2010; Greenstein & Zajonc, 2006). Quantum physics findings have enabled major advances to be made in technological development. Digital electronics, lasers and medical analysis procedures such as magnetic resonance imaging are quantum mechanical and would not be possible without the findings of quantum physics. Nevertheless, the findings of quantum physics are difficult to understand as they cannot be reconciled with parts of classical physics.

A basic principle of quantum mechanics is the probabilistic behavior of quantum systems during a measurement. "The act of a measurement turns a deterministically evolving quantum state into a probabilistically transformed existence within the macro-world" (Maier & Dechamps, 2018, p. 262). For example, since an electron is described as a superposition of several simultaneously existing locations before the measurement, the results of a quantum measurement can only ever be predicted with probabilities. This phenomenon is explained by the mathematical concept of the *wave function* (Schrödinger, 1935). During the measurement, the electron is only found at a certain position with a certain probability, which corresponds exactly to the square of the amplitude of the wave function (Born, 1926, cited in Maier et al., 2018). Superposition is not observable to humans due to decoherence, as it instantly causes a classical state (Müller, n.d.). According to the orthodox standard interpretation of quantum mechanics, no measurement or observation can influence probability. But Albert Einstein was already skeptical about this and was of the opinion that "God does not play dice" and that there must possibly be hidden variables that influence this random behavior. More recent quantum physics explanatory models state that mental processes influence the probability of a quantum result during observation and refer to the findings of quantum physics (e.g. Schrödinger, 1935).

The so-called *Generalized Quantum Theory* (GQT, Atmanspacher et al., 2002) describes a measurement in a quantum experiment as an *epistemic split*, an observation in which knowledge transfer takes place. "This epistemic split occurs when unknown potential quantum alternatives are transferred into conscious knowledge about one of them" (Maier et al., 2018, p. 2). According to this theory, the mind of the observer can influence the transfer of knowledge, for example through intentions. According to von Lucadou & Römer (2007), observer effects are described as entanglement between intended observers and the observed system. This enables non-random deviations from quantum probabilities. However, the random deviations would have to decrease again shortly after the discovery, as they represent a serious violation of the no-signal theorem in quantum mechanics. According to von Lucadou (2006, 2015), this could be the reason for the disappearance of micropsychokinetic effects in replication experiments, as this ensures the no-signal theorem at the macroscopic level.

Maier and Dechamps (2018) extend this approach to include the principle of entropy, according to which micropsychokinetic effects should change over time. "A violation of the no-signal theorem in quantum physics constitutes a severe violation of the Second Law of Thermodynamics that states that entropy needs to increase over time" (Maier & Dechamps, 2018, p. 287). Mentally induced quantum random deviation therefore leads to entropy setting in to counteract this trend. Once the micropsychokinetic effect has subsided, entropy decreases so that the effect can reappear, but with a weaker effect size. "This interplay between effect and entropy should lead to a temporal change in effect comparable to a dampened harmonic oscillation" (Maier & Dechamps, 2018, p. 287).

Another model to explain micro-psychokinetic effects is proposed by Penrose and Hameroff (2011). The so-called *OrchOR theory* also sees the measurement as a transition from unconscious "knowledge" about the nature of a quantum state to a conscious experience. According to this model, the transition is made possible by quantum gravity and is described mathematically as small curvatures between space-time geometry that represent the potential quantum states. Through specific information in the space-time geometry, for example

The transition can be influenced by mental concepts (Hameroff & Chopra, 2012). In this way, intended observers could have a non-random influence on the transition from potential quantum states to a specific classical state. Further quantum physical explanatory models are proposed by Stapp (2011) and Mensky (2011, 2013).

The theories derived from experimentally well-confirmed quantum mechanics all postulate a mental, intentional influence of the human mind on the outcome of a quantum experiment. They almost all describe that the mental influence on quantum randomness takes place before the transition from the unconscious quantum state to a conscious classical state. According to the theories, micro-psychokinetic effects should therefore be influenced primarily by the observer's unconscious mental processes: "the true causality takes place in the realm of the unconsciousness" (Maier & Dechamps, 2018, p. 267).

Pornography addiction. According to Freud, sex is the primary motive of human beings and in Maslow's hierarchical pyramid of needs, sex is assigned to the first, most basic level (Maslow, 1970). Sex can therefore be described as an unconsciously driven state of intention. Pornography addiction represents an extreme of this need. The consumption of Internet pornography has increased enormously in Western cultures in recent years (Carroll et al., 2008; Döring, 2009; Griffiths, 2012). An estimated 42.7 % of internet users watch pornographic films and approximately 25 % of daily searches are for explicit erotic material (Young, 2008). It has never been easier to access pornographic material than it is today. Permanent internet access and the lack of barriers to entry make it easy to access pornographic sites and free amateur videos in particular for a growing supply (Döring, 2011). Parallel to the growth of pornographic material on the Internet, there has been a dramatic increase in problematic pornography consumption on the Internet (Carroll et al., 2008). One of the first models to explain online pornography consumption is the *triple-A engine* (anonymity, affordability, accessibility; Cooper, 1998), whose three characteristics favor consumption. Online pornography consumption has the greatest addictive potential of all Internet-related behaviors (Griffiths, 2012) and is considered a behavioral addiction when used dysfunctionally, similar to pathological gambling, for example. However, pornography addiction is not yet included in the formal clinical classification, as there is little scientific literature in this area (Ley, Prause & Finn, 2014) and pornography addiction has so far been classified under other sexual disorders, such as hypersexual disorder (Kraus, Voon & Potenza, 2016). One consequence of the lack of recognized classification criteria is the lack of valid prevalence figures (Griffiths, 2012).

Behavior can trigger similar neurobiological mechanisms and motivational processes as substance addiction and result in similar negative consequences (Snagowski, Wegmann, Pekal, Laier & Brand, 2015; Sniewski, Farvid & Carter, 2018). Furthermore, research shows that the problematic use of pornography is characterized by a predominant urge to take behavioral action, known as *craving* (Allen, Kannis-Dymand & Katsikitis, 2017). Craving is in turn influenced by *desire thinking* (Caselli & Spada, 2011), which refers to imaginal and verbal cognitions that focus on a desired behavior (Caselli & Spada, 2011). Imaginal prefiguration is characterized by the allocation of attentional resources to behavioral information, followed by mental image processing (Allen et al., 2017). Pornography addicts therefore have an increased mental representation of pornographic content.

Emotion transgression model. According to the emotion transgression model by Maier and Dechamps (2018), unconscious needs or mental representations are reflected on the physical level. According to this model, the tRNG in pornography addicts should generate significantly fewer erotic images during observation than the random level, as a lack of erotic images is perceived on an unconscious level and the conviction of not "having enough" prevails. This "unconscious fear of not 'having enough' translates into a self-fulfilling prophecy of never getting enough" (Maier & Dechamps, 2018). The erotic images displayed less than by chance would reflect the inner state of deficiency on a physical level. In contrast, people with a positive attitude towards pornography and no existing addictive behavior with an inner state of deprivation, for example, would not experience a physical state of deprivation. Instead, it would lead to an increased presentation of erotic images, provided that erotic content is very present on an unconscious level. The results of a study with cigarette images provided an indication of the validity of the emotion transgression model (Maier & Dechamps, 2018).

Research hypotheses

In summary, the present study aims to test the validity of an alternative review of the evidence for micro-PK. According to Maier et al. (2018) and Maier and Dechamps (2018), a micropsychokinetic effect could possibly be proven if, after the discovery of a strong micropsychokinetic effect, decline effects occur in the course of the data and the further course of the effect strength can be mapped with a damped harmonic oscillation function. In addition, the frequency of the oscillation of the micropsychokinetic effect should be significantly higher than the frequency of the oscillation in simulated data if a true micropsychokinetic effect is present. This leads to the following research hypotheses:

Hypothesis 1: The micro-psychokinetic effect decreases over the course of data collection.

Whether the strength of the micro-psychokinetic effect in the course of data collection resembles a damped harmonic oscillation can only be seen with a very large sample size of at least 1000 test subjects (Maier et al., 2018), which is hardly feasible in the context of a master's thesis. Nevertheless, an analysis should be carried out. In order to be able to predict a trend, the following hypothesis needs to be tested:

Hypothesis 2: The micro-psychokinetic effect follows a systematic pattern comparable to a damped harmonic oscillation.

If a damped harmonic oscillation is present in the data set, the oscillation frequency of the increase and decrease of the micro-psychokinetic effect is compared with the evaluation of a simulation that is carried out with the same experimental design, course, etc. The result is a hypothesis. This results in the following hypothesis:

Hypothesis 3: If there is a micro-PK effect, the frequency of the increase and decrease of the effect in the sequential analysis of the data is greater than in the analysis of a simulated data set.

In order to be able to test the data-analytical hypotheses, a study on micro-PK will be conducted. The aim of the experiment is to investigate the influence of micro-psychokinetic effects, which are triggered by the unconscious needs of a person addicted to pornography when observing erotic image material, on quantum-based results. Pornography addiction because Bem (2011) obtained the strongest effects in his study on erotic stimuli.

The primarily unconscious urge for explicitly erotic material in addicts represents the independent variable in the present study and it is assumed that the unconscious need of pornography addicts for explicitly erotic material influences the results of the tRNG. It is assumed that the two image types (erotic and neutral) existing in a superposition before the observation are unconsciously selected by the viewer during the measurement process. There is a slightly higher probability that the state of the two that best matches the observer's unconscious needs will be selected (Maier & Dechamps, 2018). According to the emotion transgression model (Maier & Dechamps, 2018), significantly fewer erotic images are generated by the tRNG in pornography addicts. This results in the following hypothesis, which is a prerequisite for the application of research hypotheses 1-3:

Hypothesis 4: When observed by a subject addicted to pornography, the number of erotic images shown is statistically significantly below the random level.

Methods

To test the hypotheses, an online study was conducted, which consisted of an experimental part and a questionnaire. The study design was a quasi-experimental design in which the subjects were assigned to the experimental and control groups based on certain characteristics. In this study, the experimental group consisted of pornography addicts and non-addicted subjects were assigned to the control group. The assignment was based on the individual scores of the *Cyber-Pornography Use Inventory* (CPUI; Grubbs, Sessoms, Wheeler & Volk, 2010).

