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Techno-Dowsing: Developing a Physiological Response System to Improve *Psi* Training

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Abstract — Working under the assumption that *psi* results from the detection of a weak energetic signal propagating in space and/or time, physiological responses from 20 unselected volunteer participants were recorded. An artificial neural network (ANN) was first trained to recognize a variety of recognition responses, then used to predict a precognitive *psi* target based on participants' physiological responses to concepts related to the target. Measures taken were peripheral blood flow, electrodermal activity and electroencephalographic activity. The ANN trained on all participants' data successfully reduced the possible target pool from 8 to 2 in 8 out of 20 cases. For individually trained networks, this increased to 11 out of 20 cases. Although non-significant, ANN prediction was more successful for those participants exhibiting psychological androgyny ($t = 1.194$, $df = 17$, $p = 0.125$ 1-tailed, non-significant) and field independence ($t = -1.320$, $df = 18$, $p = 0.102$ 1-tailed, non-significant), as predicted. It is concluded that this is a viable and useful approach that would benefit further study.

Keywords: dowsing — *psi* — precognition — physiology response

Introduction

It has long been reported that some individuals possess the ability to detect a wide range of stimuli beyond the range of the acknowledged human senses. Dowsing — the supposed evocation of unconscious responses by use of ideomotor responses magnified by a physical device, such as forked twigs or a pendulum — has long been espoused as a technique for helping individuals to utilize untrained *psi* abilities (*e.g.* Eastwood, 1993). Laboratory research on direct mental influence of living systems (DMILS) and the detection of remote staring suggests that an individual's conscious response may not be a good measure of *psi,* whereas such individuals do show a physiological reaction to certain *psi*-mediated stimuli (*e.g.* Sah & Delanoy, 1994). If this is the case, then a system that looked at the physiological responses of an individual undertaking a *psi* task might be useful in helping to train that individual to

[1]Data was collected for this study in 1995 while the author was on a three-month fellowship at the University of Nevada, Las Vegas. The author may be contacted via email <Paul.Stevens@ed.ac.uk> or at the address above.

recognize when they were using *psi*. In effect, it would be a technological version of the old dowsing devices.

Furthermore, there is some indication that *psi* imposes a unique signature onto the target system. For example, Radin (1989) found that he could train an artificial neural network to recognize individual-specific "signatures" in data in a man-machine interaction setting. This implies that, at least in some situations, *psi* is not goal oriented but the result of actual patterned signals. As all humans have individual physiological differences, perhaps this patterning could be related to physiological functioning? Thus, "psychokinetic" influence of a system would show patterns in the data related to the influencing individual but unrecognizable as a physiological pattern as the target system tends not to be living. If however a DMILS scenario were used, then the target system might conceivably react to the patterned signal as though it were an internally generated signal. The situation where this would be most likely would be if the target system and the signal generation system were one and the same. It is thought that this may be what occurs in cases of precognition — the apparent foreknowledge of future events.

Rationale

The author is working under the assumption that *psi* results from the detection of a weak energetic signal propagating in space and/or time (see Stevens, 1994), the energy resulting in modified neuronal excitation. Moreover, it is proposed that a *psi* signal contains second-order information about the *psi*-source's physiological reaction to the stimulus. The classical mental radio model has the *psi*-signal containing encoded information about the target. This signal might be affected by poor encoding (*i.e.* cognitive functions of the transmitter), noise (environmental) and psychological filters applied by the receiver (see Figure 1). However, the information transmitted may be second order, *i.e.* it is information about the way in which the transmitter's brain reacts upon perceiving the target stimulus. That is, upon perceiving the original target stimulus, the transmitter's brain produces a specific pattern of activity.

