Future dreams of electric sheep: Case study of a possibly precognitive lucid dreamer with AI scoring

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Summary. A precognitive dream is a dream about seemingly unpredictable future events that nonetheless seem to be predicted by the dream. It has been most convincingly replicated in two case studies using a single skilled precognitive dreamer (Maimonides studies by Krippner et al., 1971, 1972). Instead of repeating these original studies with another skilled precognitive dreamer, here we set out to determine whether an individual with another unusual dreaming skill – that of entering a lucid dream state almost at will and sketching images seen in that state upon awakening – could become a precognitive dreamer with practice. We pre-registered a formal experiment with two sets of 5 trials. In each trial: 1) the dreamer recorded the contents of his lucid dream in a transcript, 2) the dreamer emailed the transcript to a skeptical target-selector, 3) the target-selector used a random number generator to select a target, 4) the target-selector sent the URL for the target to the dreamer, 5) the target-selector sent the target URL and the dream transcript to the analyst, 6) the analyst stored the date, dream transcript, and target together in a database. We used three methods of judging – 1) a pre-registered but flawed judging method using two skilled human judges [producing 3 hits out of 10], 2) an exploratory method drawing on unskilled human judges [producing 1 hit out of 10], and 3) an exploratory method comparing judging performance across five different text embedding models within large language AI models [producing 5 hits out of 10]. AI-judged methods offered clear evidence for precognition, including a dream-target match conservatively calculated to be highly unlikely to be obtained by chance ($p<1.2x10^{-5}$), but a confirmatory experiment is required before drawing firm conclusions. Further, several of the accurate transcript/target pair matches made by the top-performing text embedding models matched those of the skilled human judges, suggesting that the AI method captured human sensibilities and expanded on them. The differences in accuracy among the embedding models have implications for the selection of AI models for future free-response experiments and can begin to give shape to a future of AI participation in screening, training, performance, and analysis in multiple free-response contexts.

Keywords: Free-response, embedding model, lucid dreaming, precognition, AI judging

1. Introduction

Precognition is considered an extra-sensory (ESP) capability that allows one to sense or act on future events for which there seem to be no clues in the present or past (recent review: Mossbridge, 2023a). Precognitive or “prophetic” dreaming is the most commonly reported form of precognition (Mossbridge, 2023a). The ontological reality of precognition is considered controversial or fanciful by those who do not study it, while the few laboratories examining the phenomenon tend to focus on demonstrating it in groups of individuals, a project that includes physiological precognition (also called predictive anticipatory activity or PAA; Mossbridge et al., 2012, 2014; Mossbridge & Radin 2018a, 2018b), conscious precognition (such as precognitive remote viewing; Mossbridge et al., 2021; Mossbridge et al., 2024; Krippner et al., 2019), unconscious or behavioral precognition (such as pressing buttons in response to a future stimulus; Bem et al., 2015; Mossbridge et al., 2017), and dream precognition (dreaming of future randomly selected events; Storm et al., 2017; Vernon et al., 2024; Wargo, 2021; Watt, 2014). Taken together, significant results from rigorous, well-controlled group studies suggest that precognition is broadly distributed, at least enough to produce small significant effects in controlled experiments drawing from unselected populations. Based on this conclusion, it is reasonable to assume that while some spontaneous reports of precognition in non-controlled contexts may be due to confirmation bias or wishful thinking, others may be explained

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by somehow receiving information about future events (Knight, 2022; Mossbridge, 2023b). To further understand and characterize precognitive dreaming, here we examined whether a skilled lucid dreamer could, under controlled conditions, receive information about randomly selected future events during the lucid dream state and report the information after waking.

Attempts to better understand precognition by correlating precognitive accuracy with various demographic, environmental and personality characteristics among groups of participants have resulted in a complex picture of the phenomenon. Belief in precognition, belief in luck, feelings of anxiety, feelings of unconditional love, phases of the moon, geomagnetic activity, and several of the Big-5 personality traits (e.g., openness to experience, extraversion) have all been shown to be related to improved precognition of one type or another, but not necessarily precognitive dreaming (e.g., Mossbridge, 2024; Mossbridge et al., 2024; Mossbridge & Radin, 2021; Zdrenka & Wilson, 2017; Valášek & Watt, 2015; Roney-Dougal et al., 2014). In the aggregate, this work tells us that like any complex mental capacity involving perception, cognition, intention and attention, the underlying mechanisms of precognition are varied and poorly understood. In addition, dreaming – precognitive or not – is a current area of active interest among neuroscientists and psychologists because its purpose and mechanisms are still not clear even though much progress has been made (for reviews, see: Mallett et al., 2024; Mutti, 2024; Tsunematsu, 2023), so the poor understanding of dreaming itself is amplified when it comes to research on precognitive dreaming.

Another way to understand mysterious human capacities is to examine the phenomenon in individuals who are especially skilled at the capacity and determine what potentially related skills they excel in. In the U.S., this approach has been underutilized in the non-classified literature, though perhaps has been used fruitfully in literature that remains classified (see the declassified *Star Gate* files, Marwaha & May, 2018). Perhaps because many researchers still feel pressure to prove the existence of precognition itself, when they do have access to skilled precognitives the resulting research often focuses on re-demonstrating the skill under controlled conditions (e.g., May et al., 2014; Graff & Cyrus, 2017). This was the case for one of the most well-studied precognitives in the 20th century, Malcolm Bessent (Honorton, 1987; Krippner et al., 1971; Krippner et al., 1972; McDonough et al., 1990). To take an example relevant to our study on precognitive dreaming, researchers at the Maimonides Medical Center dream research laboratory in New York studied Bessent's apparent capacity to dream about future events during two successful studies taking place over multiple days in the dream lab there. For each trial of the study, experimenters asked Bessent to make the intention to dream about a future "target experience" and report his dreams the morning after he woke up. Once he had recalled the dreams and described them to his satisfaction, the "transcript" of his described dream experiences was "locked down" and kept in a file. Only at this time was the target experience randomly selected among multiple potential target experiences, and Malcolm was provided with the target experience. After all trials had been completed, independent judges who did not know the pairing between the dream transcript/target experience were asked to rate the similarity between the dream transcripts and the target experiences. In both studies, they indicated that a significant number of the dream transcripts matched their correctly paired target experiences as the highest-ranked match in the blind judging process (Krippner et al., 1971; Krippner et al., 1972). For those who believed the targets were not somehow leaked ahead of time or serendipitously matched to the prior day's events that might become "day residue" for the dreams (Langs, 1971), these experiments demonstrated the capacity of at least one human to dream about randomly selected future events.

This case-study approach with talented participants is becoming more popular in the last decade. For instance, in a study co-authored by two talented clairvoyants, the remote viewer (Patricia Cyrus) and precognitive dreamer (Dale Graff) created descriptions of future newspaper target images which, when scored by independent judges against target and non-target images, more effectively matched the target images (Graff & Cyrus, 2017). Further, in a double-blind group study associating dreams to images tied to the outcomes of future sporting events, the top three most skilled precognitive dreamers were three of the study's authors: Dr. Debra Katz (independently significant), Dale Graff (borderline independently significant), and Michelle Bulgatz (Katz et al., 2019). Together, these studies establish that some people are skilled at precognitive dreaming beyond chance expectation. Follow-up studies characterizing the nature of precognitive dreaming are underway.

Related approaches can also help to establish the ontological reality of precognition while characterizing the nature of the phenomenon itself, and we used such an approach in this case study. For example, one can examine whether individuals with a potentially overlapping skill might also be skilled at any phenomenon of interest to determine if the mechanisms underlying the two skills are related. This idea comes from the field of perceptual learning (Polley et al., 2006; Mossbridge et al., 2008; Sabin et al., 2012). The reasonable assumption used in that field is that if someone learns a specific task and their performance improves on an untrained task, the two tasks share some common mechanism(s).