Subject recruitment and participation requirements

The test subjects were mainly recruited via social media sites. These included various student forums (e.g. Studis Online), university forums (e.g. Mechanical Engineering TU Braunschweig, Stud.IP Bremen) and various Facebook groups (e.g. Psychology, LMU Psychological Studies, Bachelor's and Master's degree program groups at the University of Bremen). Furthermore, the mailing list of psychology students and those interested in psychology at the University of Bremen *Fischbecken* was used to recruit test subjects. The survey period ran from December 2017 to March 2018.

Psychology undergraduate students at both the University of Bremen and the Ludwig-Maximilians-Universität in Munich received a test subject hour upon completion of their participation in the study.

The requirements for participation in the study were a minimum age of 18 years and consent to take part in the study. It was pointed out in advance that explicit erotic and pornographic images could be seen in the study.

and questions about their sex life. Participants were informed that participation in the study was voluntary and anonymous and that they could withdraw from the study.

Sample

A total of 611 test subjects (219 women (35.8 %), 386 men (63.2 %), 6 other gender (1 %), M_{Alter} : 26 years, SD_{Alter} : 5.77 years, age range: 18-62 years) participated fully in the study. With regard to marital status, 92.5 % of the sample were single, 7 % married, 0.5 % divorced and 0 % widowed. A total of 57.8 % of the sample are in a committed relationship, 42.2 % of the respondents are single. With regard to the highest level of education, 50.4 % stated a (technical) university degree most frequently, followed by 40.4 % with a (technical) high school diploma, 4.4 % with completed vocational training and 3.4 % with a special qualification. 0.5 % of participants had no qualification and 0.8 % stated *other*. 91.3 % of the sample named Germany as their home country, 1.1 % came from Switzerland and the remaining participants occasionally named other countries as their home country. With regard to religious affiliation, 70.4 % stated that they were non-believers and 29.6 % belonged to a religion.

Of a total of 1404 subjects, 793 subjects had to be excluded from the analysis in advance. The majority of this exclusion is due to the lack of participation in the experimental part, as 726 subjects dropped out before the experimental part. A possible explanation can be found in the discussion (see p. 73). Furthermore, subjects were excluded from the data analysis if they stated that they had either answered the questionnaire dishonestly or not very honestly (7 subjects) or admitted that they had not seen the pictures shown in the experimental part at all.

to have looked attentively or not very attentively (37 test subjects). Furthermore, 21 test subjects did not complete the last page of the questionnaire, which asked about honesty and attentiveness, among other things, and were therefore not included in the data analysis. Two further test subjects were removed due to incorrect age information of over 100 years.

The sample size did not have to be determined a priori, as an accumulative data collection and data analysis using the Bayesian method was chosen for testing the hypotheses (Wagenmakers et al., 2011). The approach allows data to be collected until a BF is reached that clearly favors the alternative or null hypothesis (see Jeffreys, 1961, cited in Wetzels & Wagenmakers, 2012). Additional subjects can therefore be tested and their results included in the analysis.

Test procedure

The participants received a link that initially directed them to the homepage of Ludwig-Maximilians-Universität. After brief information about the content and requirements of the online study and a note that the study is optimized for Google Chrome and Firefox and does not work on smartphones or tablets, the participants were directed via another link to *SoSci Survey* (Leiner, 2014), where the online questionnaire was created. The participants were welcomed and further information about the length and functioning of the study, voluntariness and anonymity followed. Before the study began, participants had to confirm that they were over 18 years old and had read and understood the consent form. They were only allowed to take part in the study if they confirmed this. The first part of the questionnaire was structured as follows:

(1) socio-demographic data; (2) relationship status; (3) self-efficacy;
(4) attitudes towards pornography consumption; (5) consumption, duration, frequency, type of pornography; (6) CPUI.

After answering the questions, the participants chose the type of pornographic images they wanted to see next based on their sexual orientation. Participants were then redirected to another homepage where they could start the experiment. Participants had to reconfirm that they were indeed 18 years old and agreed to see explicit erotic and pornographic images. The experiment then began, which was controlled by an experimental program. The participants watched a total of 50 randomly generated stimuli that were either erotic or neutral.

After completing the experimental part, participants were directed back to SoSci Survey and asked to answer a few more questions. The second part of the questionnaire contained questions on the following topics: (1) Self-efficacy;
(2) picture evaluation; (3) honesty; (4) attention to picture presentation; (4) own ideas about what the subject of the study could be. On the last page there was contact information for the test subjects and a link to the image sources (http129.187.238.41isst-quellen.html).

Survey instruments

The survey instruments used are described below. Other survey instruments were also used (e.g. SWE; Schwarzer & Jerusalem, 1999). However, as the additional variables recorded with these instruments are not relevant to the research question of this study, they are not described here. A description of these can be found in Appendix D.

Socio-demographic data. Socio-demographic data was collected at the beginning of the questionnaire. This included gender, age, country of origin, highest level of education, religious affiliation, marital status, relationship status and sexual orientation.

Internet pornography addiction. Addiction to Internet pornography was assessed using the Addictive Patterns Scale from the *Cyber-Pornography Use Inventory* (CPUI; Grubbs et al., 2010). The scale consists of a total of 18 items, which focus on the sub-constructs *perceived compulsivity* (8 items, e.g. "Even if I don't want to look at Internet pornography, I feel strongly attracted to it"), *isolation* (4 items, e.g. "I try to hide the content of my computer or screen from others"), *access effort* (4 items, e.g. "I tell friends off or hide the content of my computer or screen from others"), *access effort* (4 items, e.g. e.g. "I cancel friends or do not participate in social activities to watch pornography instead") and *guilt* (2 items, e.g. "I am afraid someone might discover my secret pornography use one day"). The items were rated on a seven-point Likert scale (0 = *strongly disagree* to 6 = *strongly agree*). A high CPUI score indicates the presence of addictive behavior. To determine the internal consistency, Cronbach's alpha was calculated for each of the subscales. The internal consistency of the respective subscales of the Addictive Patterns Scale in the present study was .74,

.69, .68, .51 for perceived compulsiveness, feelings of guilt, access effort and isolation. The reliability of the subscales in this study ranged from questionable to acceptable values (Blanz, 2015). On the other hand, good internal consistency for the entire

Addictive Patterns Scale given (α = .83).

Attitudes towards pornography. Nine items were used to measure attitudes towards pornography (Svedin, Åkerman & Priebe, 2011) and were based on a five-point scale.

Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). An example item is: "I think pornography should be easily available". The scale has a

acceptable internal consistency (α = .77).

Internet pornography usage behavior. A further scale on Internet pornography usage behavior was implemented in the questionnaire. The scale contains questions on consumption (1 = *yes*, 2 = *no*), frequency (1 = *several times a day*; 2 = *daily*; 3 = *several times a week*, 4 = *once a week*, 5 = *several times a month*, 6 = *about once a month*, 7 = *less often*), duration (1 = *several hours* to 5 = *a few minutes*) and type of pornography (1 = *heterosexual pornography*, 2 = *gay pornography*, 3 = *lesbian pornography*).

Control variables. In addition, control variables were collected in the questionnaire. The *honesty* item "How honestly did you answer this questionnaire?" was rated on a four-point Likert scale (1 = *dishonest* to 4 = *honest*). A four-point Likert scale also forms the response format for the *attention* item "How attentively did you look at the pictures?" (1 = *not attentive at all* to 4 = *very attentive*). Furthermore, the test subjects rated how erotic they found the images shown on a three-point Likert scale (1 = *not erotic*, 2 = *somewhat erotic,* 3 = *very erotic*).

Observation of randomly generated erotic and neutral images

In the present study, an experimental paradigm was used in which observers were presented with a series of erotic and neutral images randomly generated by a quantum generator. The subjects' task was to follow the image presentation attentively. The subjects were given the following instruction:

> You will now be shown different images on the computer screen. Please keep your full attention on the screen for the entire duration of the experiment. Attentive viewing of the images is absolutely essential for the experiment! To do this, focus your gaze on the + in the middle of the screen. You can of course stop the experiment at any time if you feel uncomfortable. To do so, please close the window. This part is finished after about two minutes.

The experiment was run in full-screen mode in the computer's browser and the 50 stimuli were presented on a black background measuring 500 x 400 pixels. An overview of the test run can be found in Figure 5.

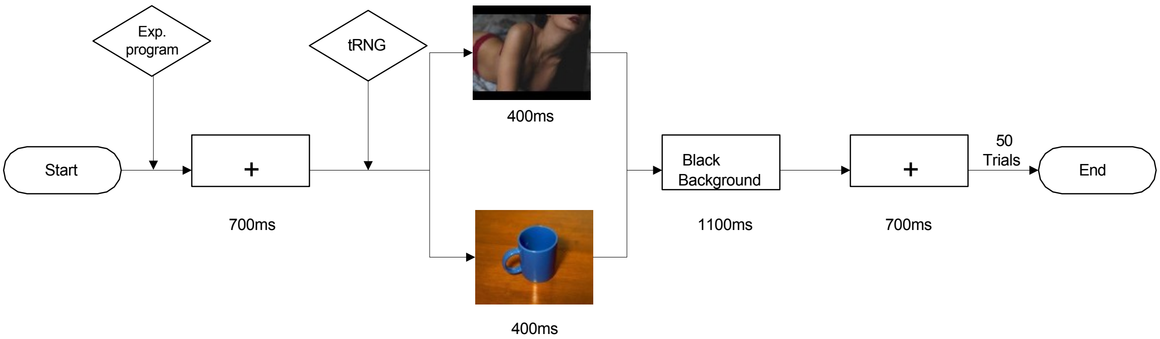

Figure 5: Selection of the stimulus and presentation times during a test run (based on Maier et al., 2018, p. 5)

After starting the program, the experimental program first generated a random number between "1" and "30" for each test run, which was used to select the stimulus from the respective image file of 30 images. In order to determine whether an erotic or a neutral image was subsequently displayed, the tRNG then randomly issued a number between "0" and "1". Meanwhile, the test subjects looked at a fixation cross (700ms). The stimulus (either neutral or erotic image) was presented to the subjects for 400ms, followed by a black background (1100ms). This test run was repeated 50 times, with the same probability for all images in each run, as a draw with a backward placement was selected. The number of trials is based on a recommendation by Varvoglis and Bancel (2015), who suggest a short test period to avoid boredom and fatigue and to maintain attention and motivation.