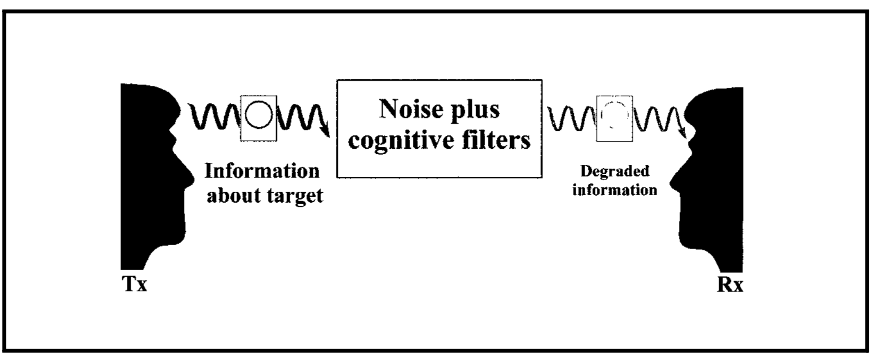

Fig. 1. The classical *psi* signal.

This activity releases energy into the environment as the "*psi* signal." This pattern then interacts with the receiver's brain causing some modification of their neuronal activity (Figure 2).

In general, this will not correspond to the specific pattern in the receiver's brain that would have been initiated had they themselves been exposed to the target stimulus, and so will most probably be misinterpreted, or even ignored (although see Stevens, 1994, for a discussion of learning through feedback). However, there may be occasions when the detected signal pattern would more closely correspond to neural activity in the receiver's brain:

1) if the signal is of a very basic pattern of activity, such as neural activity relating to basic somatic (*i.e.* hardwired) processes;
2) where the *psi* transmitter has the same neural patterns as the transmitter.

Case 2 would certainly occur if the transmitter and receiver were the same individual, such as would occur in precognition. Here, the *psi*-signals would originate in the future-self, propagating through time to be detected by the present-self's brain.

What Could Give Structure to Signals?

Assuming *psi* to be the result of an actual patterned signal related to physiological functioning, a DMILS scenario was used with the idea that the target system might conceivably react to this signal as though it were an internally generated signal. As this situation is thought to be most likely when the target system and the signal generation system are one and the same, the protocol was modified to involve a precognitive element. Essentially, precognition is being treated as though it were a case of telepathy. The only difference is that the sender is the receiver at some future time.

If the *psi* signals originate in the brain, then the best approach would be to have each of the target stimuli cause as discrete a pattern of brain activity as possible. To describe such discrete patterns, neuropsychology uses the idea of an *engram* — the neural representation of a given idea, as represented by

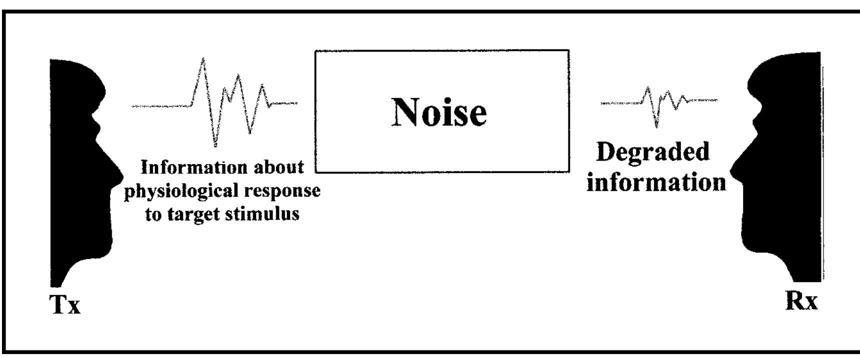

Fig. 2. A 2nd order *psi* signal.

specific patterns of stimulated neurons or neuron groups in the higher centers of progressive processing. Once encoded, engrams are thought to be represented redundantly throughout the entire brain, although the actual structure of a specific engram will be unique. It has been suggested (Kissen, 1986) that there are three different classes of engrams:

Veridical — which represent the direct perception of sensory data.
Iconic — which represent formalized abstractions of the veridical engram (*e.g.* a line drawing).
Symbolic — an engram which encompasses a whole class of veridical engrams, with an associative structure (including language).