Training individuals to become more accurate when precognitive dreaming has not yet been accomplished, but to our knowledge, it has also not been tried in a controlled experiment, despite recent innovative work on at-home precognitive dreaming (Vernon et al., 2024). Accuracy in free-response trials like those used in precognitive dreaming studies is difficult to assess in the first place, since there are flaws with every judging method, even when the dreamers themselves are the judges (Watt, 2014). Nonetheless there are people, including meditators and lucid dreamers, who have already learned to use their minds in unusual ways that seem potentially related to the mechanisms underlying precognitive dreaming. These people could be tested on a precognition task to determine whether their learned skill transfers to this novel task. Roney-Dougal and collaborators used this approach with Tibetan meditators and found that the number of hours spent meditating were significantly correlated with better accuracy on a conscious precognition task (Roney-Dougal, Solfvin, & Fox, 2008) and the trend persisted in a second study, with the two most experienced meditators scoring beyond chance (Roney-Dougal & Solfvin, 2011). Given that meditation training alters neural activity (Zanesco et al., 2021) and experienced meditators have unique neural signatures depending on the state of their awareness (Reggente et al., 2024), it seems likely that meditation training may influence the neural circuitry involved in precognition. These would likely include circuits involved in attention, perception, memory, and intention.

Lucid dreaming is closely related to deep meditation in that it is an altered state of consciousness that requires awareness during a time when low awareness is the norm (Gackenbach et al., 1986). Further, meta-awareness and daily meditation are associated with more frequent lucid dreams (Gerhardt & Baird, 2024, Stumbrys et al., 2015). Because previous waking results from Roney-Dougal showed an intriguingly persistent relationship between meditation and precognition, we wondered whether lucid dreaming in a highly practiced individual might also support precognitive dreaming. This especially seemed possible given our co-author DG is a lucid dreamer who translates his dreams into descriptions and images as a part of his lucid dream art practice.

We began this case study as an attempt to understand whether DG, a skilled lucid dreamer with little experience in precognition and a self-described open-minded skeptic, could successfully ask himself to dream about a randomly selected target to be presented to him the next day. We reasoned that this case study would not tell us whether every lucid dreaming artist could receive information about future events, nor whether DG himself could do this in any circumstance outside this study. Instead, we tested the hypothesis that for DG, precognitive dreaming could occur within the confines of this study. In addition, when we began, we did not know that we would also help further the field of free-response scoring by developing a new method for AI judging that seemingly improves upon scoring by skilled human judges. Therefore, while results from these additional analyses were useful for drawing tentative conclusions about both AI judging of free-response tasks and precognitive dreaming itself, all of the results described here require replication to be confirmed scientifically.

2. Methods

2.1. Study Background: Participant and Experimenters

Dave Green (DG) contacted Julia Mossbridge (JM) to determine whether she would be interested in studying his lucid-art dreaming process. JM agreed that she would be interested if he would be open to attempting to dream precognitively about targets that would be randomly selected after he submitted a dream transcript. DG agreed, and after a marginally encouraging pilot study, DG suggested bringing open-minded skeptic Chris French (CCF) on board to act as an informed skeptic and another experimental design expert. JM agreed, as did CCF. They then performed another pilot study, which was also encouraging. At no point had DG or CCF been promised anything other than a collaborative study, although DG and CCF are public figures who have both told their fans that they are involved in this study. Finally, open-minded skeptic Alan Pickering (AP) was brought into the study team to examine and improve the approaches to the human-judging protocol and analyses, and cognitive scientist Damon Abraham (DA) joined the study team around the same time to test his newly-developed AI-judging method.

2.2. Trial Protocol

We pre-registered with Goldsmiths, University of London a single lucid-dreaming experiment with the intention of determining whether the dreamer (DG) could describe precognitive targets in the context of his lucid dreams. A secondary intention was to determine whether improvement occurred over time. The dreamer performed 10 dream trials in total; five from 4/25/23 to 6/6/23 and five from 6/14/23 to 7/20/23. Each trial proceeded as in Figure 1, with one week between the blocks of 5 trials. First DG recorded his dream the morning after having had a lucid dream, then sent CCF his transcript. After receiving the transcript, CCF selected a target for the dream at random from a database consisting of 478 pre-pooled online targets. The target pool can be found on Lyn Buchanan's CRV website (https://www.crviewer.com/targets/targetindex.php). This is a 10-year (2006-2016) database of interesting stories/events from news and other media, and it has been used previously by hundreds of remote viewers. To select the target from this pool CCF generated a number between 1 and 10 at either Google or Random.org (https://www.random.org) to give the year (1=2006, 10=2016), then two more numbers to give the month and week of the target. All targets had not been presented in

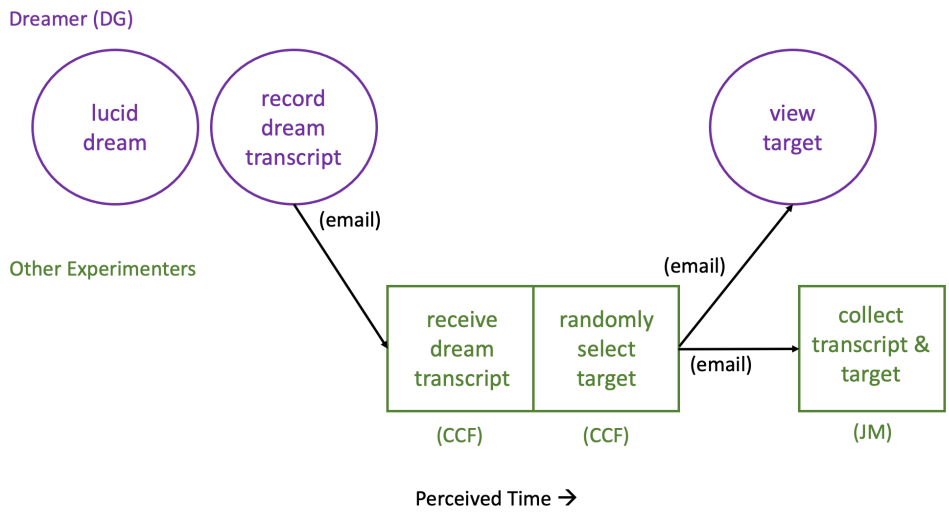

Figure 1. Schematic showing trial protocol. Initials in parentheses show authors' designated tasks.

the pilot study, and there were no repeated targets within this study.

CCF then sent the target URL to DG, who spent between 5 and 120+ minutes reading about the target and viewing any accompanying videos or images. The amount of time DG spent with the target was based on his own discretion and interest. CCF also sent the same target link and DG's dream transcript to JM. JM then filed the dream transcript, associated target link and the date in a spreadsheet. Once all 10 dream trials were complete, each dream had any identifying dates or sequence numbers removed and these were replaced by letters (A through E for the first dream set, F through J for the second dream set) according to a random order determined by Matlab's randperm algorithm (https://www.mathworks.com/help/matlab/ref/randperm.html). Then we began human judging protocols followed by AI judging protocols.

It is worth noting that Ganzfeld and related psi experiments are often judged by the percipient themselves, who are shown the target along with several decoys and are asked which stimulus is most similar to their perceptions (Bem et al., 2001). However, we did not wish to present our percipient with more than one potential target, for fear he would dream of them all – in this way, our approach to judging is more like the original studies with Malcolm Bessent (Krippner et al., 1971; Krippner et al., 1972).

2.3. Lucid Dreaming Task

During the lucid-dreaming task, DG first recognized that he was dreaming. While staying in the dream state, he made an intention to look at his smartphone or computer (in the dream) and to see the target that he would receive from CCF the next day. DG then queried the target, examining his conscious experience within the dream, to discover any additional concepts or images that might appear. When he felt he had enough information, he woke up and recorded his experience in words and images, and the trial protocol continued as described above.