Experimental program. A created experimental program controlled the experimental run. The experimental program was executed with jsPsych (de Leeuw, 2015), a Javascript library for creating and executing behavioral experiments in a web browser. The program ran on a dedicated web server in the computer center of the Ludwig-Maximilians-Universität in Munich. The quantum generator, which was responsible for the random stimulus selection, was connected via USB to the server on which the experimental program was running.

The number of erotic images shown in a test run represents the dependent variable. The dependent variable was measured by means of the experimental program created, in which the number of erotic images shown in each test run was recorded.

Stimuli. The neutral pictures come from the *International Affective Picture System* (IAPS; Lang, Bradley & Cuthbert, 2008), which provides an experimental set of 1169 digital pictures. The pictures were rated according to degree of arousal and valence on a nine-point Likert scale and are used in studies on emotions as well as in psi research (Bem, 2011). For the present study, 30 images of everyday objects that are neutral were selected from the IAPS

(*M* $_{valence}$ = 4.84, *SD* = 1.11) and have the lowest possible arousal (*M* $_{arousal}$ = 2.59, *SD* = 1.85). The erotic images were taken from the IAPS (Lang et al., 2008; *M* $_{valence}$ = 6.11, *SD* = 0.32; *M* $_{arousal}$ = 6.08, *SD* = 0.34) as well as from the *Open Affective Standardized Image Set* (OASIS; Kurdi, Lozano & Banaji, 2017; *M* $_{valence}$ = 5.09, *SD* = 0.23; *M* $_{arousal}$ = 5.41, *SD* = 0.19), a freely accessible online image index with 900 validated images. Due to a lack of suitable erotic, particularly homosexual, images in IAPS and OASIS, additional images from *pixabay* (https:// pixabay.com/en/) and *wikimedia commons* (https://commons.wikimedia.org/) were used, both of which have a large database of license-free erotic images. The additional images were validated internally by having several psychological experts rate the images according to valence and arousal, using the values from IAPS and OASIS as a guide (*M* $_{valence}$ = 5.73, *SD* = 0.41; *M* $_{arousal}$ = 5.83, *SD* = 0.42). In line with Bem (2011), three different sets of erotic images were provided in order to take into account the respective sexual orientation of the test subjects. The test subjects had the option of choosing between homosexual and heterosexual images. In addition to heterosexual erotic imagery, men could also choose male erotic imagery and women female erotic imagery. There were 30 different erotic images per image set. The sources of the royalty-free images from pixabay and wikimedia commons are available at the following link: http://129.187.238.41/isst-quellen.html

Generation of quantum randomness. A tRNG from the company *ID Quantique* in Geneva was used to generate random numbers (Quantis-v10.10.08). The device is based on Young's famous double-slit experiment in 1801, which is used in quantum physics and was developed for the detection of wave-particle duality. The tRNG generates quantum states using photons that are sent through a semi-transparent mirror. Each photon has a 50 % probability of either being reflected or not reflected, so that it is either deflected in a different direction by the reflection or passes through the semi-transparent mirror and thus does not change direction. Until the photon is measured on the respective path by the detectors, the photon consists of a superposition of the wave and particle states. Depending on which detector then registers the photon, a number "0" or "1" is output. Figure 6 shows this process schematically.

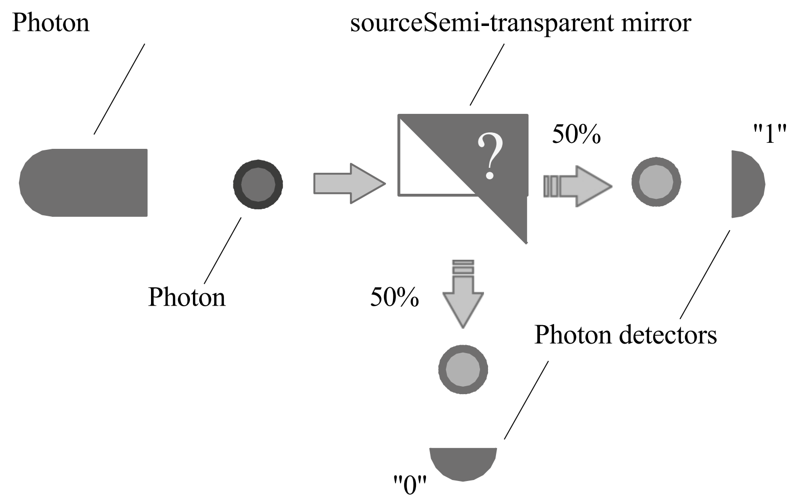

Figure 6: Functionality of the tRNG (Quantis-v10.10.08) for generating random numbers (based on ID Quantique, 2017)

This tRNG has passed serious validation tests of randomness, such as the NIST test (ID Quantique, 2017). Quantis-v10.10.08 is currently the most effective tRNG worldwide (Turiel, 2007).

The tRNG was connected to the server with the experimental program via USB. It was controlled via a wrapper that is compatible with the experimental program. As the experimental program works without a buffer, it was possible to ensure that the image selection was made individually for each test subject. In addition, the random number was generated immediately before each image was displayed.

Statistical evaluation

The statistical analysis of the data was based on the methodological approach of Maier et al. (2018) and Maier and Dechamps (2018). Following the recommendation of Wagenmakers et al. (2011), the statistical analysis procedures were carried out using the Bayesian inference technique. Before conducting the study, it was decided to analyze the data using Bayesian one-sided one-sample *t-tests*. The statistical software JASP (version 0.8.2, Jasp Team, 2017) was used for all Bayesian analyses, and further calculations were performed using *IBM SPSS Statistics 18* software.

For the calculation of the BF, a probability distribution for the effect size was determined a priori using the scale parameter r. This so-called Cauchy

distribution (δ ~ Cauchy (0, r)) is the prior, i.e. the probability that in the

data there is an effect ($p(data|H_1)$). The JASP software developed specifically for bayesian analyses uses an r of .707. Other authors, however, recommend a lower r of .5 (Bem, Utts & Johnson, 2011) or .1 (Maier et al., 2014, 2018) for psi research, as psi effect sizes are generally very small. The choice of prior represents a certain degree of freedom in the Bayesian method. In

of the present data analysis, an r = .1
(δ ~ Cauchy (0, .1)) and is based on Maier et al. (2018).

To check whether the course of the effect is subject to a damped harmonic oscillation, the parameters of the mathematical formula of the damped harmonic oscillation were estimated by means of regression analysis using the *scipy.optimize.curve_fit* function of the Python module SciPy (The SciPy community, 2018). SciPy is a collection of mathematical algorithms and functions based on the *Numpy* extension of the *Python* programming language. The function uses a *Levenberg-Marquardt algorithm* to estimate values for the parameters of the mathematical function according to the principle of the sum of least squares (The SciPy community, 2018).

Results

In order to test the first three research hypotheses, it was first necessary to test the fourth research hypothesis, which assumed a micro-psychokinetic effect in pornography addicts. It was assumed that the number of erotic images shown would be statistically significantly below the random level when observed by a subject addicted to pornography. The verification of this research hypothesis formed the basis for testing the subsequent research hypotheses (1-3) and was defined as a prerequisite for application.

However, the descriptive analysis showed that the sample did not contain enough pornography addicts (*n* = 3) and that it was therefore not appropriate to form two subgroups of addicts and non-addicts. Data from 556 participants could be used to calculate the mean value and form an individual CPUI score. The remaining 55 test subjects stated that they had never viewed pornography on the internet and for this reason no CPUI data was available from them. The mean value of all CPUI scores of the 556 test subjects was *M* = 1.36 (*SD* = 0.82, range = 0-4.22), with a high individual score indicating addictive behavior. The uneven distribution can be seen in Figure 7.

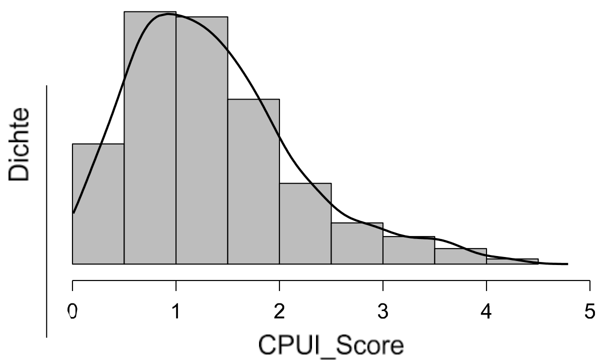

Figure 7: Distribution of the CPUI score of the pornography-consuming test subjects

The division of the sample into two groups based on the CPUI score (group 1 = < 3 and group 2 = > 3) resulted in unequally sized subgroups (group 1 = 527 subjects, group 2 = 29 subjects). However, since it cannot be assumed that a subject with a CPUI score of 3-4.5 is addicted to pornography, this division is not meaningful. A more differentiated division into three groups, with one standard deviation from the mean CPUI score as the cut-off value in each case, made it possible to assess the marginal groups, with the critical upper group containing only 3 test subjects. It was therefore not possible to test the fourth research hypothesis using the data obtained.

However, the exploratory data analysis revealed a difference between the male and female test subjects with regard to the course of the micro-psychokinetic effect in the data collection period in the sequential Bayesian analysis. The difference was already apparent in the descriptive analysis. The statistical parameters of the number of erotic images shown, the attitude towards pornography, the image rating and the CPUI score for the entire sample and for women and men separately are shown in Table 3. A separate presentation of the participants indicating a different, third gender (6 participants) was omitted here.