The first type would be location and sensory mode specific, the last two would become more global, involving networks of veridical engrams. As each engram is associated with a specific pattern of electrical activity (amongst other types) in the brain, this seems a good way of classifying signal structure. If the engram structure can be represented externally as a patterned signal, then this signal may be able to excite the brain it interacts with, reproducing a similar (if degraded) pattern of activity as that which produced it. Now, neurons have the peculiar property of becoming more sensitive to a stimulus if that stimulus is maintained (Greenfield, 1995). This occurs when stimulus presentation causes a search of engrams in memory, priming the neurons associated with each stored engram. If an engram is found that matches the preperceptual input, the neuronal activity underlying that engram is enhanced (Kissen, 1986). If the reception of a *psi* signal also served to prime engram-associated neurons in the receiver's brain, then this could give a weak recognition response. If this is the case, the *psi* information would be experienced as a (probably degraded) perceptual experience. It may also be more likely to occur in conditions of sensory deprivation (*e.g.* ganzfeld, meditation, day dreaming) where the brain is looking for input. *Psi*-signal detection might also be influenced by expectation and mental set.

Minimizing Internal Sources of Interference

- *Remove expectation and set bias.* If recognition is influenced by expectation and set, then these could interfere with the detection of a weak *psi* signal. By taking physiological measures rather than conscious responses, we hoped that such cognitive biases would be circumvented. Furthermore, any information that could allow the participant to guess the experimental rationale was minimized. Participants were aware that the laboratory conducted parapsychological research, but were not initially told the nature of the experiment.
- *Reduction of somatic noise.* If participants are thought to be detecting weak energetic signals through modification of somatic processes, then reducing the amount of activity in the somatic systems should act to

increase the signal-to-noise ratio. Fortunately, participants are required to stay as still as possible during physiological recording, providing a feasible explanation for a relaxed state.

Varying the Originating Engram Structure (The Precognitive Target Stimulus)

If an energetic signal does underlie *psi* perception, then the best results would be expected from a strong signal. Such signals, in this experiment, would have to be seen as being generated by the brain physiology of the participant at a future time, and then propagating through time to interact with the present-time receiver's brain. This represents a case of true precognition *i.e.* one where there is an interaction between two systems in a temporal direction which is reversed with respect to our normal experience of time. If the signal originates through physiological activity of the source brain, then any target stimulus that gave large-scale, clear physiological responses would generate the strongest signals. Variables were therefore chosen to give the most discrete engrams in response to presentation of the target stimulus. These variables were *Engram Class* (Veridical, Iconic or Symbolic as discussed above), *Emotional Valence* (positive, neutral or negative), and *Face Bias* (face present *versus* not present).

Emotional Valence was chosen because the affective qualities of a percept are thought (Davidson, 1983) to give hemispheric asymmetries in activity, with positive emotions giving more left hemisphere activity from the frontal lobes, negative emotions giving more right hemisphere activity in the frontal lobes, and neutral emotions showing no significant hemispherical differentiation. *Face Bias* was chosen because humans have a strong cognitive bias for efficient processing of faces (Purcell & Stewart, 1986). Classifying the stimuli in terms of having faces or not having faces should then give strong differences in neural activity. The images which were used as target pool pictures were thus classified in the ($3 \times 3 \times 2$) grid shown in Figure 3.

Identifying a Response

To see if the participant is detecting a *psi* signal, we must first find out how the physiology of the signal source reacts when a recognizable perception is encountered. These reactions could then be used to create a template of recognition responses. It was decided that the physiological response patterns needed would be a conscious recognition response (*R*), a vague (or weak) recognition response (*V*) and a null-recognition response (*N*). By presenting the participants with a series of images, each one chosen to evoke one of these three basic responses, the patterns of physiological activity for each basic response could be found.

That same participant could then be shown further images, each chosen to evoke one of the engram combinations (the boxes in the Figure 3 grid). If their physiological responses were again recorded, it should be possible to