2.4. Human Judging Protocols & Data Analysis

We used two human judging protocols in this experiment – only the Skilled Human Judges approach was formally pre-registered with Goldsmiths. The second human judging protocol was agreed upon across experimenters prior to its execution, so in this case we used our email thread as a version of pre-registration.

2.4.1 Skilled Human Judges Protocol & Analysis

Our skilled judges were two trained observers who volunteered for the pilot study and had thus become familiar with DG's transcripts and the target types. We asked these two judges to complete two surveys, one survey for each set of five trials. Judges were asked to rate the relationship between the five comparison targets and the 5 dream transcripts using a proportional rating method in which all ratings must add up to 100 for each dream. For example, if judges were considering similarity to target 1, they were shown dream transcripts A through E and were asked to enter a number in a box next to each dream transcript. The higher the number, the higher they perceived the similarity between target 1 and the dream transcript. We required that these numbers add up to 100 – we made this constraint because we were interested in the range between the highest and lowest-scored matches, and we wanted the possible range to be the same for each target. However, as a result, the scores were not independent. The judges were blind to the correct matches between dream transcripts and targets; the dream transcripts were presented in a scrambled order that was agreed upon by CCF and JM. Once the judging was complete, we debriefed the judges on the correct target associated with each dream.

Our pre-registered data analysis approach was to take the ratings for each dream and average them across the two judges, then choose the top-ranked average as the "winner" of the rating. If that top-ranked average was also the correct target, this would count as a "hit" and if not, this would

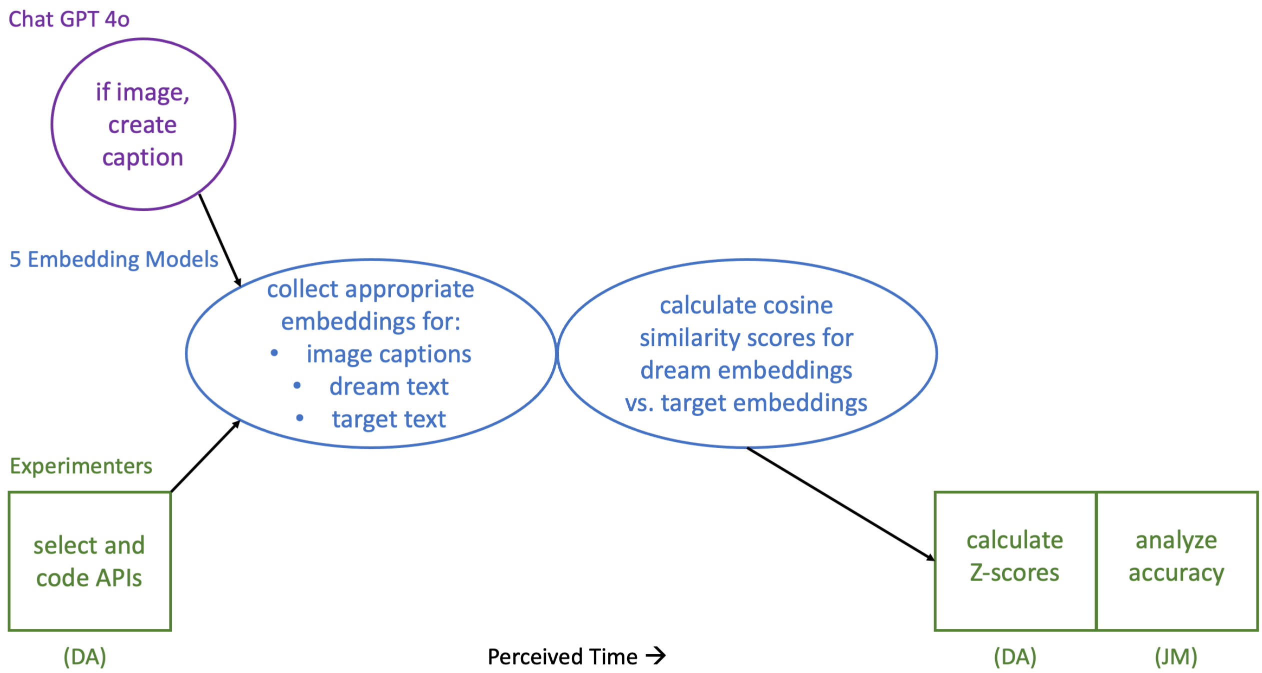

Figure 2. Schematic showing processing flow for AI judging. Initials in parentheses show authors' designated tasks.

count as a "miss." Then we planned to compare the number of hits to chance as our statistical test. However, after preregistration, AP later recognized that this judging method made the rankings given by each judge difficult to analyze, because the survey software forced the rankings to add up to 100. This made each ranking dependent on the others in an unusual way, making statistical analysis very difficult. Thus, here we present the original results without statistical analysis. We then designed exploratory judging protocols to address the original intention of the study and potentially contribute to understanding the nuances of judging protocols used in free-response experiments.

2.4.2 Unskilled Human Judges Protocol & Analysis

We knew we could not go back to our debriefed judges with the same material. Further, the team agreed an approach less likely to produce dependent responses would be to offer a single dream per judge to score against five potential targets. So, we used Amazon Mechanical Turk to find unskilled judges to perform the task of rating each target's similarity to the only dream they were shown on a scale of 1 (not similar) to 10 (very similar). There were 10 judges per dream and each judge was paid $2 USD. Filters were used to select judges who had submitted more than 5,000 projects ("hits") and had a > 95% acceptance rate. The task was meant to take 5 minutes per dream if judges read and thought about each target. The presentation order of targets and dreams was randomized.

To analyze the unskilled judging data for each dream, we calculated the mean similarity score across all 10 judges for each dream-transcript pair. The top-scoring transcript was selected as the judges' top choice. In one case there was a tie, and the tie was broken by taking the highest median score rather than the highest mean score across all 10 judges. When the top choice matched the actual target, this was considered a hit, and when it did not match, this was considered a miss. Then we calculated significance based on a binomial test with expected accuracy as 0.2, as there were five equiprobable target options per dream.

2.5. AI Judging Protocols & Analysis

To examine the range of capabilities of AI judging across different parameters, each dream was independently rated by five different text embeddings within appropriate large language models (LLMs). The processing flow is described in Figure 2. To examine how the materials used for judging influenced the performance of AI judges, we used four different material sets consisting of different combinations of dream transcript materials compared to target materials. We called these the "transcript-text-vs-target-text," "transcript-images-vs-target-text," and "transcript-text-and-images-vs-whole-target-text" and "transcript-images-vs-target-images" approaches. Note that we only included one approach using target images. This is because one target (the target for Transcript A) did not include an image. We thought the image-to-image comparison was the fairest comparison for our single target-image approach.

As appropriate for each material set, prior to rating the similarity between dream transcript materials and target materials, the text portion of the dream and/or image portion of the dream was extracted from the dream transcript. The text portion of each target was either broken down into paragraph-length "chunks" of text (in all material sets except the transcript-text-and-images-vs-whole-target-text material set) or combined into a single file (in the transcript-text-and-images-vs-whole-target-text material set). For material sets that included transcript and/or target images, Open AI's ChatGPT 4o was used to semantically "caption" images in a way that conveyed their meaning, rather than strictly their visual content. The model was prompted with: *"You are a professional caption generator. Please describe what you see in this image."* Output was limited to a maximum of 175 tokens, resulting in paragraph-length descriptions for each image. For all four material sets, the next steps in the AI judging process were the same.

Each one of five LLM embedding models was used to create text embeddings, which are vectors representing the semantic structure of the text and its association with other words and concepts, for the text derived from both dream transcripts and targets. A cosine similarity score was then calculated for each pair of text embeddings derived from the dream transcript materials and materials from all five of the dreams in each set, providing a discrete measure of the closeness of meaning between each dream and each target. Cosine similarity is a widely used metric for assessing the semantic similarity between high-dimensional vectors, such as those generated by large language models and computer vision models, etc. It is essentially a measure of the angle between two vectors in a high-dimensional space reflecting how similar the vectors are in terms of direction, but not magnitude. Because the embeddings from LLMs are normalized, the cosine similarity values range from 1 (completely aligned) to 0 (completely orthogonal).