Table 3

Mean values and standard deviations of the number of erotic images, attitudes towards pornography, image rating and CPUI score for the entire sample and shown separately for women and men

	Total (N = 611)	Female (n = 219)	Male (n = 386)
	M (SD)	*M (SD)*	*M (SD)*
Number of erotic images	25.08 (3.51)	24.90 (3.67)[a]	25.17 (3.43)
Attitudes towards pornography	3.35 (0.66)	3.06 (0.63)	3.51 (0.63)
Image rating	2.48 (0.66)	2.48 (0.69)	2.48 (0.65)
CPUI Score	1.36 (0.82)[a]	0.88 (0.59)[b]	1.58 (0.82)[c]

Notes.[a] refers to an n = 556,[b] to an n = 169 and[c] to an n = 382, as these variables were only collected from participants who had already consumed pornography.
Value range of the variable attitude towards pornography: 1 (*do not agree at all*) to 5 (*fully agree*) Value range of the variable image rating: 1 (*not erotic*) to 4 (*very erotic*)
Value range of the CPUI score variable: 0 (*strongly disagree*) to 6 (*strongly agree*)

In the descriptive analysis, a gender comparison shows a difference in the number of erotic images shown, the attitude towards pornography and the CPUI score. On average, the quantum generator generated more erotic images for men than for women, and men's attitudes towards pornography were on average more positive than those of women. Only the rating of erotic images is the same for both genders.

In one analysis, the group differences in gender were tested for significance. The *t-test* revealed significant gender-specific group differences with regard to the CPUI score ($t(434)$ = -11.27, p = .000, d = -0.70, 95 % CI for d [-0.82, -0.58]) and with regard to attitudes towards pornography ($t(603)$ = -8.39, p = .000, d = -0.45, 95 % CI for *d* [-0.55, -0.34]). The degrees of freedom differ greatly, as only participants who stated that they had ever consumed pornography were included in the calculation of the CPUI score. For this reason, the sample size is different, which explains the difference in the degrees of freedom.

Furthermore, the data showed that the frequency of pornography consumption is significantly higher among men than among women. This is shown graphically in the following figure:

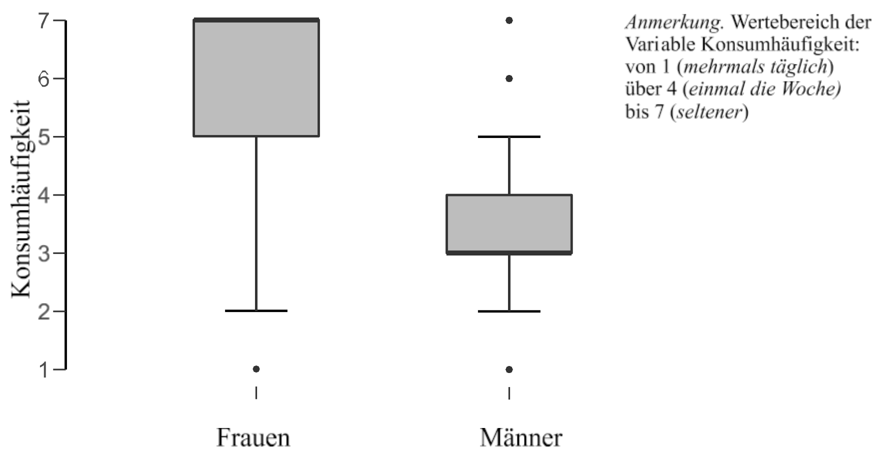

Figure 8: Boxplots for the variable frequency of consumption for women and men

48.7 % of the male test subjects stated that they consume pornography several times a week, followed by 13.9 % who consume it daily. In contrast to this
53.3 % of the female participants stated that they consume pornography less than once a month and 14.8 % would consume it once a month. In addition, 91 % of the participants who stated that they had never consumed pornography were female.

It can be concluded from the analyses that men react more strongly to erotic stimuli than women and t h a t men are therefore more likely to experience a micro-psychokinetic effect in response to erotic stimuli. To answer the first three research questions

For this reason, the data analysis was carried out below using the subgroups of *men* and *women* as examples. In addition to the higher consumption of pornographic material among men and the significant gender differences identified in the analyses carried out, findings from sexual research also support this assumption. For example, a stronger desire for sex was found in men (Baumeister, Catanese & Vohs, 2001). In addition, there are gender differences in reproductive strategies, according to which, from an evolutionary biology perspective, men tend to pay more attention to the external characteristics of women and women, on the other hand, attach importance to the resources of potential partners in order to be able to ensure the supply of offspring (Buss, 1989). Furthermore, the view that the emotional motivational mechanisms that mediate sexual arousal and attraction are sexually dimorphic can be confirmed (Townsend, 1995).

In contrast to pornography addicts, men who watch pornography and do not exhibit addictive behavior are assumed to generate significantly more images than the random level. This assumption is based on the emotion transgression model (Maier & Dechamps, 2018; see p. 34).

This is followed by analyses to test the research hypotheses. First, the Bayesian one-sample *t-tests* are conducted for the female and then for the male sample to test the fourth hypothesis, which assumes that the number of erotic images shown is statistically significantly below the random level when observed by a subject addicted to pornography, and the first hypothesis, which assumes a decrease in the micro-psychokinetic effect over the course of data collection. The parameter estimates for the male sample and the simulated sample are then carried out in order to analyze the second hypothesis, the micro-psychokinetic effect follows a systematic pattern comparable to a damped harmonic oscillation. Finally, the two oscillation frequencies of the course of the effects are compared to test the third hypothesis (if a micro-PK effect is present, the frequency of the increase and decrease of the effect is greater in the sequential analysis of the data than in the examination of a simulated data set).

Bayesian one-sample t-tests

A one-sided Bayesian *t-test* was carried out for each subgroup to test the number of erotic images shown against the random level (50%) in the respective subgroup. The random level is 25, as a total of 50 images were presented.

Female subjects. The bayesian t-test with 219 women resulted in a BF_{01} of 3.03. The mean value of the erotic images is M = 24.90, SD = 3.67. This result indicates moderate evidence for the correctness of the null hypothesis. It is three times more likely that the null hypothesis is true among the data obtained than that the alternative hypothesis is true. It can be deduced from this that women saw an average number of erotic images that did not deviate greatly from the random level. There is therefore no significant random deviation. Figure 9 on the next page shows a sequential analysis of the BF for women.

Male subjects. The same analysis was carried out with the male subjects. The bayesian *t-test* with 386 men resulted in a BF_{01} of 1.30 and the mean value of the erotic images is M = 25.17, SD = 3.43. The null hypothesis therefore predicts the data 1.30 times better. However, the BF of 1.30 is very small and indicates an insufficiently informative data set (Wetzels & Wagenmakers, 2012). Figure 10 shows the sequential analysis of the BF for men.

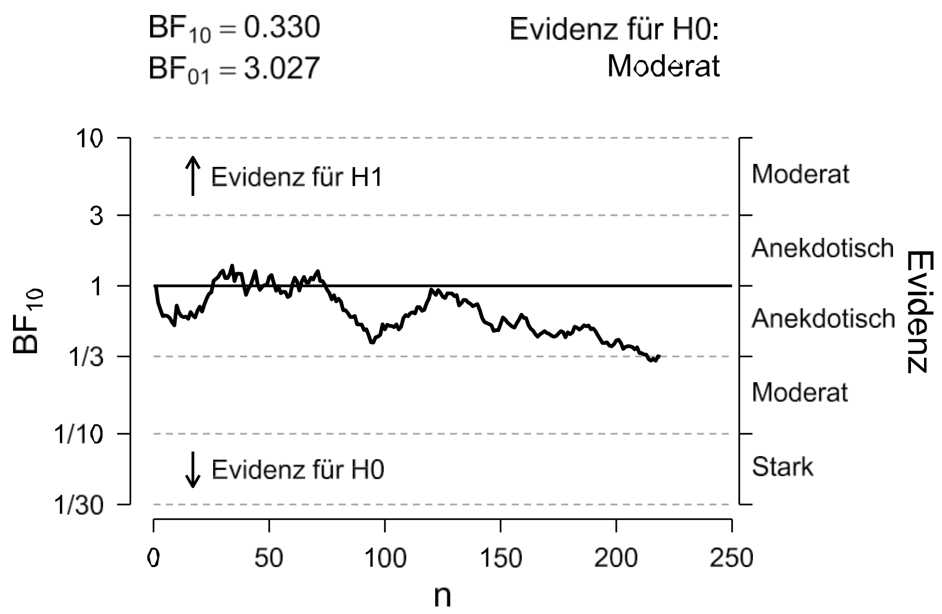

Figure 9: The curve in the diagram shows the change in BF over time with the addition of female study participants

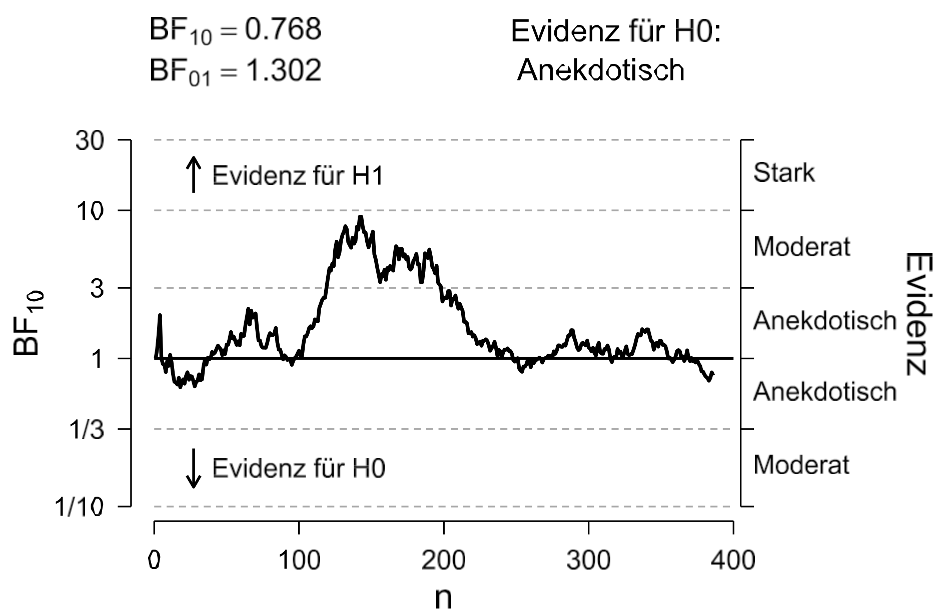

Figure 10: The curve in the diagram shows the change in BF over time with the addition of male study participants

Figure 10 shows that the 142nd participant had a BF_{10} of almost 10. This suggests strong evidence for the alternative hypothesis, which assumes a micro-psychokinetic effect. However, this effect decreases again with further data collection. Based on this observation, the first research hypothesis can be confirmed, as the decline effects are present in the study results.