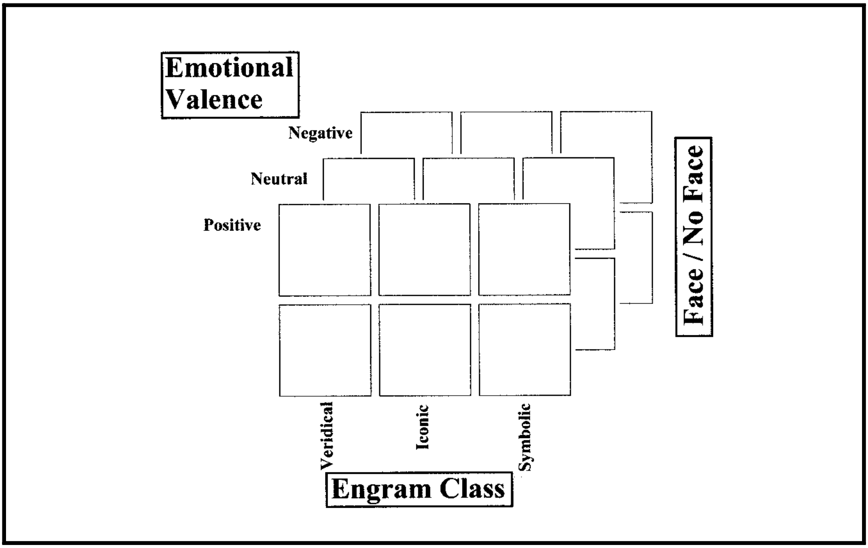

Fig. 3. Target pool classification scheme.

determine which images give the strongest or the most consistent response. The common engrams associated with such images would then be the ones chosen as being significant to the participant. If it is assumed that this significance were due to *psi*-signal induced priming effect, a prediction could be made as to the precognitive target.

Psychological Measures

Two psychological measures thought to relate to perceptual style were used — the shortened version of the Embedded Figures Test (Witkin *et al.,* 1954), and the Bem Sex-Role Inventory (Bem, 1974). The former measures the individual's ability to perceive a stimulus independently of the context within which it is presented, called *field independence.* The latter measures self-perceived gender trait possession. Although past studies have found sex differences in different areas of perceptual ability (*e.g.* males are traditionally better at spatial tasks, females at verbal ones), it had been noted that there was also considerable variation within, and a considerable overlap in distribution between, sexes, suggesting a psychological as well as a biological difference. Studies (*e.g.* Hamilton, 1995) have found that there is an association between psychological androgyny (defined by Bem as being the difference between a person's self-perceived masculine and feminine score, normalized with respect to the standard deviations of their masculine and feminine scores) and perceptual ability. As this study is postulating an emotion-inducing signal, it was decided that those participants exhibiting female sex-typing would be more successful in detecting the stimulus (*i.e.* would show a stronger or more consistent physiological response).

Method

Apparatus: Physiological Recording[2]

Physiological data was recorded using the I-410 physiological monitoring system (Physiological Data Systems, USA). This is a system which interfaces with a standard IBM compatible personal computer, and is essentially an analogue-to-digital signal converter. It has several channels for data acquisition, allowing different combinations of physiological measurements through the use of plug-in modular sensors and electrodes. The system opto-isolates the participant from the main power supply for safety reasons. For this study, the measures taken were:

PPG — a measure of peripheral blood flow, dependent on blood pressure and heart rate.
EDA — Electrodermal activity, based on the skin conductance response.
BL/BR, AL/AR, TL/TR — Electroencephalographic (*EEG*) activity for frontal lobe left and right hemispheres, for Beta (15-30 Hz), Alpha (8-14 Hz) and Theta (4-7 Hz) frequency bands.

PPG was measured using a photoplethysmograph attached to the ring finger of the non-dominant hand. *EDA* was measured using an electrode attached to the index finger of the non-dominant hand. *EEG* measures were taken by monopolar recording, with two scalp electrodes at positions F3 and F4 (International 10-20 Electrode System — see Stern *et al.,* 1980) and a reference lead attached to the surface of the mastoid process behind the left ear. All electrodes were silver/silver-chloride, and the sites were cleaned and prepared with a commercial skin abrading solution prior to electrode application. The controlling software performed a real-time fast Fourier transform on the *EEG* data to calculate the relative strengths of the three frequency bands used before saving to hard disk.

Apparatus: Response Calibration Images

These were the images that would be used to obtain physiological responses for the recognition template construction. Two images were chosen for each engram class (refer back to Figure 3). It was hoped this would give representative overall response patterns. Images chosen to evoke a conscious recognition response were:

A photograph of the laboratory building (Veridical)
The Experimenter (Veridical)
Drawing of computer (Iconic)
Drawing of a car (Iconic)

[2]I am indebted to Jannine Rebman for her invaluable assistance in participant recruitment and in setting up the physiological monitoring system.