The five embedding models included two from OpenAI: text-embedding-ada-002 and text-embedding-3-large ("Ada" and "L3"; https://platform.openai.com/docs/models#embeddings). The remaining three models were from three different organizations: Nomic ("Nomic"; https://huggingface.co/nomic-ai/nomic-embed-text-v1), Beijing Academy of Artificial Intelligence ("BAAI"; https://huggingface.co/BAAI/bge-large-zh-v1.5), and Snowflake ("Snowflake"; https://huggingface.co/Snowflake/snowflake-arctic-embed-l).

We took advantage of the speed of AI judging and our familiarity with a new semantically-normed image database (Abraham et al., in prep) to use one of the top-performing AI models to determine the similarity of all dream/target pairs in the context of 2707 possible "targets." These possible targets included 2606 text captions derived from 2606 photos of a variety of non-pornographic objects and scenes and 101 text and image captions from the 10 targets used in this study. All captions were obtained from Open AI's ChatGPT 4o using the same methods already described, above. Embeddings were obtained for the dream text and images as well as the 2707-item database via one of the top-performing models as assessed in the first analysis (L3; https://platform.openai.com/docs/models/text-embedding-3-large).

2.6. Statistical Analyses of AI Judging Scores

In both a limited and an expanded analysis, we generated a distribution of cosine similarity scores by comparing each dream transcript to each of the possible target vectors using Matlab via 1-pdist2(var1, var2, 'cosine'), which is the inverse of cosine distance. *Z*-score transformations of cosine similarity scores were calculated across all cosine similarity scores within each of the two target sets (limited analysis), and across all scores in the 2707-item expanded database (expanded analysis). We calculated Z-scores for two reasons. First, this allowed a probabilistic interpretation of the results. Second, cosine similarity is one of several standard methods for evaluating vector similarity, including Euclidean distance, dot product, and inner product similarity, all of which preserve the relative relationships between vectors. As a result, once normalized, the cosine similarity scores would yield the same rankings and ultimately the same statistical outcome in our Z-score and p-value analyses.

For the limited analysis, we used two slightly different approaches to analyze the Z-scores; the approach depended on the number of Z-scores obtained per target. For material sets producing multiple Z-scores per target (i.e., not the transcript-text-and-images-vs-whole-target-text material set), we selected the maximum Z-score within each target for each embedding model. For the transcript-text-and-images-vs-whole-target-text material set, this step was not necessary, as there was only one Z-score for each target and embedding model. After each dream had been associated with one Z-score for each target and embedding model, we recorded the highest Z-score across targets within that embedding model. If that Z-score was the score for the correct target paired with that dream, we considered this a hit for this embedding model. If not, this was recorded as a miss for that embedding model. This approach echoes our human judging methods. We also calculated the difference between the Z-score for the correct target and the average Z-score across all incorrect targets within an embedding model as a selectivity score for that model. This is not something we did with the human judging approach, but it provided extra information for those who wish to pursue the AI-judging approach. Results from the pre-registered analysis method (hits vs. misses) were compared to chance without correction for multiple comparisons, thus we had a low bar for significance in the limited analysis. Selectivity scores, a post-hoc method of differentiation between models, generally tracked hit rate and are presented without further analysis.

For the more conservative expanded analysis, to analyze the similarity between dream content and the extended possible-target database, we averaged Z-scores for all comparisons to elements from the correct target. We did this in two material sets: 1) dream images vs. every possible item in the 2707-item database, and 2) dream text vs. every possible item in the 2707-item database. Here we report average Z-scores and report corresponding uncorrected p-values for each dream, while noting p-values that exceed Bonferroni-corrected cutoffs (with alpha at .05, cutoff for significance would be .0025, based on two materials sets and 10 possible targets). Thus, the expanded analysis was more conservative than the limited analysis.

3. Results

3.1. Dreamer's experience

The dreamer (DG) was able to reach his goal of one lucid dream per week devoted to this experiment. There were times when he reported that he was worried he had dreamed about a past target – or had fears that the judges would confuse the correct target if a new dream seemed too much like a previous target. But he felt the final dream in the first set of 5 – women playing backgammon in a large stadium filled with people watching (Dream B, Figure B, left, see Appendix) – would be seen by the judges as very clearly matching the target for the day, which was about Iranian women's rugby (Figure B, right, see Appendix). This encouraged DG to continue the experiment – several other targets seemed to him and both CCF and JM to be at least somewhat related to the dream he'd had the night before, so we were all interested in what judging would tell us. Throughout the judging analysis, we used the dream of women's backgammon/women's rugby as a "bellwether" transcript/target pair for an additional check on judging quality, given that we believed most reasonable people who thoroughly looked at and read both the dream transcript and the target would pair these two. DG notes that it was the target related to this dream that he spent the most time investigating after it was revealed to him, and he was aware that this intense amount of target investigation could have theoretically (retrocausally) been responsible for the match with his dream. He reported that this idea "makes my head hurt."

	Humans: Skilled Volunteer Judges	**Humans: Unskilled Paid Judges**	**AIs: Five Embedding Models, Material Set 1**	**AI: Five Embedding Models, Material Set 2**	**AI: Five Embedding Models, Material Set 3**	**AI: Five Embedding Models, Material Set 4**
Judges per Dream	2 total for all 10 dreams	10 per each of 10 dreams	5 total for each of 10 dreams	5 total for each of 10 dreams	5 total for each of 10 dreams	5 total for each of *9 dreams*
Material Judged	whole transcripts vs. whole targets	whole transcripts vs. whole targets	transcript images vs. target text	transcript text vs. target text	transcript text & images vs. whole target text	transcript images vs. target images
Proportion Correct	0.30	0.10	mean: 0.36 best: 0.5	mean: 0.36 best: 0.5	mean: 0.38 best: 0.5	mean: 0.33 best: 0.44
Correct Dream Transcript/ Target Pairs	B, F, G	A	any of 3 top-performing models: **A**, **B**, E, G, **H**, J	any of 3 top-performing models: **A**, **B**, F, G, **H**, I, J	any of 3 top-performing models: **A**, **B**, C, F, **H**	any of 3 top-performing models: **B**, D, E, G, **H**, I

Table 1. Results from each form of judging (human, first two columns; AI, last four columns with each of four different material sets). Letters in bold highlight A, B, and H, the three commonly paired transcript-target pairs across the top-3 performing models and material sets.

Figure 3. Mean difference scores (bars) and total correct of the number of dream transcripts (circles) for all five embedding models and all four material sets. Orange circles differentiate that for the image-only material set, the highest possible score was nine correct because one target had no images in it. Asterisks indicate that the embedding model successfully paired the bellwether transcript-target pair (see text).

3.2. Skeptic's experience

The primary open-minded skeptic on our team (CCF) was struck both by the bellwether transcript/target pair and by another dream transcript (dream E, Figure E1, see Appendix). While there was little similarity to the target material except discussion of homes and moving from one place to the other, the drawn portion of the dream E transcript was surprising for CCF because the sketch looked very much like his own home (Figure E2, see Appendix) – which at the time had an advertisement for a local estate agent who was offering to make donations to his granddaughter's school in exchange for being allowed to put up a sign advertising their services for a few weeks outside relatives' homes (very similar to typical "For sale" signs but without those actual words). Although the sign was temporary and the home was not really for sale, the transcript surprised him. He did not tell either DG or JM about the coincidence until after all dreams were collected for the study. This is when DG revealed that he hadn't fully remembered the image of the town house he had seen in his dream, so he had searched on the internet for a picture of a town house, and drew the one that showed up (which is similar to many English town houses). CCF lived in an English town house, so this may have explained the similarity even though the "For Sale" sign felt remarkably coincidental.