Parameter estimation for the male sample

The second research hypothesis assumes that the course of the micropsychokinetic effect resembles a damped harmonic oscillation. To test this assumption, the parameters of the mathematical equation of the damped harmonic oscillation were estimated by regression analysis using the function scipy.optimize.curve_fit of the Python module SciPy (The SciPy community, 2018). The function uses a Levenberg-Marquardt algorithm to estimate values for the parameters of the mathematical equation according to the sum of least squares principle. The script created with the commands used and a description can be found in Appendix C.

The equation of the oscillation function given in the script contains the parameter period (*T*) and thus differs from the equation (3) given in the theory section, the damped harmonic oscillation, which directly determines the

contains the angular frequency ω. The output period duration *T* must therefore be the same for the

comparability into the angular frequency ω ($\omega = 2 \cdot \pi \cdot 1/T$) so that the parameters match.

The parameter estimation was carried out for the male sample, as only in this subgroup was there a short-term micropsychokinetic effect with a BF of almost 10, which indicates strong evidence, was observed in the course of data collection (see Figure 10).

The start vector was determined on the basis of the course of the cumulative *Z values* (see Appendix B) and composed in the following form [a, β, T, φ, m, h]. In this case, the start vector is defined as follows: [1.5, -0.01, 200., 3.0, 0.0, 1.5]. The estimated function found for the male sample data is:

$$y = 1.5660e^{-0.0061t} \cos(0.0225345t + 2.60525) - 0.0015t + 1.8307 \tag{4}$$

The error variance obtained is 0.096. Table 4 shows the estimated parameters with their respective confidence intervals.

Table 4

Estimated parameters and their confidence intervals

Parameters	Estimated values	Confidence intervals $[Wert - t \cdot \sigma, Wert + t \cdot \sigma]$
a	1.57	[1.28, 1.85]
β	-0.0061	[-0.0079, -0.0044]
ω	0.023	[0.021, 0.024]
φ	2.61	[2.40, 2.86]
m	-0.0015	[-0.0023, -0.0008]
h	1.83	[1.65, 2.01]

The vibration function together with the empirical effects presented as cumulative *Z-values* can be seen in Figure 11. Appendix A in Figure 14 shows a graphical representation of the estimated vibration function together with its 95 % confidence bands.

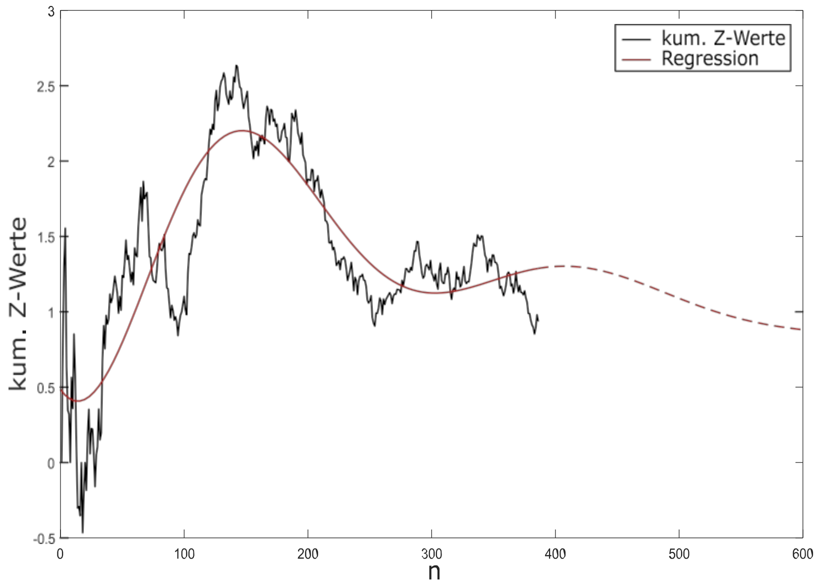

Figure 11: Cumulative Z value for the male subjects with graphical representation of the oscillation function and extrapolation up to *n* = 600 (dashed line)

However, a very large data set of more than 1000 test subjects is required to detect a damped harmonic oscillation (Maier et al., 2018). This sample size is not given here and therefore a trend statement is made. The dashed line in Figure 11 represents a possible further course. A damped harmonic oscillation is clearly recognizable. However, as only a trend can be identified, the second hypothesis cannot be clearly confirmed. Further data collection is required to obtain a larger sample.

Analysis of the simulated data

The third research hypothesis assumes that there is a difference in the oscillation frequencies in the sequential analysis of the data to be examined and the simulated data if a micro-PK effect is present. The oscillations of the increase and decrease of the micro-psychokinetic effect are higher in frequency than those of the effect of the simulated data. For this purpose, a Bayesian

A one-sample *t-test* was calculated with the simulated data in order to be able to estimate the parameters. The oscillation frequencies could then be compared. The simulation contained data from 386 simulated test subjects. To generate the simulated data set, a program loop was created that automatically started the experimental program 386 times with the same experimental design, course and material etc. without human observation and saved the number of erotic stimuli shown.

Bayesian one-sample *t-test*. The one-sample *t-test* for the simulated data was carried out in the same way as the one-sample *t-tests* for the male and female samples. The sample size of the simulated data is the same as that of the male sample (N = 386), as these two groups are to be compared with each other. The reason for this is that the conspicuous pattern and a possible micro-psychokinetic effect are present in the male sample.

The bayesian one-sample t-test for 386 simulated data determined a BF_{01} of 5.52 and the mean value of the number of erotic images shown was M = 24.80, SD = 3.47. There is therefore moderate evidence for the correctness of the null hypothesis,
i.e. no significant random deviation. The sequential analysis can be seen in Figure 12.

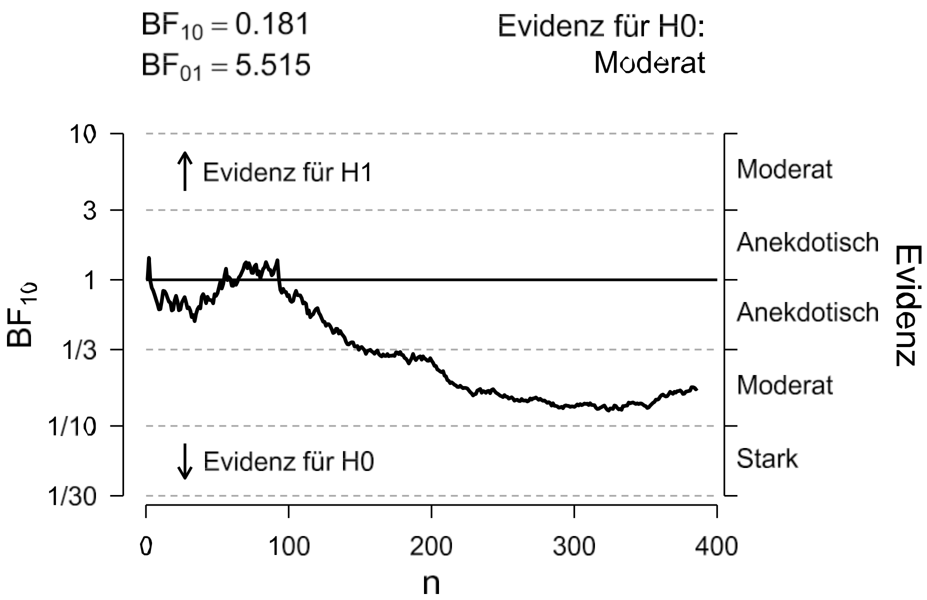

Figure 12: The curve in the diagram shows the change in the BF over time when new simulated data was added

Parameter estimation for simulated data. The parameters of the mathematical equation describing the damped harmonic oscillation for the simulated data were also estimated by means of regression analysis using the scipy.optimize.curve_fit function of the Python module SciPy. The script created, as described above, was also used for this purpose (see Appendix C). The start vector is represented in the following form [a, β, T, φ, m, h] and in this case was as follows [1.5, -0.016, 350.0, -7.0, 0.0, -0.5]. The starting vector was again determined based on the course of the cumulative *Z values*. This increased the probability of reaching the global minimum during optimization.

The estimated function determined for the simulated data is as follows:

$$y = 3.6380e^{-0.0024t} \cos(0.0113t - 0.7906) + 0.0080t - 2.9377 \quad (5)$$

The error variance in this case is 0.084. Table 5 shows the estimated parameters with their respective confidence intervals.

Table 5

Estimated parameters and their confidence intervals

Parameters	Estimated values	Confidence intervals $[Wert - t \cdot \sigma, Wert + t \cdot \sigma]$
a	3.64	[-0.33, 7.61]
β	-0.0024	[-0.0036, -0.0012]
ω	0.011	[0.008, 0.019]
φ	-0.79	[-7.32, 3.99]
m	0.008	[-0.008, 0.024]
h	-2.94	[-7.23, 1.36]

Figure 13 shows a graphical representation of the vibration function together with the cumulative *Z-values*. A graphical representation of the vibration function together with the 95 % confidence bands can be found in Figure 15 in Appendix A.

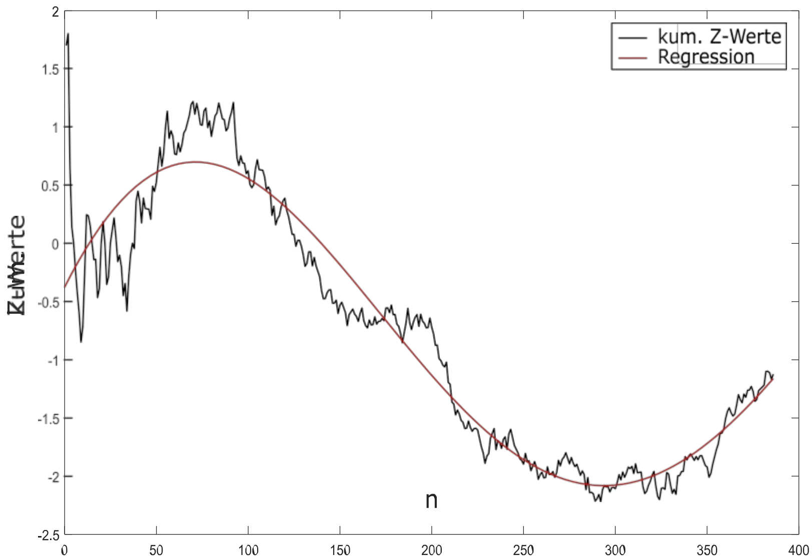

Figure 13: Cumulative Z-values for the simulated data with graphical representation of the vibration function

Figure 13 shows that the simulated data can also be mapped using a damped harmonic oscillation function. The reason for this is that random effects asymptotically approach zero with increasing data accumulation (Maier et al., 2018).