The name of the participant (Symbolic)
A map of the USA (Symbolic)

Images to evoke a null-recognition response were:

A photograph of an Edinburgh building (Veridical)
An unknown person (Veridical)
Drawing of a mechanical component (Iconic)
A strange-looking plant (Iconic)
A fictional nonsense name (Symbolic)
A map of Venus (Symbolic)

The last category was the most difficult as the images had to be recognizable yet not something that would be immediately obvious as being known. In the end, it was decided to use images that related to things of which the participants would be unlikely to have had personal experience. Images for a vague recognition response were thus:

Photograph of a pyramid (Veridical)
Photograph of a lesser film star (Veridical)
Drawing of platypus (Iconic)
Drawing of satellite (Iconic)
The word “Human” (Symbolic)
A map of New Zealand (Symbolic)

Apparatus: Images Relating to the Precognitive Target

These were the images that would be used to obtain physiological responses for the precognitive target prediction. These images, in their pre-randomized order of presentation were:

1) Woman: a photograph of an emotionless woman.
2) Buddha: a stylized statue of the Buddha.
3) Dali-Vis: Dali’s “Visage of War.” Skulls within skulls and death motif.
4) One dollar: a reproduction of a U.S. one-dollar bill.
5) Roger: cartoon character Roger Rabbit.
6) Cross: a stone cross gravestone with a raven sitting on.
7) Fire: stylized drawing of a forest fire.
8) Time zone: color coded outline world map with time zone markings.
9) House: a picture of a family house with trees around.
10) Rose: a soft-lit drawing of a red rose.
11) Akira: a gun-wielding cartoon Manga character dripping blood.
12) Escher: drawing of 2 hands, each drawing the other.
13) Crow: photo of film character “The Crow” in half shadow.
14) Shore: a seaside scene with sandcastle, bucket and spade.
15) Wface: outline drawing of a woman’s emotionless face.
16) Kitten: photograph of cute kitten sitting in a flower bed.

17) Christmas: a Christmas tree with colored lights in snow.
18) Mushroom: photograph of nuclear explosion mushroom cloud.

These images were each chosen to represent a combination of variables as in Table 1.

Apparatus: Images In the Target Pool

Eight images were constructed for the target pool, each one primarily representing one of the engram structures. To get the strongest possible physiological response at the time of the target viewing (which would relate to the strength of the *psi* "signal"), it was decided to present a collection of images. Each target image was thus a montage of smaller items, which could be drawings or photographs, and represented ranges of emotions. The criteria was that the overall appearance of the image would most consistently evoke the required engram structure. As an example, the "symbolic" target image consisted of a drawing of some mythical creatures, a photo-realistic ankh, a photo of some dice, a lightbulb symbol, a photo of the American flag, a drawing of some clasped hands and the word "Religion" in black text. Thus, although the image contained elements of other engram structures (faces of the mythical beasts, emotional overtones depending on individual reactions, iconic and veridical aspects), the consistent theme should have been that the objects all had symbolic associations. The actual target was not selected until immediately before presentation to the participant. Selection was by means of the Quick BASIC internal pseudo-random algorithm. This is a standard and widely used algorithm which has been shown to give apparently random sequences (Dalton *et al.,* 1994)

The images for all three stages were presented full-screen on a computer monitor using a Quick BASIC program written by the author. Images were presented for five seconds followed by five seconds of blank, black screen.

Apparatus: The Neural Network

A neural network was used to determine a template for each of the three basic responses — conscious recognition, vague-recognition and null-recognition. Such networks have been shown to be useful at "learning" to find patterns in noisy or highly complex data. A commercial software product, *Brainmaker* (Lawrence & Petterson, 1992) was used. This is a back-propagation network which in this case used a sigmoid transfer function with a gain of 1 (giving an output which is a semi-linear, continuous, monotonic function of the input — see Lawrence & Lawrence, 1992). For training, 90% of the data was fed into the network. The remaining 10% of the data was used to test that it could make successful predictions based purely on physiological data. When making a prediction, the neural network produced output values between 0.000 and 1.000 images relating to the precognitive target. Higher values indicated a stronger pattern match between the image-related physiological data and the trained template. These values were then used to produce an average response strength for each of the engram structures in Table 1. A value for the strength of the total response (*TR*) to each engram was then calculated such that:

$$TR = V - R + N \qquad \text{where} \quad \begin{array}{l} V = \textit{Vague Recognition Average Strength} \\ R = \textit{Recognition Average Strength} \\ N = \textit{Non-recognition Average Strength} \end{array}$$