3.3. Human Judging Methods

Judging by skilled human judges (3 hits out of 10; Table 1, first column) produced more hits than judging by unskilled human judges (1 hit out of 10; Table 1, second column). The three transcript/target pairs correctly picked by the human

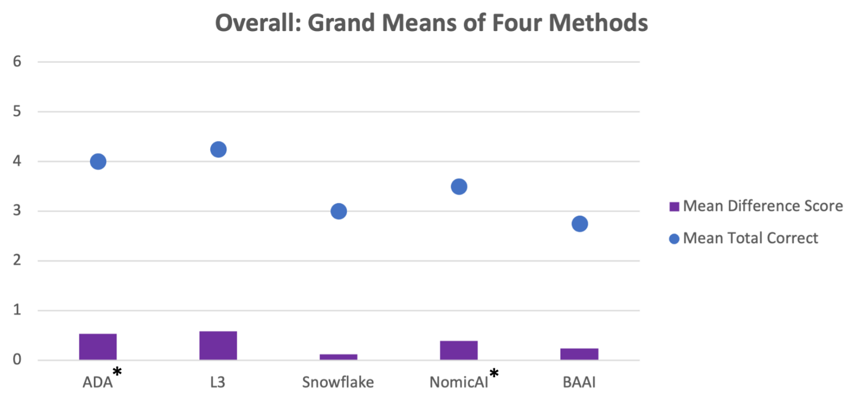

Figure 4. Mean difference scores (bars) and mean total correct (circles) averaged across all four material sets within each of the five embedding models. Asterisks indicate that the embedding model always successfully paired the bellwether transcript-target pair (Figure B, see *Appendix*), regardless of material set.

judges were dreams B (Figure B, see Appendix), F (Figure F, see Appendix) and G (Figure G, see Appendix). Further, both of the skilled human judges correctly matched the bellwether transcript/target pair as their top choice, while the unskilled judges missed what we had believed was a clear match.

The unskilled judges showed high variability in their similarity judgments. For example, for transcript A, mean similarity scores ranged from 3.3 to 5.8 on a scale from 1 (least similar) to 10 (most similar), with standard deviations in similarity scores ranging from 2.05 to 3.65. For the bellwether transcript/target pair, mean similarity scores ranged from 3.4 to 4.5 with standard deviations from 2.01 to 3.65. The only hit made by the unskilled judges was the match between dream transcript A, which contained the word "Mexican" and in which the dreamer sketched a woman and two children peeking around a mound of dirt (Dream A, Figure A, left, see Appendix). The correct target for transcript A was a story about a Native American woman whose daughter was said to be healed in a cave that had an image of the Virgin Mary on the walls (Figure A, right, see Appendix). This was also the only target among the 10 targets that was an all-text target with no images, so to make an appropriate judgment the unskilled judges would have had to read at least some of the target text. In contrast, for the other targets, they could have made an assessment by ignoring the text and looking at the images – and because they did not select our bellwether transcript/target pair (dream B), we believe that this is probably what they did.

3.4. AI Judging Methods: Limited Analysis

In the analysis limited to only the dream transcripts and the 10 targets, five AI embedding models performed variably across the four material sets (Table 1, last four columns), with clear "winners" for each model (Figure 3; asterisks mean that the bellwether transcript/target pair was correctly judged by that AI model for that method). The best material set was transcript-text-and-images-vs.-whole-target-text, with 5 hits out of 10 trials as the best performance across models and a mean accuracy across models at 38%. The other material sets were quite close, however – and the transcript-images-vs-target-images material set was at a disadvantage because one of the most common hits (Dream A) was absent from the material set because there were no target images. Keeping in mind we did not adjust for multiple comparisons in the limited analysis (see Methods), the results from the top-performing material sets were significantly above chance expectation (5 hits out of 10; success = 0.5, chance = .20, binomial test p = .033).

In terms of embedding models, the overall accuracy rate was easy to rank by averaging the number correct across material sets: L3 (best), Ada, Nomic, Snowflake, and BAAI (worst) as shown in Figure 4 (asterisks mean that the bellwether transcript/target pair was always correctly judged by that AI model). The only models that consistently correctly judged the bellwether transcript/target pair were Ada and Nomic. Interestingly, Snowflake was only in the top three scoring models when target images were involved in the material set (i.e., transcript-images-vs-target-images), and BAAI only occupied that position when the entire target text was included in the material set (i.e., transcript-text-and-images-vs-whole-target-text).

Observing the particular pairs that were judged correct by any of the three top-performing models (L3, Ada and Nomic) allows us to understand more about model consistency for the AI judging method and also determine whether the models were functioning by pulling in irrelevant noise or actual signals relating dream transcripts to targets (Table 1, last row). For instance, transcript/target pairs B, F and G were the three pairs selected by skilled human judges – these were among the correct transcript/target pairs selected by the top-performing models only for the transcript-text-versus-target-text material set, suggesting that this material set most closely reflected the factors (text from dream transcripts and targets) that might have had the greatest influence on the choices of the skilled human judges. Also note that there was no dream that was not correctly matched with its target pair by at least one top-performing model, but several dreams were matched within more than one material set: A, B, E from the first dream set and F, G, H (Figure H, see Appendix), I (Figure I, see Appendix), J (Figure J, see Appendix) from the second dream set. This leaves

	Dream images *Z*-scores	Dream images *p*-values	Dream text *Z*-scores	Dream text *p*-values
A	-.46	.64	1.22	.22
B	-0.15	.88	**4.99**	**$6x10^{-7}$**
C	-1.53	.13	-1.32	.19
D	-1.09	.28	-0.38	.70
E	-0.34	.73	-0.49	.62
F	-0.77	.44	-0.01	.99
G	-0.54	.59	-0.57	.57
H	-0.29	.77	0.01	.99
I	-0.49	.62	-0.38	.70
J	-2.66	.01	-1.34	.18

Table 2. Mean *Z*-scores and uncorrected 2-tailed *p*-values from AI judging comparing similarity between images and text from dream transcripts A-J with items in the expanded 2707-item possible-target database. The significant *p*-value (see Methods) and corresponding *Z*-score for the bellwether target/transcript pair (dream B) are bolded.

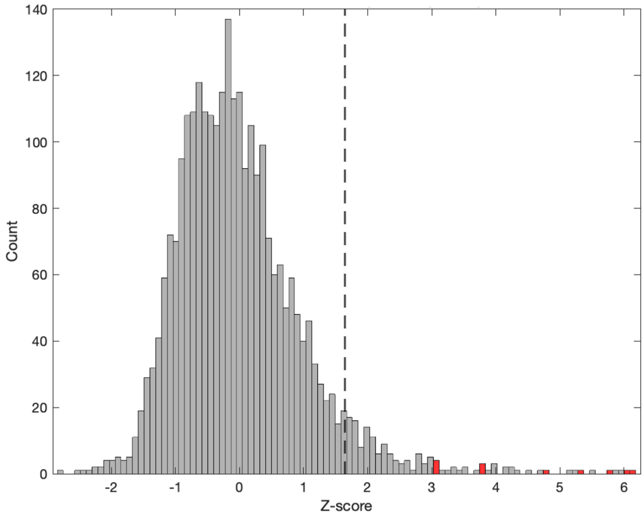

Figure 5. Distribution of *Z*-scores of the comparisons between the bellwether dream text (dream B) and the 2707-item expanded database. The bars containing the items belonging to the intended target are filled with red. Dotted vertical line gives single-tail significance value (*Z*=1.66, uncorrected).

dreams C and D as the least likely to be matched dreams (Figures C and D, see Appendix). Note that these two transcript/target pairs also seemed the least obvious matches to the experimenters.

