Dream Denoising Model: Generative Artificial Intelligence as a theoretical model for understanding dream-building

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Summary. Artificial Intelligence (AI) has been rapidly developing in recent times, and with it, new ways of understanding psychological constructs based on their underlying mechanisms. The purpose of the present article is to propose a theoretical model for phenomenological dream-building based on non-equilibrium statistical physics, particularly through core processes observed in Latent Diffusion Models and Generative Artificial Intelligence. Drawing upon the Integrated World Modeling Theory (IWMT) of consciousness, diffusion models and current literature about the phenomenology of dreams, the present model (henceforth, Dream Denoising Model [DDM]) argues that dreams are the result of a denoising process by which the Dreaming Brain System (DBS) resists entropic states caused by impaired information integration, which reaches its lowest during dreamless sleep or Slow Wave Sleep (SWS). To do so, the DBS relies on memories (dataset), conditioners such as Stable Traits and Transient States of the dreamer (prompt) and predictive processing (cross-attention) in order to generate and predict an internally-generated model. The article also proposes the notion of a Denoising Circuit by which the repetition of sleep cycles between alpha waves and slow waves enhances the DBS ability to generate and predict more complex, vivid and bizarre oneiric experiences.

Keywords: Dream Denoising Model, Latent Diffusion Models, Dream-Building, Artificial intelligence, Dream Phenomenology

1. Introduction

Artificial Intelligence (AI) has greatly advanced in the last few decades, and has advanced even more rapidly in recent years. From intuitive chatbots and machine learning models to deepfakes and AI-assisted storytelling, AI is becoming an ever-growing tool in various domains, impacting people's lives in different ways (Aggarwal et al., 2022). Many AIs function on the basis of machine learning and data mining, which have also become more sophisticated and precise as research progresses. One of the most common models currently used in *Generative Artificial Intelligence* (GAI) engines are *Diffusion Models* (DMs). In other words, a diffusion probabilistic model (or "diffusion model", for short) is an advanced machine learning algorithm that creates high-quality data by gradually adding "noise" to a dataset, and then reversing such a process. By analogy, one could think of diffusion models as the process by which a drop of ink diffuses through a glass of water until the water is completely colored, and then reversing the process to achieve its initial state ("reverse diffusion"). Through this complex process it is possible, for instance, to create fairly precise, realistic and high-quality images based on prompts (text-to-image AI generation), other images (image-to-image AI generation), or a mix of both (multi-prompting).

Many fields have posed their own debates and questions about AI and its potential, psychology being one of them. For instance, Abrams (2023) has stated that "AI chatbots can make therapy more accessible and less expensive. AI tools can also improve interventions, automate administrative tasks, and aid in training new clinicians." (p. 46). Not only could AI directly impact the professional exercise of clinical psychologists, but also provide researchers with a model in itself for better understanding and studying psychological constructs (See Halina, 2021; Hoel, 2021; Munnik & Noorbhai, 2024; Prasad, 2023; Sufyan et al., 2024), in a rather similar fashion as the computational analogy invoked during the cognitive revolution.

One of the increasingly studied domains in psychology that could make good use of modern AI is dream phenomena, as approached by oneirology. Although brain activity, phenomenological experiences, and some cognitive functions are relatively similar between *Rapid Eye Movement* (REM) sleep and the waking state (Nir & Tononi, 2010; Siegel, 2021), the oftentimes bizarre and seemingly arbitrary images evoked in dreams raise numerous questions about the nature and genesis of its content.