This value was decided beforehand as it was expected that a subconscious "*psi* recognition" response would relate more to a vague recognition (*V*) response than to a conscious recognition (*R*) response, possibly also showing a conscious non-recognition (*N*) response. Thus, a *psi*-recognition response would ideally show High *V,* Low *R* and High *N.* (*V*–*R*+*N*) should then give the highest value for a *psi*-recognition response.

Participants

Twenty volunteer participants were used, recruited by poster display and word of mouth on and around the university environs. No selection criteria were used.

Procedure

Participants arrived at the laboratory and were seated one at a time in a high-backed armchair in front of a computer monitor. They then carried out an on-screen version of the embedded figures task and Bem sex-role inventory. Once they had completed the inventory, the meaning of their results for both tests were explained.

The physiology electrodes were then put in place, with an explanation of what each was measuring and a reassurance that these were perfectly safe and isolated from the main power supply. Participants were instructed to remain as still as possible, breathing as normal. They were then told that they would be shown a series of thirty-six pictures on the screen which they should watch with as much attention as possible. Reassurances were given that they would not be expected to remember any details afterwards, nor were there any other aspects of the experiments about which they had not been informed. The ex-

TABLE 1
Classification of Images

	Faces			Non-Faces		
	Positive	Neutral	Negative	Positive	Neutral	Negative
Veridical	Kitten	Woman	Crow	Shore	House	Cross
Iconic	Roger	Wface	Akira	Rose	Escher	Fire
Symbolic	One dollar	Buddha	Dali-Vis	Xmas	Timezone	Mushroom

perimenter then retired behind a screen to start the physiological data collection and image display. Once finished, participants were thanked and debriefed.

Once all 20 participants' data had been collected, all of the physiological data from the first 18 images (the response calibration images) were combined and used to train a general neural network to distinguish the recognition, vague recognition and non-recognition response patterns. The particular neural network characteristics used were based on successful training data.

Predictions

H1: A neural network could be trained that would identify the precognitive target based on a participant's physiological responses to target-related images.

H2: Female sex-typing would be related to successful prediction of the precognitive target.

H3: The *EFT* scores would correlate with success in the prediction of the precognitive target.

H1 is the primary hypothesis, affirming that there would be physiological responses that would enable a successful prediction of an undetermined future event. *H2* investigates the anecdotal claim that a feminine personality is more likely to "be psychic." *H3* stated that participants with high field independence would be better at perceiving the *psi* signals as they would be less inclined to attempt to interpret those signals as being related to their current surroundings.

Results

The most accurate neural network, based on the combined data of all participants, was found to be correct only 21% of the time (15 facts correct out of 72). This was for a network with one hidden layer of 200 connections. As this was still highly unreliable, it was decided to allow for a margin of error by looking for the top two total response strengths as indicators of the engram structures which corresponded to the *psi* target. If this procedure proved to be valid, this would reduce the possible target pool from eight to two, increasing the probability of a successful *psi* experiment from 12.5% to 50%.

The general response network results showing the response for engram structures corresponding to actual *psi* target are given in Table 2. As can be seen, eight out of the twenty sessions showed the correct engram structure to give one of the top two responses, as opposed to the five that would be expected by chance. *H1* is therefore supported for the general case.

Note that, once a network had been successfully trained, there was no further selection based on successful or unsuccessful prediction of the precognitive target.

The next step was to see if the usefulness of the procedure would be increased by creating an individual network for each participant, which would allow for any individual differences in physiological recognition responses. The main problem with this procedure was that there were only 18 sets of physiology data inputs for each participant, which would result in a less generalizable network and very few training facts (recall that typically 10% of the data set is used to train a neural network for later use. In this case, this gave only two items of data)! As a result, the standard network of one hidden layer of eighty connections got none of the two training facts right in seventeen cases and only one right in three cases. The individual response network results are given in Table 3.