Comparison of the oscillation frequencies

To test the third hypothesis, the parameters of the damped harmonic oscillation function of the male and the simulated sample were compared with each other, as a higher frequency oscillation was assumed in the sequential analysis of the data with a micro-psychokinetic effect. Following the recommendation of Maier et al. (2018), the 95 % confidence intervals for both circular frequencies Omega were compared and found not to overlap. The parameter estimate for the data of the male sample resulted in a circular frequency

of ω = 0.023 with a 95 % confidence interval of [0.021, 0.024], whereas the parameter estimation for the simulated data showed a circular frequency of ω = 0.011 with a 95 % confidence interval of [0.008, 0.019]. As a result, the oscillation of the effect in the course of the data collection in the data of the male sample is clearly more frequent than that in the simulated data.

Discussion

In the present research work, the data were examined using the Bayesian method for a systematic decrease in the micropsychokinetic effect over the course of the data collection. It was assumed that the course of the effect resembles a damped harmonic oscillation. The oscillation frequency should be significantly higher than the frequency of the oscillation of the effect in simulated data. In order to answer the research questions, an experiment on micro-PK was carried out. The research questions are based on an assumption by Maier et al. (2018) and Maier and Dechamps (2018), who discovered this systematic pattern in studies on micro-PK and then derived a possible alternative review of the evidence for micro-PK, among others. They suggest that future psi research should focus on systematic decline effects rather than significant random deviations due to assumptions of quantum mechanics and the law of conservation of energy. The aim of the present study was to test the validity of an alternative data analysis and to conclude whether there might be evidence for micro-PK if the assumptions are confirmed.

The micro-PK experiment in this study investigated micro-psychokinetic effects with erotic imagery, as this is where the strongest effects were obtained (Bem, 2011). It was assumed that pornography addicts have an influence on quantum-based random outcomes and are shown significantly fewer erotic images than chance due to their unconscious needs (Maier & Dechamps, 2018). Testing this hypothesis was considered a prerequisite for the data analytic hypotheses based on it. It

However, the descriptive data analysis revealed a sampling problem. The sample did not contain enough pornography addicts to be able to carry out the planned analyses in a meaningful way. There may be various reasons for this deficiency. Firstly, the sample was homogeneous, as the subjects were recruited via various student forums, particularly in the context of their studies, and the majority of the subjects were academics (50.4 % had a university degree as their highest educational qualification) or were in the process of obtaining an academic degree (40.4 % had a university degree as their highest educational qualification). It turned out to be extremely difficult to recruit pornography addicts to participate in the study, as counseling centers did not agree to forward the study to their clients for understandable ethical reasons. Another reason could be that the topic of pornography is associated with shame (e.g. Chisholm & Gall, 2015). For example, the item "I try to hide the contents of my computer or screen from others" received average agreement and had the highest score compared to other items on the CPUI. It can therefore not be ruled out that the respondents did not answer honestly. The hypothesis that the number of erotic images shown is statistically significantly below the random level when observed by a pornography addict could therefore not be answered due to too few pornography addicts in the sample.

In the exploratory data analysis, however, the sequential Bayesian analysis revealed a striking trend in the data for the male sample, which also differed greatly from the trend in the data for the female sample. The fact that men have an increased desire for sex (Baumeister et al., 2001) could be explain a micro-psychokinetic effect in men in relation to erotic image material. Furthermore, significant gender-specific group differences were found. The data show that the men in this sample consume pornographic material much more frequently and also have a more positive attitude towards pornography. This could also explain a micro-psychokinetic effect of erotic image material. It is assumed that the images existing before the observation in a superposition of both types are unconsciously selected by the viewer during the measurement process. There is a slightly higher probability that the state of the two that best matches the unconscious needs of the observer will be selected. Since, from an evolutionary-biological perspective, men should have an increased mental representation of sex (Baumeister et al., 2001; Buss, 1989), the emotion transgression model (Maier & Dechamps, 2018) would result in an increased erotic image presentation.

To ensure that the data analytical research questions could be verified, the planned analyses were carried out using the female and male samples as examples. This was followed by the analyses to test the assumptions of Maier et al. (2018). When interpreting the findings here, the unsuccessful manipulation of the independent variables and the fact that the further analyses are based on an exploratory data analysis must be taken into account, as they limit the reliability and generalizability of the results.

The bayesian one-sided one-sample *t-test* of the male subgroup yielded a BF_{01} of 1.30. This result shows that the data are not informative enough and that there is no evidence for either the alternative hypothesis or the null hypothesis (see Table 1). Further data collection is required in order to obtain a clear statement regarding the evidence of micro-psychokinetic effects in men in relation to erotic image material, whereby the significant random deviation from the mean value, should the assumptions of Maier et al. (2018) prove to be true, would not be suitable for this purpose at all. The result is therefore not a surprise and rather supports the assumption of Maier et al. (2018). The fourth hypothesis, which is merely a prerequisite for the subsequent analyses, cannot be confirmed.

However, the sequential analysis clearly shows decline effects. Although the first hypothesis cannot be confirmed due to the sampling problem, the assumption is correct with regard to the male participants. The bayesian one-sided one-sample *t-test* of the male subgroup shows a BF_{10} of almost 10 after 142 subjects, i.e. strong evidence for a micro-psychokinetic effect. The effect then decreases, which indicates the expected decline effects (see Figure 10). The difference to the women, whose data course shows no short-term effect and thus no subsequent decrease in the effect, supports the assumption of decline effects in the men. Although the first hypothesis cannot be clearly confirmed due to the sample problem at hand, the alternative assumption regarding the decline effect can be proven. The findings are consistent with the results of other studies (Jahn et al., 2000; Maier & Dechamps, 2018; Maier et al., 2018). Maier et al. (2018) and Maier and Dechamps (2018) justify the decline effects with the model of pragmatic information (von Lucadou, 2006, 2015). According to the model, existing quantum effects in micro-PK violate the no-signal theorem, which results in the disappearance of the micro-psychokinetic effect. The present finding provides a further evidence for the validity of the theoretical explanation, although clear proof of this theory is still required.

The data collection could also have been terminated when a BF of almost 10 was reached after 142 participants, as there was strong evidence for micro-PK at this point. This would have led to the conclusion that there was evidence for micro-PK. With further data collection, however, it becomes clear that after around 250 participants there is no longer any evidence for the alternative hypothesis. This means that different results are obtained depending on when the data collection is stopped.

In the course of the replication crisis, the use of samples that were too small was also criticized, which often led to false conclusions (Button et al., 2013; Vadillo, Konstantinidis & Shanks, 2015). The small sample sizes are also one of the consequences of the misguided scientific culture, as it triggers a high pressure to publish and rewards significant results (Gervais et al., 2015). Especially in studies on micro-PK or other psi phenomena as well as in experiments involving unconscious processes, undetected decline effects could be present, since from a physical point of view the effects would also arise automatically here and thus the law of conservation of energy would also be violated and entropy would set in (Maier et al., 2018). According to Maier et al. (2018), researchers should reanalyze their data and examine it for systematic decline effects. The Bayesian method is very well suited for this, as it shows the progression of the effect during the data collection period and indicates the strength of the evidence. If the data collected is not informative enough, this also becomes apparent with the sequential bayesian analysis (Wagenmakers et al., 2018).

The second hypothesis, which assumes that the course of the micro-psychokinetic effect resembles a damped harmonic oscillation, cannot be clearly substantiated. This is partly because the analysis is based on exploratory data analysis and partly because too few test subjects were available. Nevertheless, the course of the micro-psychokinetic effect can be mapped with an oscillation function and a meaningful course can be seen. The obtained error variance of

0.096 indicates a good regression. A trend prediction is therefore possible. With further data collection, the micro-psychokinetic effect, shown as a dashed line in Figure 11, could move slightly upwards and then downwards again. This is consistent with the findings of Maier et al. (2018) and Maier and Dechamps (2018), whose data show the same pattern. The finding also suggests that the assumption of Maier et al. (2018) and Maier and Dechamps (2018) that micro-psychokinetic effects interact with entropy may prove to be correct.

It was shown that the parameter estimation is very dependent on the respective starting values. In this study, both parameter estimates were carried out with different starting values, as the error variance determined was greater with the same starting values. The smallest possible error variance was achieved with starting values that were based on the respective course of the cumulative Z values. The aim of optimization is to achieve the global minimum of the sum of least squares, i.e. the best possible adaptation of the function to the value pairs.

Most statistical software packages calculate the coefficient of determination R^2 for the non-linear regression in addition to the error variance. A study was able to show that the use of R^2 to evaluate the fit of non-linear models often leads to incorrect conclusions (Spiess & Neumeyer, 2010). The coefficient of determination R^2 tends to be equally high for both very poor and very good models and the adjusted coefficient of determination R^2 only leads to the correct model 28-43 % of the time. In the regression analyses of this study, the coefficient of determination for the male sample is R^2 = 0.730 (73 %) and for the simulated sample R^2 = .927 (93 %), but is not taken into account in the interpretation for the reasons given.

The effects of the simulated data could also be depicted as an oscillation function in the present study, as random effects asymptotically approach zero. Therefore, detecting a difference between random effects and true effects proves to be very difficult. The comparison of frequencies could be a possible solution to this problem (Maier et al., 2018).