The three top performing models were consistently correct across material sets for the transcript/target pairs of dreams A (where the Dream A target, which had no images, could be included in the material set), B, and H (bold letters in last row of Table 1). In the order of their occurrence in DG's dream life, these were the third (A) and fifth (B) dream in the first dream set, and the third (H) dream in the second dream set. All dream transcripts, associated targets, scores across scoring methods and AI-produced captions are available online for those who wish to analyze these results further (https://figshare.com/articles/dataset/Data_for_Future_Dreams_of_Electric_Sheep_Case_study_of_a_Precognitive_Lucid_Dreamer_with_AI_Scoring/28057937?file=51294638).

3.5. AI Judging Methods: Expanded Analysis

Examining the AI-ranked similarity between dream transcripts and every item in the expanded 2707-item possible-target database revealed that the bellwether transcript/target pair was statistically very unlikely to represent a chance similarity between the dream and the target. While the similarity between dream images and the correct targets corresponding to each dream was not impressive (Table 2), dream text was clearly related to the correct target in the case of the bellwether transcript/target pair (dream B), and much less similar to other targets from the experiment as well as the 2606 normed-image possible targets (Z=4.99; corrected p<0.000012 [see Methods], Table 2, Figure 5). No other transcript/target pair was judged to be more closely semantically associated with the intended target than expected by chance (see Methods), further underscoring the similarity between skilled human judgments and AI judgments in this dataset.

4. Conclusions and Discussion

In these data we find weak but encouraging evidence for the possibility that our case study participant and co-author DG is a precognitive lucid dreamer. The skilled human judging process that was originally pre-registered did not allow independent judgments, so we cannot easily assess whether the three "hits" exceeded chance. Meanwhile, the best-performing AI models (L3, Ada and Nomic) each performed beyond chance (50% correct) for one of the material sets, but the AI analyses themselves were exploratory. To determine whether DG can successfully dream precognitively at a rate higher than chance, a pre-registered confirmatory experiment will need to be performed. However, the expanded AI-judging analysis revealed a significant correspondence in the bellwether pair with respect to the expanded 2707-item database, strongly supporting the precognition hypothesis. We note that in the initial Maimonides research on Malcolm Bessent, the authors suggested a follow-up confirmatory study, which later emerged to show similarly compelling results (Krippner et al., 1971; Krippner et al., 1972). It remains to be determined whether the same results will be obtained for this lucid dreamer in the context of our approach. Further, because our results did not show a clear improvement between the two sets of dreams, it also remains to be determined whether precognitive dreaming can be learned by a skilled lucid dreamer.

4.1. Insights into precognitive dreaming

We again point out that there is no "proof" of precognitive lucid dreaming in this dataset as it currently stands, partially for the reasons already described and partially because there is rarely scientific proof of any natural phenomenon. The best scientists can hope for is a deepening understanding of the boundaries and characteristics of a phenomenon. We believe we have learned much about the boundaries and characteristics of precognitive lucid dreaming from this one case study. Intriguing insights arose from treating the dream transcripts like remote viewing transcripts, which we discuss presently, with similar insights arising as a result of comparing multiple forms of human and AI judging (below).

Precognitive lucid dreaming is similar to precognitive remote viewing done in a lucid dreaming state. Thus, it is relevant that at least two operational precognitive remote viewing team leaders have anecdotally reported to JM that one informative assumption is to assume the viewer's transcripts are always on target, then to consider any relationship between the transcript and the target informative. JM performed this exercise for the 10 transcript/target pairs. For most pairs, it was easy to see correlations between the transcripts and their targets, and these correlations were not particularly enlightening. But for the two transcript/target pairs that seemed to both the experimenters and the AI models to be the least well matched (C and D), the exercise was more fruitful.

If DG was truly accessing information about the targets precognitively, then for dream C the "mist on the mountain" and his rainbow may have referenced the name of the tow boat, CAHABA, which comes from the Choctow words meaning "water" and "above." Similarly, if DG was truly accessing the target for dream D, one interpretation is that the apparent "otherness" of the target (i.e., Afghan men in Kabul washing cars in a text written by an American) was expressed via an image of a Japanese woman surrounded by stickers (i.e., an unfamiliar sight for both the dreamer and the writer of the target text). Further, the stickers surrounding the woman's face may have been an interpretation of the beards and turbans seen in the target images. Each of these interpretations is clearly a stretch, otherwise each dream transcript would have been more often matched with its correct target. But the exercise provides two potentially useful insights: 1) precognitive dreamers may be able to obtain more information from a future target than first suspected (e.g., the name of the tow boat), and 2) a precognitive dreamer's relative familiarity with the target may influence how the target is perceived and depicted. These insights match those obtained anecdotally from precognitive remote viewing analysts. However, they would need to be tested in a controlled case study or larger experiment to determine if they are indeed reflective of DG's capacities or those of precognitive dreamers in general.

Comparing results across judging methods may also further our understanding of the nature of lucid precognitive dreaming. If the results from AI judging are compared to human judging, the AI judging process appears better at matching transcripts and targets. This may be because of the human tendency to fixate on particular unusual, emotional or action-related aspects of each target. The AI judging process constructs a semantic map or structure but does not focus on a particular type of meaning, so unusual connections are less likely to be missed. For instance, here is the image caption from Dream J (Figure J, see Appendix):

"In this image, we see a concerning and somber scene unfolding. The focal point of the image is a person lying in a hospital bed, connected to a ventilator machine via a mask that appears to be aiding their breathing. The individual is wearing a shirt with the name 'Keith Haring' visible, along with a graphic design characteristic of Haring's work. This might indicate that the person or those around them have an affinity for the renowned artist, though it doesn't necessarily provide context to the medical situation at hand. Surrounding the patient are three individuals who seem to be in a state of worry or deep concern. One of these individuals is more prominently featured, standing closest to the bed and wearing glasses. Their expression, though simplistic in representation, gives an impression of seriousness and perhaps distress, indicating the gravity of the situation. To the right of the patient's bed, there is what appears to be an oxygen tank, a critical piece of medical equipment suggesting that the patient is in dire need of respiratory support. The overall scene depicted suggests an emergency or critical care scenario in a hospital or medical facility, reflecting the fragile state of the patient and the emotional weight on the individuals present. Their presence conveys a sense of support and vigilance as they stand by the patient's side during what seems to be a challenging and uncertain time."

Upon reading the text of the target with which this was correctly paired within the transcript-images-versus-target-text material set (https://www.crviewer.com/targets/070905/070905.htm), it is clear that the text is written almost as if there is a war or battle playing out on the chess boards described there. This may be the explanation for the correct match within this particular material set. Further, the emphasis of the dream text on Keith Haring, who created blocky art not dissimilar to chess boards, is likely what most matched the target text within the transcript-text-versus-target-text material. These similarities could easily be missed by humans who would be likely to focus on the most dramatic aspect of the dream (e.g., someone in a hospital bed breathing from a machine) and the target (e.g., lots of people playing chess). Together, the improvement of AI judging upon human judging seems to suggest that precognitive dreams contain an array of information that does not always match our waking everyday expectations about the important aspects of a target.

4.2. Recommendations for Scoring Free-Response Tasks

Even if one does not accept that the scientific case for precognition has been already established, which is the view held by CCF and ADP, the AI judging process has shown itself to be reasonably useful for creating an autonomous and relatively unbiased judging method for free-response studies. Further, we were able to use the AI judging process to quantify the striking similarity of the bellwether transcript/target pair with respect to a much broader database of possible targets. We believe this to be a first for the field, comparing favorably to the standalone "figure of merit" approach used in precognitive remote viewing research (May et al., 2014).

Creativity, insight, and other human performance measures screen for and train performance using free-response tasks that have, up until now, required time-consuming human qualitative judgment to score. Using AI to turn these qualitative scores into quantitative scores – and in so doing, to better reflect the capacities of the individual(s) creating the free response – can potentially usher in a novel and more effective era of human performance assessment. To that end, we present several recommendations for researchers attempting to find the best scoring method for free-response tasks.