In this case, the networks again showed the correct engram structure to give one of the top two responses in eight out of the twenty sessions. However, as the individual networks were smaller, it was practical to try to train some more complex networks in the hope that they would be more accurate. For each participant's data, the number of layers was increased until the testing showed an increase in accuracy. Once the maximum number of possible layers had been reached, the network was reset to the basic configuration, but the number of

TABLE 2
General Response Network Results
(H= highest of 8, L= Lowest of 8)

Participant	All Network Output
1	H
2	4th L
3	2nd H
4	3rd L
5	2nd L
6	4th L
7	2nd L
8	2nd H
9	2nd H
10	H
11	3rd L
12	2nd H
13	L
14	3rd H
15	4th H
16	4th H
17	2nd H
18	4th H
19	L
20	2nd H
Total Correct (2H and H)	8

TABLE 3
Individual Response Network Results
(H= highest of 8, L= Lowest of 8)

Participant	3L-80 network Output
1	2H
2	3H
3	2L
4	2H
5	H
6	3L
7	3H
8	4H
9	2L
10	4H
11	H
12	2H
13	4H
14	4H
15	2H
16	2H
17	4L
18	4H
19	3H
20	2H
Total Correct (2H and H)	8

TABLE 4
Additionally Trained Individual Network Details

Ps	Layers	Connections
1	4	80
2	3	160
3	7	80
7	5	80
9	7	80
14	4	80
18	5	80

connections doubled. Details of the seven individual networks for which this produced an increase in testing accuracy are given in Table 4.

For these networks, the *psi*-session data showed the following results in Table 5.

Of these networks, only one (participant 1) had correctly predicted the *psi*-target engram structure for the original configuration network. Thus, if the best networks were used for each case, then the total successfully predicted engram structures was eleven out of twenty. *H1* is thus supported for the individual cases.

A *post-hoc* attempt was made to see if a network could be trained using only the *EDA, PPG* or *EEG* data on their own, training one network per individual. In no cases could a network be trained, suggesting that each measure on its own did not provide enough specific information. This could be due to the low-resolution data recorded, or indicate that the effect was a very weak one. In an attempt to see if there were some physiological differences between those people for whom the neural network successfully reduced the *psi* target pool and those for whom it could not, it was decided to look at the variance of each of the physiological measures taken. It was hoped that this would provide a crude measure of the lability of their physiology. Table 6 shows the Spearman

TABLE 5
Individual Response Network Results
(H = highest of 8, L = Lowest of 8)

Participant	Best Network Output
1	H
2	H
3	3L
7	H
9	3L
14	2H
18	4L
Total Correct (2H)	4

correlations for each of the physiology measures and whether the neural network was successful or not.

For the measures of psychological androgyny (shown in Table 7 and Figure 4), a *t*-test was performed to compare differences between the success and non-success groups.

Results were thus non-significant although in the predicted direction, suggesting that a feminine sex-typing (positive androgyny score) was superior either for *psi* performance, or at least for having the characteristics that enabled the neural network to make a successful prediction. The total *N* for this analysis was only 19 due to the corruption of recorded data for one of the participants, due to a spontaneous hard-disk access error. As the differences were not significant, *H2* was therefore not supported.

TABLE 6
Spearman Correlations for Overall Variance of Data *vs.* Success
(coded : yes = 1, no = 0)

	ppg	eda	bl	br	al	ar	tl	tr
Success	–0.113	0.341	0.044	–0.044	0.200	0.026	0.009	–0.096

To be statistically significant at the $p = 0.05$ level, Spearman's r would have had to have achieved a value of 0.450 ($N = 20$) or above. None of the correlations reached significance.

