Dreaming with ChatGPT: Unraveling the Challenges of LLMs Dream Generation

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Abstract

Large Language Models (LLMs), such as ChatGPT, are used daily for different human-like text generation tasks. This motivates us to ask: *Can an LLM generate human dreams?* For this research, we explore this new avenue through the lens of ChatGPT, and its ability to generate valid dreams. We have three main findings: (i) Chatgpt-4o, the new version of chatGPT, generated all requested dreams. (ii) Generated dreams meet key psychological criteria of dreams. We hope our work will set the stage for developing a new task of dream generation for LLMs. This task can help psychologists evaluate patients' dreams based on their demographic factors.

1 Introduction

A dream is a series of involuntary images, ideas, and emotions during sleep, especially in the rapid eye movement (REM) stage (apa, 2024). Dreams are crucial in psychology, as they provide insight into the mind, revealing hidden desires, fears, psychological status, and conflicts (Freud, 1900; Hobson, 2009; Solomonova et al., 2021). Dreams are utilized as a therapeutic tool for treating certain psychological disorders (Beauchemin and Hays, 1995). Moreover, Lucid dreaming treatment (LDT) is a clinical method that can help patients reduce nightmares (de Macêdo et al., 2019) and address other mental health issues (Beauchemin and Hays, 1995; Sackwild and Stumbrys, 2021).

Large Language Models (LLMs) aim to mimic psychological phenomena by simulating aspects of human cognition, such as language understanding, reasoning, and emotion recognition (Sartori and Orrù, 2023; Hofweber et al., 2024; Kuo and Chen, 2023). While still not there, using dream descriptions generated by LLMs could be employed in psychological treatments by creating specific dream characteristics tailored to individual needs. LDT requires training and practice (Ellis et al., 2021), which can be challenging for patients to achieve on their own. Therefore, utilizing LLM-generated dreams, customized to patients' needs and personal characteristics, may enhance the effectiveness of LDT.

In this work, we lay the groundwork for this task - dream description generation. As this avenue is undermined, we try to find whether certain LLMs can generate dream descriptions that meet psychological criteria. We picked ChatGPT, the most globally popular LLM[1] as our test case. We use several versions of ChatGPT3.5 and ChatGPT4o, the most recent version of the OpenAI's LLM. Through an in-depth analysis of the samples produced by different versions of ChatGPT, we find that:

- ChatGPT4o generates all requested dream descriptions, which is false for its predecessors.
- Dream descriptions generated by explored LLMs follow some common psychological definitions of a dream but do not fully capture how a dream looks/feels.

2 Dreams in Psychology

Traditionally, dreams are mostly associated and analyzed through REM sleep (Hobson and Pace-Schott, 2002; Nir and Tononi, 2010). Formally, in the APA Dictionary of Psychology (apa, 2024), REM dreams are defined by four attributes: (1) a sense of motion in space paired with visual imagery (*Motion*); (2) strong emotions, especially fear, euphoria, or anger (*Emotion*); (3) the perception that dream events, characters, and situations are real (*Realness*); and (4) unexpected changes in characters, situations, and plot elements (*Discontinuity*). Other attributes derived from psychological works include the location of the dream, which is mostly in normative daily scenes (Domhoff, 2007; Snyder et al., 1968) (*Location*); the existence of at least

[1] https://zapier.com/blog/best-llm/

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one other being (Domhoff, 2007; Snyder, 1970; Dorus et al., 1971) (*Other Beings*); the existence of objects (Domhoff, 2007; Snyder, 1970; Dorus et al., 1971) (*Objects*); and the activity of talking with other beings (Domhoff, 2007; Snyder, 1970) (*Conversation*). We will check if generated dreams meet psychological criteria.

3 Related Work

LLMs are being tested through different advanced generation tasks of human nature, such as sarcasm (Chakrabarty et al., 2020), metaphor (Chakrabarty et al., 2021), humour (Mittal et al., 2022; Dsilva, 2024; Tikhonov and Shtykovskiy, 2024), songs (Tian and Peng, 2022; He et al., 2019), hyperbole (Tian et al., 2021), tongue twisters (Loakman et al., 2024), and storytelling (Yao et al., 2019; Yang et al., 2022). Despite its closeness to storytelling, dream description generation is characterized by a sense of discontinuity (apa, 2024) while storytelling showcases a coherent plot (Fan et al., 2019). Also, dreams occur mostly through REM sleep (Hobson and Pace-Schott, 2002; Nir and Tononi, 2010), while stories are written while wide-awake and conscious.