- Any human judge should be an experienced judge who has previously worked with, and received accurate feedback, about the type of materials you desire to be scored.

- Consider using non-real-world targets and controlling the amount of time the percipient has to examine the target to determine whether the amount of time observing the target relates to accuracy.
- To avoid biases introduced by human memory of other transcript or target materials, consider using the present LLM approach to score the materials in addition to, and potentially instead of, human judges.
- If using the present LLM approach, ensure that the semantic structure of any images included in the transcript or target sets is captioned in a reasonable way.
- Consider drawing from machine learning/computer vision approaches to assess syntactic rather than just semantic similarity (beyond the scope of this paper) between images drawn by the percipient and images selected as targets.
- Compare results from different material sets (text and images) as a way to gain insights into how different models respond to different material sets and, perhaps, what types of materials on which each human judge is focusing their attention.
- Consider pairing AI and human judges in a human-AI team to offer even better judging performance.

While current results present some evidence for dream precognition within the context of lucid dreaming, we continue to caution that thoughtful approaches to both human and AI judging are necessary to fully understand the evidence for, and characteristics of, dream precognition using any protocol or paradigm..

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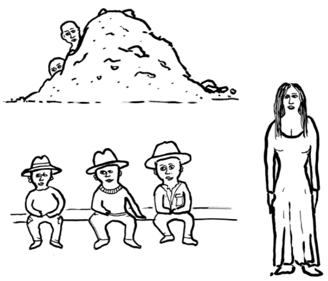
Appendix

Dream Transcript A

I was in a lucid dream and I went into my office. I walked over to my computer in order to see the target image. A piece of paper caught my eye. I tried to read it but the only word I can remember is **'Mexican'.** Then I turned on the computer monitor. I saw a grainy black and white film of **two children peeking out from behind a pile of dirt and debri.** The scene was kind of dirty and I had the feeling it was a **slum.** Then I saw the same kids sitting down on a kerb all wearing cowboy hats. I had a feeling these were **street kids**. There was also a **woman with a low cut top.**



Portion of Target

THE LEGEND

Back in 1754, a native indian woman from a small village often walked the six miles between her village and the neighbouring one. One day as she was making the journey, she approached the place where the trail passes down the steep sides of a deep gorge, across a river and up the other steep side of the gorge. Nobody ever liked this part of the trail, because there were stong beliefs among the Indians that a cave in the area was haunted. Beliefs in spirits and evil beings were strong amongst the indians.

She was carrying her daughter, a dumb-mute, in the Indian way, on her back, for safety, even though the girl was well old enough to walk on her own. By the time she had climbed part-way up the canyon slope, she was weary and sat on a rock to rest. (NOTE: Another version of the legend was that a storm arose, and she and her child hid in the rocks near the cave in order to get away from the storm. You can compare your results to the two versions of the legend.)

The daughter wandered up to the cave and began shouting (in her native language), "Mummy, there is a woman in here with a boy in her arms! She is calling me." The mother was beside herself with fright, because the cave was said to be haunted, and this was the first time her daughter had ever been able to speak. The mother did not see the figures her daughter was talking about, nor did she want to. She grabbed the child and hastened on to the other village.

When she told what happened, nobody took her seriously at first. However, as the news spread some asked if maybe it was true. After all, the child was now able to speak. So clearly, something had happened.

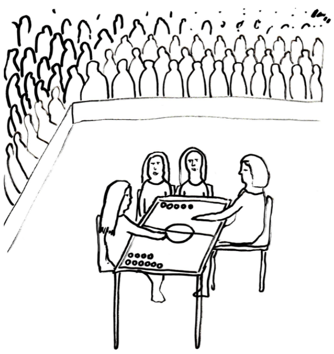
A few days later the child disappeared from her home. After looking everywhere the anguished mother guessed that her daughter must have gone back to the cave. Those few intervening days, the daughter had often said that the woman in the cave was calling her. The mother ran to the cave to find her daughter kneeling in front of a picture on the wall of the cave. The picture depicted a strangely dressed woman carrying a child, and two strangely dressed men with partially shaven heads in attendance.

Fearful of ridicule and fearful of the commonly held supersititons about the area being haunted by spirits, the mother kept quiet about the picture. But frequently she and her daughter went back to the cave to place wild flowers and candles in the cracks of the rocks near the picture, as a way of thanking the woman in the picture for giving the daughter the ability to speak. Some months went by, with both mother and daughter keeping their secret.

Figure A. Dream transcript A (left) and a portion of the paired target (right). Note that there were no images in this target. The full target can be found at: https://www.crviewer.com/targets/091104/091104.htm

Dream Transcript B

I had the sensation of separating from my body into a dream version of my bedroom. I walked downstairs into the office, went to my computer screen and said "Show me the target photo" I saw some women sat around a table playing **backgammon** although the markings on the table looked more like a **football (soccer) pitch**. They were sat in the centre of a **large stadium** with an audience watching.



Portion of Target

Women's rugby was first introduced to Iran 10 years ago, and has grown in popularity ever since.

Wearing tight-fitting headscarves and full tracksuits to protect their modesty, the players caused quite a stir when they played in Europe for the first time.

Taking to the field in a women's seven-a-side tournament in Cortina D'Ampezzo, Italy, they were dealt a 10-0 defeat by the host nation and then suffered a further 33-0 setback in a second game.

Unstoppable

Figure B. Dream transcript B (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/100811/100811.htm. This is the bellwether transcript-target pair.

Dream Transcript C

I had the sensation of separating from my body into a dream version of my bedroom. I walked over to my office and looked at my computer screen with the intention of seeing the target. I was looking at my Gmail inbox and could see lots of emojis in the subject lines of my received emails. There were cartoon **horses, pigs** and a **rainbow.** I also remember seeing an email from a woman called Naureen. I then said out loud "Show me the image Chris will send me tomorrow". I then saw what looked like a **forest in the mist,** this then transformed into a **temple on the top of a forested mountain.** There was what looked like Chinese writing on the temple and tourists stood in front of it.

Portion of Target

Towboat meets bridge

Tow boats guide barges loaded with coal down the Tombigbee river Mississippi. Near Demopolis, Alabama, the Rooster Bridge crosses the river. It has a narrow drawbridge on one side, and a very wide, low span of bridge on the other. Instead of trying to guide the loaded coal barges through the narrow span of the drawbridge, the tow boats customarily guide the barges toward the wide, low side, cut them loose, and let the current drift them under the bridge. The tow boats then race over to the drawbridge side, go through it easily, and then speed up to reconnect with their barges. They then hook up with the barges and continue down the river. That is how it was planned on April 28, 1979, but on that day, the river was at an all-time high, and the water was flowing much faster than normal. Just about everything that could go wrong did.

The tow boat CAHABA, commanded by Capt. Jimmy Wilkerson, approached the bridge, dropped its connection to two coal barges, to allow them to drift through the non-lifting East span of Rooster Bridge.

Figure C. Dream transcript C (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/110413/110413.htm

Dream Transcript D

I had the sensation of separating from my body into a dream version of my bedroom. I walked into my office. I attempted to switch on the light but it didn't really work so I just went straight to the computer and willed the screen to turn on. I asked to see the image for the LucidPrecog experiment and immediately an image of a **Japanese woman's face appeared.** She was surrounded by lots of **stickers containing cartoon images of animals.**

Portion of Target

An Afghani Car Wash

Washing the undercarriage

Even in war-torn Afghanistan cars need to be washed.

Taking into consideration how seedy and dusty roads in Afghanistan can be, the car wash business there has always remained active. It also provides more than a hundred Afghan men and boys in the Kabul area with at least a meager income in one of the poorest countries in the world.