Despite some progress being made on the psychological and neurobiological mechanisms involved in dream generation (See Hobson & McCarley, 1977; Medrano-Martínez & Ramos-Platón, 2014; Ruby, 2011; Vitali et al., 2022), several questions about such processes remain unanswered. For instance, what dream-building mechanism accounts for phenomenological differences throughout different sleep stages, why bizarreness (hereby understood as "unusualness", as later described), although unlikely, is still more commonly reported in some stages, what is the connection (if any) between deep sleep and the fading of consciousness

in relation to the generation of dreams, and what general criteria are met for the dreaming brain to "pair" some dream elements with others, are among these questions. Whether dreams help to consolidate and/or forget certain memories (Feld & Born, 2017); aid to regulate emotions (Cartwright, 2005; Walker, 2009); prevent the takeover of the visual cortex (Eagleman & Vaughn, 2021); prepare for real-world problems (Jouvet, 1998; Momennejad et al., 2018); or simply are the by-product of imaginative waking cognitive capacities that have adaptive value (Domhoff, 2022), what has been clear is that most contemporary theories of dreams do not fully address *how* dreams elements are organized into a visual narrative. Within the framework of neurocognitive theory, computational sciences, phenomenology, and deep learning research, the aim of this paper is to hypothesize and describe an isomorphic relation between the underlying mechanisms of diffusion models and the capacity for "dream building". In other words, it is argued that dream content emerges in a way that resembles GAI through diffusion models.

A brief overview on the basic functionality of DMs is presented in Section 2. Section 3 describes the association between consciousness and sleep and its relation to the proposed model, while Section 4 describes the Dream Diffusion Model itself. The main findings, as well as the discussion, are included in the final section.

2. Diffusion models in GAI

To better understand the present model, it is necessary to briefly describe how diffusion models operate at a conceptual level. For practical purposes, the examples herein outlined correspond to AI image generation, even though such mathematical models can be and are indeed used for a wide range of applications.

First and foremost, it is important to note that DMs are inspired by thermodynamics. "Diffusion" refers to a natural phenomenon, which involves "the passage of elementary particles through matter when there is a high probability of scattering and a low probability of capture" (Rennie & Law, 2019). Since systems tend to reach equilibrium, energy moves from an area of high concentration to one of lower concentration. Even though the reversed process of diffusion is physically impossible to achieve, it is possible to do so in the digital world through algorithms.

Text-to-image generation is probably the most popularly utilized feature, in which an AI generates an image based on a text prompt, provided by the user. DMs are trained on preestablished databases (e.g., a *pool* of images), with which are then capable of transforming and generating new data. The way they work is by adding *gaussian noise* to an image (i.e., gradually "destroying" the data, increasing its entropy) until a point in which the resulting image is nothing but noise (X_T), and then reversing the process by deducting noise through a step-by-step-like Markov chain (in the number of thousands of times) to obtain a completely denoised result based on the text command. Sohl-Dickstein et al. (2015) described it as it follows:

The essential idea, inspired by non-equilibrium statistical physics, is to systematically and slowly destroy structure in a data distribution through an iterative forward diffusion process. We then learn a reverse diffusion process that restores structure in data, yielding a highly flexible and tractable generative model of the data (p. 1).