The third hypothesis assumes that in the presence of a micro-PK effect, the frequency of the increase and decrease of the effect is greater in the sequential analysis of the data than in the examination of a simulated data set. The results of this study confirm this assumption. The oscillation frequency of the increase and decrease of the effect of the data of the male subjects, with a possible micropsychokinetic effect, is twice as high as the oscillation frequency in the examination of the simulated data. This corresponds to the findings of Maier et al. (2018) and Maier and Dechamps (2018). One possible explanation for the higher-frequency oscillation of the micropsychokinetic effect in the data is the interaction of micropsychokinetic effects and entropy (Maier & Dechamps, 2018). The latter is used to counteract the micropsychokinetic effect. There could therefore be more activity here than in the simulated data, as there is no effect there and

This means that no counter-movement is required to maintain the law of conservation of energy, which could lead to less activity, i.e. a lower-frequency oscillation.

Alternatively, the reciprocal of the oscillation frequency, the period duration *T,* can be *used* to compare the oscillations. In contrast to the

Circular frequency ω does not have the factor 2π. The period duration parameter for the function of the

Data from the male sample has a value of T = 278.82 [261.23, 296.42] and the period duration parameter for simulated data is T = 553.93 [324.52, 783.34]. This means that the oscillation reaches a full cycle after approximately 279 subjects. For the simulated data, almost twice as much data was required for a full cycle.

As the findings of this study are only based on exploratory data analysis, further studies are needed to test the findings more precisely. On the one hand, a study could be conducted that repeats Bayesian one-sample *t-tests* for the male and female sample with new data and then applies the further analyses. For this, however, a sample size of over 1000 subjects is desirable in order to be able to clearly prove the hypothesis of damped harmonic oscillation (Maier et al., 2018). Furthermore, the selection of erotic images should be revised, as they were rated as only moderately erotic by the participants in the present study. Secondly, a study could deepen the alternative manipulations of the independent variables by using a different addiction, as the topic of pornography is associated with shame and subject recruitment in this area proved to be very difficult. An alternative suggestion is smartphone addiction (e.g. Augner & Hacker, 2012; Park & Lee, 2012), which is also a very recent research topic, but the

It is likely to be much easier to recruit test subjects here and there is a high potential for addiction (Griffiths, 2012). In order to check whether systematic decline effects also occur in other studies in which unconscious processes are involved, investigations should also be carried out in future research. One example is priming studies. As Maier et al. (2018) already recommend, researchers from this research area should reanalyze their data and examine for a systematic decline in the effect over the course of data collection. This is particularly important because priming studies have been affected by replication problems in recent years (e.g. Harris, Coburn, Rohrer & Pashler, 2013).

The systematic decrease in the effect due to physical laws that counteract a violation of the law of conservation of energy could explain part of the replication crisis. This applies to micro-PK studies, among others, as quantum effects come into play here, which in turn counteract the restoration of the validity of the law of conservation of energy (von Lucadou, 2006, 2015). However, it cannot be clearly proven that the findings of this study are related to the replication crisis. Nevertheless, there could be an analogy between the decline effects and the replication crisis. The systematic decrease in the micropsychokinetic effect in the form of a dampened harmonic oscillation and the clear difference in frequency compared to the investigations of simulated data were already present in other studies (Maier & Dechamps, 2018; Maier et al, 2018) and could be confirmed in this study. The observation therefore has a systematic character. The replication crisis could therefore be influenced to a certain extent by these mechanisms. It

There are also other reasons for the replication crisis, which were mentioned in the theory section (see p. 14f.). Nevertheless, the mechanisms discovered are of a systematic nature and must not be ignored in future studies. However, further investigations are urgently needed.

Limitations

The hypothesis that there is a micro-psychokinetic effect in pornography addicts could not be answered because the sample did not include enough pornography addicts. The manipulation of the independent variables therefore failed.

Moreover, no BF greater than 10 could be obtained in the results, which would indicate strong evidence for the alternative or null hypothesis (Jeffreys, 1961, cited in Wetzels & Wagenmakers, 2012). Further data collection is required for a clear conclusion. This is not feasible within the scope of a master's thesis.

It should also be noted that this research focused on the unconscious intentional states of the observers and that the participants' goals were manipulated rather indirectly. In contrast, the majority of micro-PK research uses explicitly induced intention states (cf. Varvoglis & Bancel, 2015). A direct comparison of the different manipulations should be investigated in future micro-PK research.

The fact that the experimental program did not work on either the smartphone or the tablet led to a large sample loss (over 700 test subjects). Future research should take this into account and ensure that the experimental program is carried out on the smartphone or tablet.

Furthermore, the selection of license-free erotic images was very limited. Validated images from the OASIS and IAPS image files were not sufficient, so that additional license-free images from the Internet were necessary. These images were only validated by a team of experts. Furthermore, the images were neither described as erotic nor rated as very erotic by the participants in comments (only 2.48 out of 4 in total).

Furthermore, it must be criticized that the results of the present study are only based on an exploratory data analysis. A study that can replicate these study results is necessary to ensure the reliability and generalizability of the results.

Conclusion

There is no clear evidence for micro-PK in erotic image material in the available data. The hypotheses could not be clearly confirmed, as the results are only based on an explorative data analysis. The present research nevertheless provides an indication of the validity of the assumptions that there is a systematic decrease in the micro-psychokinetic effect over the course of data collection. However, further studies with large data sets are required to confirm the findings before the present findings can be transferred into practice.

If the assumption underlying the study proves to be correct, it would make more methodological sense for future psi research working with tRNG not to focus on significant deviations from chance, but rather to compare oscillating patterns of the effect during the data collection period with those of simulated data. "This would be a more fruitful approach than fighting a basic premise in quantum mechanics and it would fit the law of conservation of energy and therefore avoid theoretical paradoxes within science" (Maier et al., 2018, p. 10).

Furthermore, micro-PK could then possibly make an important contribution to solving the replication crisis, at least for studies in which unconscious processes play a role.

The replication crisis shows the need for a rethink in psychological research. As the quote from physicist and Nobel Prize winner Werner Heisenberg at the beginning of this article demands, it is necessary to leave the ground on which science rests in order to open up new territory in a science. Maier et al. (2018) and Maier and Dechamps (2018) have followed this advice and ventured a new approach. This study can support the validity of the assumptions of Maier et al. (2018) and Maier and Dechamps (2018). As already indicated, further research is needed to further investigate this systematic pattern and to consolidate the assumptions.

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Appendix A

Supplementary illustrations

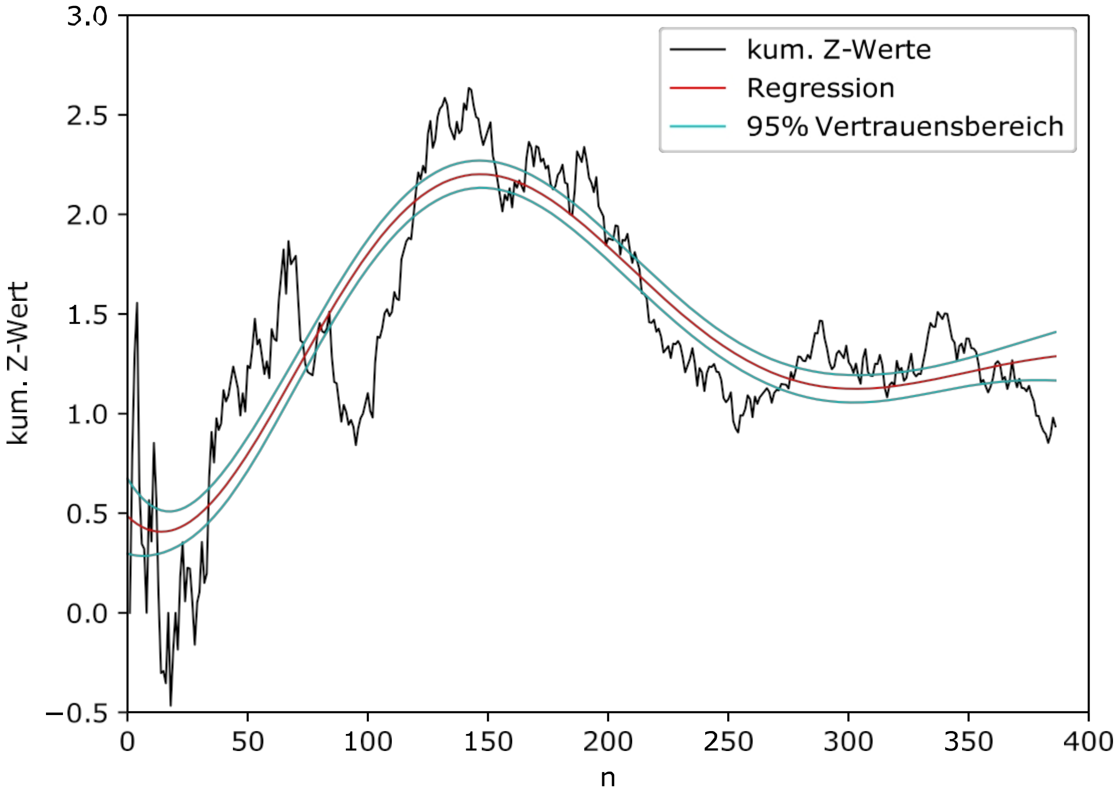

Figure 14: Cumulative Z value for the male subjects with graphical representation of the vibration function (red line) and the 95 % confidence bands (green lines)