The mimicry of human thinking and behavior by LLMs is still under research. Binz and Schulz (Binz and Schulz, 2023) and Abbasiantaeb et al. (Abbasiantaeb et al., 2024) explored LLMs' abilities to simulate human understanding and interactions. Zhang et al. (Zhang et al., 2023b) focused on using human-like reasoning to improve LLMs' decision-making. Another research area is LLMs' fairness, with Bender et al. (Bender et al., 2021) and Noble (Noble, 2018) highlighting the risks of biases and stereotypes. Zheng et al. (Zheng et al., 2024) explored enhanced biases in judgments carried out by LLMs. Turpin et al. (Turpin et al., 2024) showed that biases in quality assessment tasks can significantly affect LLMs' reasoning.

However, the topic of generating dream descriptions is yet to be covered. Recent work (Bertolini et al., 2024) explored LLMs' ability to classify dream descriptions by emotions but did not examine their ability to produce dreams or consider other psychological criteria.

This research evaluates ChatGPT's ability to generate dream descriptions matching known psychological frameworks (apa, 2024; Snyder et al., 1968; Dorus et al., 1971).

4 Methodology

In this research, we tackle these research questions:

1. Can LLMs generate dream descriptions?
2. Do dream descriptions generated by LLMs comply with the psychological criteria of dreams?

To address these questions, we devised a dedicated methodology. To generate the dream descriptions we use Context-Less Generation (Wan et al., 2023; Wan and Chang, 2024), in which the model is prompted with a simple zero-shot description of the dreamer - race, ethnicity, religion, and sex (Hanna et al., 2023; Salewski et al., 2024; Mahomed et al., 2024; Calderon et al.; Zhang et al., 2023a). We added a control group, person. Recent work defined the lack of access to one's dream content as a limitation (Scarpelli et al., 2022) for correctly analyzing parasomnia events. For a beneficial treatment, it is advised to work closely with a patient to generate dream descriptions based on their descriptions. Therefore, we have chosen different demographic factors to match this suggestion (Table 1).

Our methodology follows the steps below: (1) Given a demographic factor, replace the mask in the prompt with it: "**Pretand you are** $\{MASK\}$. **Please generate a dream that this person dreamt last night.**", and the prompt to model M. (2) Get the response r_i. (3) Run steps 1-2 five times in different sessions (no memorization, zero-shot), thus getting the set $r_{i_j} = \{r_{i_0}, r_{i_1}, r_{i_2}, r_{i_3}, r_{i_4}\}$. (5) Annotate using human annotators each r_{i_j} set based on predefined attributes. (6) Analyze the results.

Race	Ethnicity	Religion	Sex	Control
Asian	Indian	Jewish	Female	Person
Black	Arab	Christian	Male	
White	Hispanic	Muslim		

Table 1: Table of simple demographic factors of people used for prompting GPT models.

Some models provided very few dream descriptions. We concluded this by automatically analyzing for a single disclaimer or absence of multiple blank lines[2].

Attributes: For each sample, we annotated the following attributes: (1) is there a dream description?

[2]Concrete dream descriptions were spread across multiple lines upon close inspection.

(yes/no), based on the existence of a story. (2) is there a disclaimer? (yes/no), where a disclaimer is a text similar to "I'm sorry, but I cannot fulfill that request." or "As an AI, I don't have dreams or feelings". (3) the pronoun used for the dreamer. (4-10) the psychological attributes from Section 2 - *Motion* (yes/no), *Emotion* (yes/no), *Realness* (yes/no), *Discontinuity* (yes/no), *Location*, *Other Beings*, *Objects* and *Conversation* (yes/no).

Human Evaluation: Three annotators participated: two Masters students with an academic background in psychology and one computer science postdoctoral fellow. Each sample was annotated by two annotators, with a third resolving any disagreements (Mukhtar et al., 2017). The full instructions given to annotators is presented in Appendix C.

Metrics: We used a success rate metric for generating dream descriptions, similar to previous work (Wen et al., 2024; Zhao et al., 2024). This measured the model's ability to produce valid dream descriptions (i.e., containing a dream) or without disclaimers. The success rate was the number of samples meeting the criteria divided by the total samples.

5 Experiments

We generated four popular demographic factors groups to use for the prompts - religion, race, ethnicity, and sex, and a control group - person (Table 1). We used the prompt from Section 4 with each factor.