TABLE 7
Androgyny Scores

Success	N	Mean	StdDev
Yes (1)	10	0.40	2.2
No (0)	9	–0.80	2.1

$t = 1.194$ (df = 17), $p = 0.125$ (1-tailed)

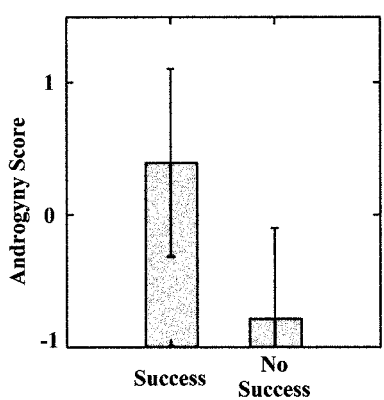

Fig. 4. Androgyny scores by success.

TABLE 8
Field Independence Scores

Success	N	Mean	StdDev
Yes (1)	11	23.6	8.6
No (0)	9	35.2	27.5

$t = 1.194$ (df = 17), $p = 0.125$ (1-tailed)

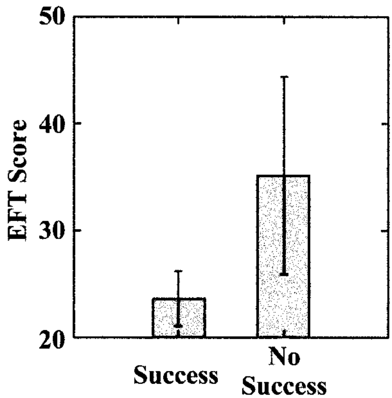

Fig. 5. EFT mean times (s) by success.

For the measures of field independence (see Table 8 and Figure 5), a *t*-test was again performed to compare differences between the success and non-success groups. Results were again non-significant but in the predicted direction (a low *EFT* score meant good field-independence). This suggests that field-independence was also superior either for *psi* performance, or at least for having the characteristics that enable the neural network to make a successful prediction. As the differences were not significant, *H3* was also not supported.

Discussion

The findings of this study seem to support the idea that there is, at least for some individuals, a discrete physiological response to a real-time perception related to a future perception. This is interpreted as being demonstrative of a low-level precognitive ability in humans. To some extent, the characteristics of this response may be generalizable to all individuals, as an artificial neural network trained on all participants' data was able to reduce the possible target pool from eight to two in eight out of twenty cases. However, that there are individual differences was apparent as the individually trained networks were more successful, achieving a correct prediction in eleven out of twenty cases.

In both cases, the expected number of correct predictions by chance alone would have been five out of twenty (eight possible targets for twenty participants, with the top two physiological responses being taken as possible *psi* predictions). It is concluded that this approach is a worthwhile one, with the possibility of being a useful tool for (a) aiding in the training of *psi* abilities in a manner similar to biofeedback training and (b) helping to determine when *psi* is present.

Looking at the physiological data, there are possible indications that neural-network prediction success was achieved for individuals with low variance photoplethysmograph (*PPG*) readings, high variance electrodermal response (*EDA*) , and high variance of left-hemisphere alpha activity. However, a Spearman correlation did not show these findings to have reached a level of significance ($r = -0.113$, $r = 0.341$, $r = 0.200$ respectively). Part of the problem may have been that relatively low resolution physiological data was collected, samples being taken only every second and with only one channel *EEG*. Future studies might benefit from taking more frequent samples.

For the psychological measures, the predicted superiority of individuals who were classed as showing significant feminine sex-typing was found ($t = 1.194$, $df = 17$, $p = 0.125$ 1-tailed) although it was non-significant. As the measure used — psychological androgyny — has been found to be related to perceptual ability, this is taken as being indicative that *psi* is in part a perceptual ability. For the measure of field independence, neural network prediction was successful for individuals who were rated as being field independent ($t = -1.320$, $df = 18$, $p = 0.102$ 1-tailed). If this superiority is due to the individual's *psi* ability, it implies that the initial hypothesis that *psi* is related to the ability to recognize the presence of weak signals that are not part of the current perceptual environment is correct.

Conclusion

It is concluded that the use of artificial neural networks and physiological responses promises to be a useful tool in *psi* research, offering not just a training aid but a possible indicator of the presence or absence of *psi* within any given laboratory experiment. Although the psychological measures did not show significant differences in this study, they were in the predicted directions, indicating that future research with larger numbers of participants could benefit from taking psycho-perceptual measures into account when selecting participants.

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