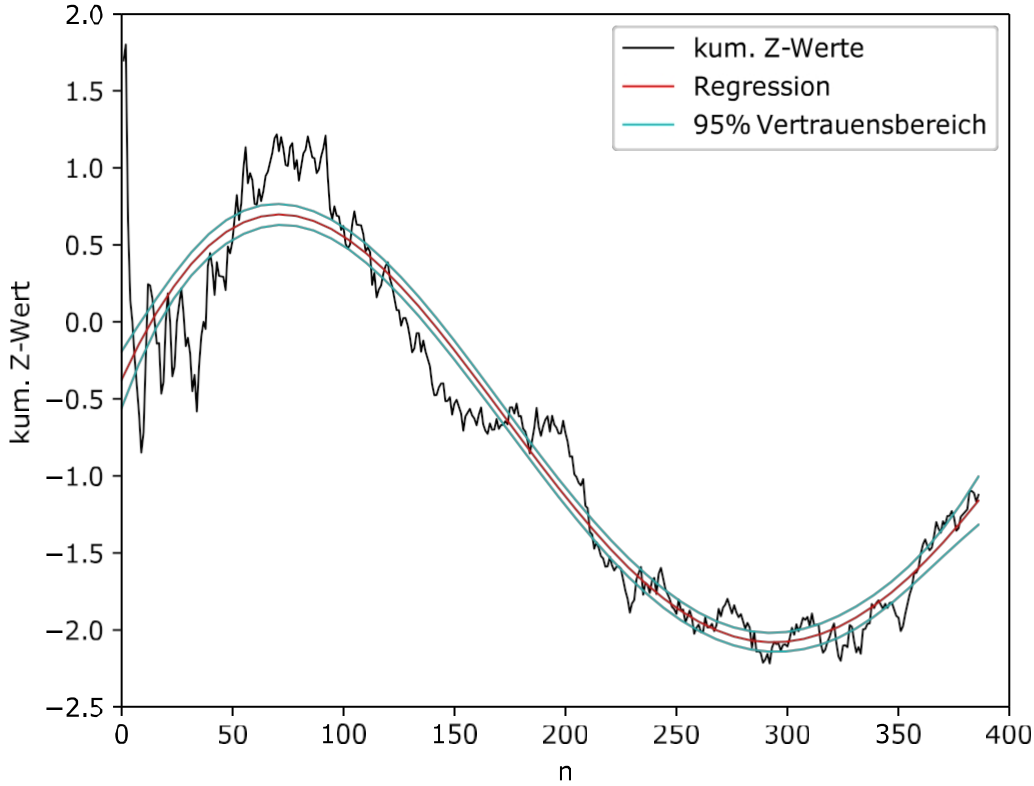

Figure 15: Cumulative Z-value for the simulated data with graphical representation of the vibration function (red line) and the 95 % confidence bands (green lines)

Appendix B

Calculation of the cumulative Z-values

The cumulative *Z value* is derived from the *Z value*. There is a binomial distribution, as the quantum generator generates one of the two states "1" or "0". The probability of both states occurring is the same and the random processes are independent of each other. The variables are defined as follows:

N_T = Number of test runs

p = Probability for erotic Stimuli

q = *1-p*

k = Subscriber number in chronological order Sequence

cum. value = $\sum_{i=1}^{k} sums_i$

$sums_k$ = Number of erotic stimuli of the k-th Participant

Expected value for participant *k*

$\mu_k = N_T \cdot p \cdot k$

Standard deviation for participant *k*

$\sigma_k = \sqrt{N_T \cdot p \cdot q \cdot k}$

Calculation of the cumulative Z-value Z_k for the kth participant:

$$Z_k = \frac{kum.\ Wert - \mu_k}{\sigma_k} \tag{6}$$

$$Z_k = \frac{\sum_{i=1}^{k} sums_i - N_T \cdot p \cdot k}{\sqrt{N_T \cdot p \cdot q \cdot k}} \tag{7}$$

Example for this study for Z_{142} : $N_T = 50$ $p = 0.5$ $q = 0.5$ $k = 142$

$$Z_{142} = \frac{\sum_{i=1}^{142} sums_i - 50 \cdot 0.5 \cdot 142}{\sqrt{50 \cdot 0.25 \cdot 142}} = 2.63$$

Appendix C

Description of the script

The created script first loads all packages that are relevant for a non-linear regression analysis including the calculation of confidence intervals. The data with which a regression analysis is to be carried out is then loaded from a text file. The first column (number of subjects) and the second column (cumulative *Z-value*) are each saved in NumPy arrays. This is followed by the definition of a function with the equation for a damped harmonic oscillation and the definition of the respective start vectors for the regression. The equation of the oscillation function given in the script contains the parameter period duration (T) and thus differs from the equation (3) given in the theory section, the

damped harmonic oscillation that directly contains the angular frequency ω. The

period T must therefore be converted into the angular frequency ω

($\omega = 2 \cdot \pi \cdot 1/T$) so that the parameters match. Furthermore

the probability 1-alpha = 95 % is defined for the confidence intervals. In addition, the error variance and the coefficient of determination of the regression are calculated. In the following steps, the previous calculations are displayed graphically. The next step is to calculate the confidence bands, which are then displayed graphically. The Python code of the script is shown below.

Script

```
# Nonlinear curve fit with parameter confidence intervals
import numpy as np
from scipy.optimize import curve_fit
from scipy.stats.distributions import t
import matplotlib.pyplot as plt
import uncertainties as unc
from uncertainties import unumpy


# ----- DEBUGGING -----
# x = np.array([0.5, 0.387, 0.24, 0.136, 0.04, 0.011]) # values for testing the script
# y = np.array([1.255, 1.25, 1.189, 1.124, 0.783, 0.402]) # values for testing

# function for testing
# def func(x, a, b):
#     'nonlinear function'
      #return a * x / (b + x)

# initial_guess = [1.2, 0.03] # values for testing
# ----- DEBUGGING -----

# import data from textfile
x, y = np.genfromtxt('adjusted.Maenner.cum.zscore.csv', delimiter=";", unpack=True)
# x, y = np.genfromtxt('sim-386 -.csv', delimiter=";", unpack=True)
# print x,y # command to print imported data for crosscheck


# function definition for damped harmonic oscillation
def func(x, b1, b2, b3, b4, b5, b6):
    return b1 * np.exp(b2 * x) * (np.cos(2 * np.pi * x / b3 + 2 * np.pi / b4)) + b5 * x + b6


# initial_guess = [1.5, -0.016, 350.0, -7.0, 0.0, -0.5] # values for simulated data points
initial_guess = [1.5, -0.01, 200., 3.0, 0.0, 1.5] # values for data points from study
pars, pcov = curve_fit(func, x, y, p0=initial_guess)

alpha = 0.05 # 95% confidence interval = 100*(1-alpha)

n = len(y)       # number of data points
p = len(pars) # number of parameters

dof = max(0, n - p) # number of degrees of freedom

# student-t value for the dof and confidence level
tval = t.ppf(1.0-alpha/2., dof)
```

```

# calculation of confidence intervals for all parameters
for i, p, var in zip(range(n), pars, np.diag(pcov)):
    sigma = var**0.5
    print 'p{0}: {1} [{2} {3}]'.format(i, p,
                                       p - sigma*tval,
                                       p + sigma*tval)

# Calculation of mean variance error
f_x = func(x, pars[0], pars[1], pars[2], pars[3],
pars[4], pars[5])
y_diff = (y - f_x) ** 2.
sum_y_diff = np.sum(y_diff)
sigma_mean_err = 1.0 / dof * sum_y_diff
print 'Mean variance error: ' +
str(sigma_mean_err)
# calculation of R-squared / regression coefficient
# R-squared = 1 - residual sum of squares (RSS) / total
variation (TSS)
y_mean = np.mean(y)
y_mean_diff = (y-y_mean) ** 2.
sum_y_mean_diff = np.sum(y_mean_diff)
r_sq = 1 - sum_y_diff / sum_y_mean_diff
print 'R-squared: ' +
str(r_sq)
# calculation of data points for the plot
xfit = np.linspace(0., 386., num=386)
yfit = func(xfit, pars[0], pars[1], pars[2],
pars[3], pars[4], pars[5])

# plot raw data
plt.figure(1)
plt.plot(x, y, 'k-', linewidth=0.8)
plt.show()

# plot raw data + fitted function
plt.figure(2)
plt.plot(x, y, 'k-', linewidth=0.8)
plt.plot(xfit, yfit, 'r-', linewidth=0.8)
plt.legend(['data', 'fit'], loc='best')
plt.show()
# plt.savefig('nonlin-curve-fit-res.pdf') # uncomment,
if figure shall be exported to pdf

# plot fitted function
plt.figure(3)
plt.plot(xfit, yfit, 'k-', linewidth=0.8)
plt.show()

# Calculation of confidence bands
b1, b2, b3, b4, b5, b6 = unc.correlated_values(pars, pcov)
# calculate y-values with uncertainties
```

```
py = b1 * unumpy.exp(b2 * xfit) * (unumpy.cos(2 * np.pi * xfit / b3 + 2 * np.pi / b4)) + b5 * xfit + b6
nom = unumpy.nominal_values(py)
std = unumpy.std_devs(py)

# create new plot with confidence bands
plt.figure(4)
axes = plt.gca()
axes.set_xlim([0., 400.]) # set x limits
axes.set_ylim([-0.5, 3]) # set y limits
plt.plot(x, y, 'k-', linewidth=0.8) # plot raw data
plt.plot(xfit, nom, c='r', linewidth=0.8) # plot the fitted curve

# add the 2-sigma uncertainty lines to plot
plt.plot(xfit, nom - 2 * std, c='c', linewidth=0.8)
plt.plot(xfit, nom + 2 * std, c='c', linewidth=0.8)

# add axis labels and legend entries
plt.xlabel('n')
plt.ylabel('cum. Z-value')
plt.legend(['cum. Z-values', 'regression', '95% confidence interval'], loc='best')
plt.show()
# plt.savefig('nonlin-curve-fit-res-confi.pdf') # uncomment, if figure shall be exported to pdf
```

Appendix D

Other survey instruments

General self-efficacy expectation (SWE; Jerusalem & Schwarzer, 1999)

Breakdown of the items in the questionnaire:

Part 1 of the questionnaire; (1) Self-efficacy

Please indicate how strongly you agree with the following statements at the moment:

1. When resistance arises, I find ways and means to assert myself.
2. I always succeed in solving difficult problems if I put my mind to it.
3. I have no difficulty in realizing my intentions and goals.
4. In unexpected situations, I always know what to do.
5. Also with surprising events believe I believe that I well with get on well with them.

Part 2 of the questionnaire; (2) Self-efficacy

Please indicate how strongly you agree with the following statements at the moment:

6. I take a relaxed approach to difficulties because I can always trust my abilities.
7. Whatever happens, I'll be fine.
8. I can find a solution for every problem.
9. When a new thing comes my way, I know how to deal with it.
10. If a problem arises, I can overcome it on my own Answer format: four-

point Likert scale; 1 = *not true* to 4 = *exactly true*

Relationship status and satisfaction

Part 1 of the questionnaire; (2) Relationship status

Item: How satisfied are you with being single? or How satisfied are you in your relationship?

Response format: four-point Likert scale; 1 = *not satisfied* to 4 = *very satisfied*