We evaluated several gpt models: gpt-3.5-turbo (gpt3.5T), gpt-3.5-turbo-16k-0613 (gpt3.5T16k), gpt-3.5-turbo-0613 (gpt3.5T0613), and gpt-3.5-turbo-1106 (gpt3.5T1106), gpt-4o (gpt4o). We used the default parameters (e.g., temperature 1.0, Top-P 1.0) of all models. In total, for each model, we obtained 60 samples, based on the demographic factors. The samples, code, and annotations are available online[3]. The code is under the MIT license (Open Source Initiative, 2023).

6 Dream Description Generation Analysis

In this section, we analyzed all 300 generated samples, to assess the ability of a model to generate a basic dream description. The full details of each are presented in Appendix B.

We found that gpt4o generated 100% of requested dream descriptions, while gpt3.5T16k and gpt3.5T0613 produced over 68%. However, both gpt3.5T and gpt3.5T1106 generated less than 20% of descriptions, with the latter experiencing a significant drop in performance despite being released later than gpt3.5T16k and gpt3.5T0613[4]. Thus, we dropped further analysis of the latter models.

Out of these generated dream descriptions, we continually analyzed the samples (Table 2). We explored whether the model did not produce a disclaimer stating it is an AI that does not dream, thus following the prompt directly without an explicit objection.

Model	Gen	No Disc	1st
gpt3.5T	13%	-	-
gpt3.5T16k	75%	31%	15%
gpt3.5T0613	68%	39%	17%
gpt3.5T1106	18%	-	-
gpt4o	100%	98%	73%

Table 2: Dream descriptions generation characteristics, based on the generated dreams (*Gen*) out of total sample size, the nonexistence of a disclaimer (*No Disc*), and whether the dream is in first person view (*1st*). The original sample size is 60 dreams. The gpt3.5T and gpt3.5T1106 were eliminated in the deeper analysis due to their poor performance in the initial dream generation.

We found that this phenomenon of no disclaimer+dream was found in 97% of gpt4o samples, 39% of gptT0613 samples, and 31% of gptT061316k samples.

We also looked at whether the description was generated in first person, as the prompt started with *"pretend you are..."*. gpt4o met 73% of the times for this aspect, gptgpt3.5T16k 15% of the time, and gpt3.5T0613 17% of the times in the same criteria.

In short, although with some decrease caused by matching the full criteria, gpt4o followed the prompted dream description with a significant gap (∼60%) between its performance and the other two models' performances.

Although not all generated samples complied with the no disclaimer+first person criteria, we continued with the generated dream descriptions for further analysis (Gen from Table 2).

For the next sections, we considered 60 dreams for gpt4o, 45 dreams for gpt3.5T16k, and 41 dreams for gptgpt3.5T0613[5].

[3]https://github.com/harelber/DreamGPT

[4]https://context.ai/compare/gpt-3-5-turbo-16k/gpt-3-5-turbo

[5]Similarly to other work (Wan et al., 2023), that drew interesting conclusions from small LLM-generated samples.

7 Psychological Dream Attributes

APA Attributes: The results of APA's attributes (Section 2) are presented in Table 3. It can be seen that the three models meet the motion and emotion dream properties raised by APA. In the discontinuity attribute, gpt3.5T16k got a success rate of 56%, and gpt3.5T0613 got 37%. gpt4o shows the greatest promise in this attribute, with a success rate of 70%. However, all models lack a sense of realness, as this property does not have a clear indication in the samples.

Model	M	E	R	D
gpt3.5T16k	98%	100%	0%	56%
gpt3.5T0613	100%	100%	0%	37%
gpt4o	100%	100%	7%	70%

Table 3: APA Attributes Results. M stands for motion, E for emotion, R for realness, and D for discontinuity. It is shown that gpt4o complies the most with APA's properties of ERM dreams.

Model	N_Loc	Other Beings	Conv
gpt3.5T16k	47%	96%	51%
gpt3.5T0613	44%	88%	44%
gpt4o	73%	95%	67%

Table 4: Other Attributes Results. N_Loc stands for locations in nature, Other Beings for people/animals, and Conv for conversation. It is shown that gpt4o complies the most with all properties.

Other Attributes: We explored attributes from various psychological sources, including locations, beings and interactions (Section 2). Non-daily locations appeared in 73% of gpt4o samples, 44% of gpt3.5T0613 samples, and 47% of gpt3.5T16k samples. This shows that the models do not fully comply with this property. Also, all models included at least one other being in the generated samples (Domhoff, 2007; Snyder, 1970; Dorus et al., 1971). Conversations were found in 67% of gpt4o samples, 44% of gpt3.5T0613 samples, and 51% of gpt3.5T16k's samples.