Figure D. Dream transcript D (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/110914/110914.htm

Dream Transcript E

I had the sensation of separating from my body into a dream version of my bedroom. I walked downstairs into the office, turned on the computer and said “Show me the photo that I will see in a couple of hours for the LucidPrecog experiment”. A photo of a **fancy looking townhouse** appeared. It had a **wrought iron fence** in front of it and a **park or garden** behind it. I waited a little longer then a **For Sale sign** appeared.

Portion of Target

The location is a relatively flat valley in a very mountainous area at a high altitude. In fact, Kyrgyzstan is often called, "The roof of the world". Kyrgyzstan has 88 major mountain ranges, making up about more than 70 percent of the country’s territory. More than 60 percent of its people live in these very rural mountainous areas, mostly in poverty-level conditions, and mostly raising livestock.

A proud Kyrgyz family and their home.

The round-topped structure on the left of the top picture, like the one shown here with the proud family that calls it home, is a "Yurt". It is matted wool stretched over a wooden frame. The inside is a rug over a dirt floor, with portable furniture that can be easily moved when it is time to move the flocks. There is no electricity or piped-in water, so their

Figure E1. Dream transcript E (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/130116/130116.htm.

Dream Transcript E

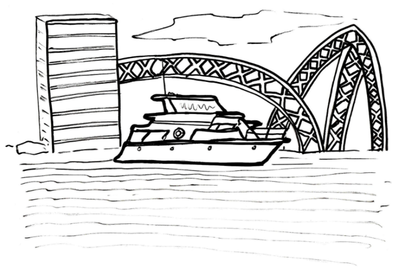
I had the sensation of separating from my body into a dream version of my bedroom. I walked downstairs into the office, turned on the computer and said “Show me the photo that I will see in a couple of hours for the LucidPrecog experiment”. A photo of a **fancy looking townhouse** appeared. It had a **wrought iron fence** in front of it and a **park or garden** behind it. I waited a little longer then a **For Sale sign** appeared.

CCF’s Home

Figure E2. Dream transcript E (left) and target-selector CCF’s home (right).

Dream Transcript F

I went into my office room. I went to the computer and said “show me the target photo for tomorrow” A photo of a **boat** appeared. There was a **city** behind it with **tall buildings**. There was also a **metal structure** with lots of **steel girders.**



Portion of Target

Figure F. Dream transcript F (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/060621/060621.htm.

Dream Transcript G

I had the sensation of separating from my body into a dream version of my bedroom. It looked a bit like my old house. I went into the office room, went to the computer and asked to see the target photo. I saw an image of a **supermarket checkout.** There was a **person laying on the conveyor belt** of the checkout. There were also **bananas, aubergines, a knife, chopping board, a poster of some tomatoes** and some **weighing scales.**

Portion of Target

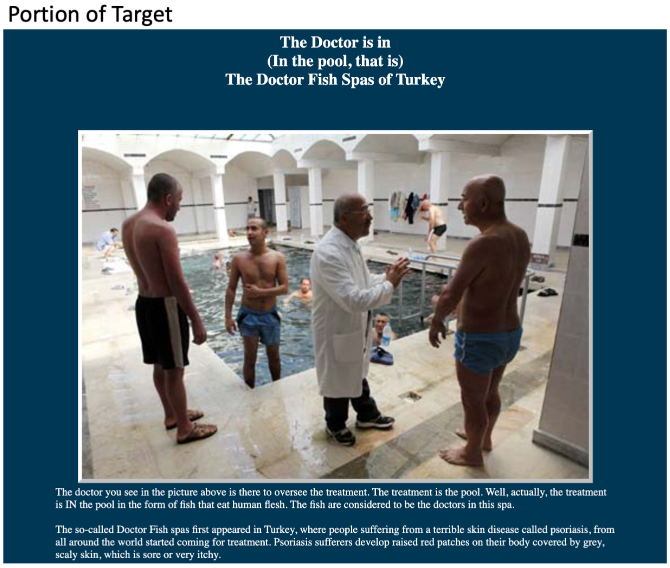


Figure G. Dream transcript G (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/090722/090722.htm

Dream Transcript H

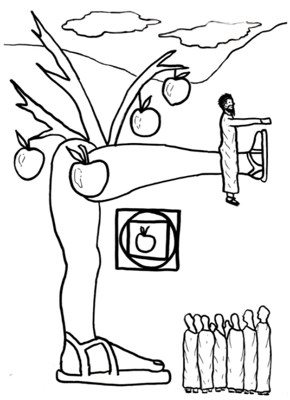
I was in a kitchen. I became lucid and remembered my task of seeing the photo. I went into the office. I don't think I vocalised my goal to see the target photo but I was definitely thinking it. On the screen appeared a **bike going up a mountain,** lots of **arches,** what looked like a **ruined cathedral**, lots of **tall piles of bricks or stones** and a **playground.** There were lots of **hills in the background** and a **black fence** in the foreground. There was also a **cluster of circles** in the bottom right, I'm not sure if these were people or not.

Portion of Target

Figure H. Dream transcript H (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/130206/130206.htm

Dream Transcript I

I had the sensation of separating from my body. The house looked a bit like my old house. I went into my brother's room and went on the computer. I asked to see the target image. I saw a **pair of legs** intertwined with an **apple tree** and an **apple at the groin.** There was a **robed bearded man** sat on one of the legs and a **crowd of robed people watching.** The whole thing had a **biblical** feel to it.



Portion of Target

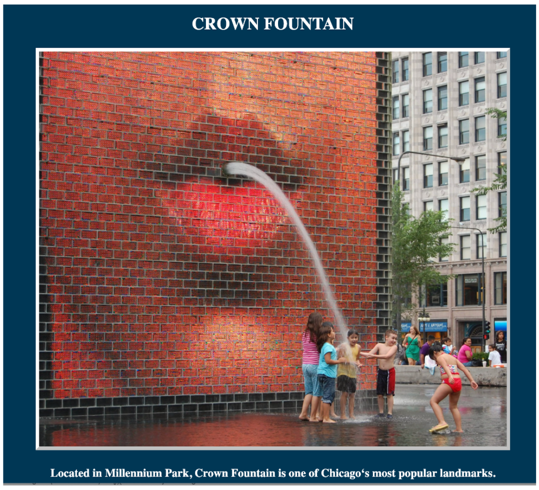
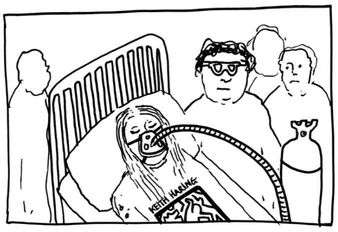


Figure I. Dream transcript I (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/160727/160727.htm

Dream Transcript J

I had the sensation of separating from my body into a dream version of my old bedroom. I went over into my brother's room where the computer is and I said "show me the target photo". I saw a photo of a **woman laying in a hospital bed.** She was on a **respiratory machine**. There were **tubes coming out her mask** and a **cylinder** of some sort next to the bed. There were people surrounding the bed, one of which was a **large lady with black hair wearing glasses.** The lady in the bed was wearing a **t-shirt of the artist Keith Haring.**



Portion of Target

The largest game of chess, ever!

(The following is exerpted from a report by Dagobert Kohlmeyer)
October 10, 2006 – Imagine: a simultaneous exhibition with (close to) 14,000 participants – possibly the only chess event that is visible from space. The signing of almost 2000 books in one go by the 12th world champion Anatoly Karpov. Mexico sets new records in chess.

(The following is coverage by the Associated Press)
More than 13,000 chess players waged war in Mexico City's central square on Sunday, battling to break the world record for the most chess games played simultaneously in one place.

Huge video screens in the plaza beamed a message announcing that the record had been broken. However, the event will not be official until it is certified by representatives of Guinness World Records, who attended the display.

The standing record was set last year in the city of Pachuca, 95 kilometers (60 miles) northeast of the capital, when 12,388 players sparred with their kings and queens.

Figure J. Dream transcript J (left) and a portion of the paired target (right). The full target can be found at: https://www.crviewer.com/targets/070905/070905.htm