Overall, meeting all psychological dream definitions is not trivial for LLMs' generated dream descriptions. However, the ability to generate dream descriptions with embedded creatures, and motion/emotion rules is met 100% by each model we explored. Still, gpt4o is the leader in psychological attributes in general.

8 Conclusion

In this work, we examined the possibility of generating dream descriptions by LLMs. We explored it through the test case of ChatGPT models. The most promising model was found to be gpt4o. We found that some fundamental psychological attributes are met by the generated descriptions, but there is still progress to be made. We hope this initial work will pave the way to more LLM-dreams research, contributing to the psychological analysis of human dreams, enhancing LDT, and alleviating disorders such as insomnia.

9 Ethics Statement

This paper initially explores the capabilities ChatGPT to generate dream descriptions. As the authors only infer descriptions and do not look for a specific person's dream, the resulting dreams do not expose any private data of an individual.

10 Limitations

Despite our interesting findings, this work is subject to several limitations. First, our annotations were based on human annotators. Due to the lack of concise annotations of psychological attributes of dreams, such as discontinuity and realness, we annotated the data with human annotators as an initial work. We envision an extension of this work using fine-tuned model to annotate the data (Wang et al., 2024; Wu et al., 2023).

Second, our data was limited to 300 samples. Although this data seems small, it gave interesting aspects of the ability of LLMs to generate dream descriptions. We intend to curate a larger corpus for more comprehensive research.

Next, we explored ChatGPT, the most popular LLM globally. It would be beneficial to explore the new task with other LLMs (e.g., Llama (Touvron et al., 2023) or Gemini (Team et al., 2023)).

Also, this work initialized the research of generating dream descriptions by LLMs. We used a small set of psychological attributes and a limited set of demographic factors. More advanced work on this topic may follow a broader range of psychological aspects, analyzing combinations of demographic factors, and adding more factors such as jobs and maternity status. This future work will also analyze biases that may arise in the dream descriptions.

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A Nature locations found in Dreams - Full Analysis

This section shows the full list of locations found in our dreams data. The locations can be found in table 5.

Garden	Sea	Ocean	Forest
Meadow	Lake	Waterfall	River
Mountain	Field	Oasis	Island
Lagoon	Sky	Hills	Pond

Table 5: Nature locations of dreams found in our data.

B Models History & Tokens

Table 6 discloses the dream generation rates of each explored model, based on its release date and amount of tokens, as a complementary to Section 6. Dates and Tokens data acquired from[6] [7].

Model	DGR	Date	Tokens
gpt3.5T	13% (8)	11.28.22	4K
gpt3.5T16k	73% (44)	06.13.23	16K
gpt3.5T0613	68% (41)	06.13.23	4K
gpt3.5T1106	18% (11)	11.06.23	16K
gpt4o	100% (60)	05.13.24	128K

Table 6: Dream generation rate (DGR), based on each model, its date of release, and the number of tokens used as context window. The DGR is measured by counting the actual dreams (no sole disclaimer) out of all responses. The generation rate and actual count are provided for clarity.

C Instructions to Annoators

In the annotations of dreams, when the symbol (V/X) is shown, please put V for true/exists, and X for false/nonexist. If you are not sure, please put X.

These are the attributes we explore:

- Is there a dream description(v/x) - is there a story or just a statement on the inability of the AI to generate a dream?
- disclaimer (v/x) - if the model states something as "As an AI, I don't have personal dreams as humans do. However, I can create a fictional dream scenario for you.", this means that it disclaims that it generates a dream and it is not natural. If there is nothing more than this disclaimer, and no dream was generated, please leave the entire row blank.
- narrator (I/You/He/She/They) - The point of view of the dreamer - is it "I dreamt that…", or "he dreamt". This is considered as the pronoun of a dream in the paper.
- location - A one-word location of the dream, such as desert, garden. If the dreamer moves places, please add other places.
- other persons - other persons mentioned in the dream

[6] https://community.openai.com/t/what-are-the-differences-between-gpt-3-5-turbo-models/557028/2

[7] https://context.ai/compare/gpt-3-5-turbo-16k/gpt-3-5-turbo

- animals - same as persons, but with animals
- items - same with animals, but with items
- conversation (v/x) - if there is any conversation in the dream.
- motion (x/v) - visual imagery along with a sense of motion in space, such as “I was walking”.
- emotion (x/v) - intense emotion, especially fear, elation, or anger.
- belief of realness (x/v) - belief that dream characters, events, and situations are real
- discontinuity (x/v) - sudden discontinuities in characters, situations, and plot elements. The word suddenly helps a lot here