For AIs to revert the diffusion process from X_T to X_n (whereas X_n represents the aspired outcome elicited by the prompt), they rely on *Artificial Neural Networks* (ANNs), an interconnected group of nodes that collaborate to approach complicated problems (similar to the organization and functioning of neurons in the human brain). These ANNs are
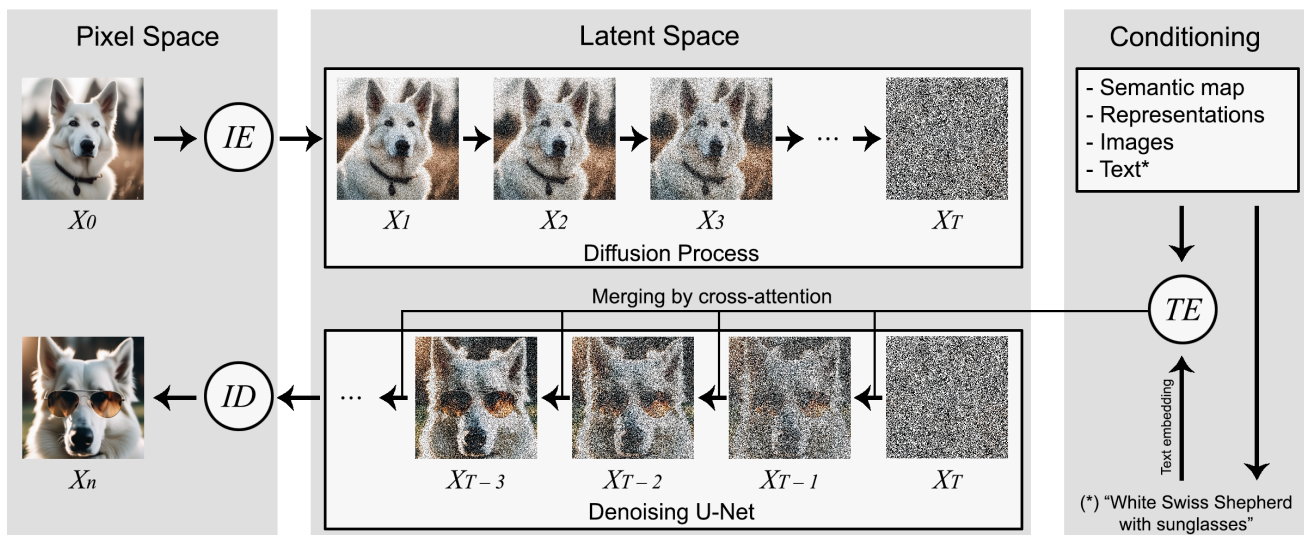

Figure 1. Latent Diffusion Model scheme.
The two main components in LDMs are forward diffusion and reverse diffusion (Zhao, 2023). Through forward diffusion, images from a dataset (here represented by a picture of a dog, X_0) go through an Image Encoder (IE), which transforms them into vectors (hence entering the Latent Space, where processing occurs more rapidly). Once in the Latent Space, the vectors representing the images are "destroyed" (i.e., noised) gradually and sequentially through thousands of steps, until these are transformed into latent noise samples (X_t). A Text Encoder (TE) translates the prompt (text instructions) into vectors called "text embeddings", so that the model can understand its semantic meaning. The image generation takes place due to the process of the second component: reverse diffusion. The model gradually removes the noise thanks to a trained noise predictor (U-Net noise predictor) that removes noise step by step, following the instructions given by the prompt, until a clearer image is generated. In this example, only text conditioning is used, being "White Swiss Shepherd with sunglasses" prompted. A cross-attention mechanism merges the text embedding with the resulting image in each denoised step. Conditioning constantly informs the noise predictor about whether each denoising step is correctly replicating what the prompt indicates. The Image Decoder (ID) then translates the image from the Latent Space to observable pixels: the resulting image (X_n). Figure simplified and adapted from Rombach et al. (2021). *Note*. Images generated using the prompts "White Swiss Shepherd" and "White Swiss Shepherd with sunglasses" respectively, by Stability.ai, *Stable diffusion online*, 2023. (https://stablediffusionweb.com).

trained to successfully denoise images in order to produce detailed, realistic and visually coherent images. One key problem of previous diffusion models used in GAI was its high consumption of resources, requiring more expensive and efficient hardware. To solve this issue, Rombach et al. (2021) proposed a *Latent Diffusion Model* (LDM) that was performatively better and relied on limited computational resources, allowing for "near-optimal point between complexity reduction and detail preservation, greatly boosting visual fidelity" by applying DM training in a latent space of pretrained autoenconders. What is innovative about LDMs is that the diffusion process is applied to an encoded latent representation of the image, rather than to the image itself. As further explained in subsequent sections, one can think of the realm of dreams in a similar way to how we conceive latent space in LDMs, insomuch oneiric images are not just enacted –or "projected"– directly from visual stimuli stored in memory, but are rather generated from an as-accurate-as-possible representation of them. Dream reports featuring incongruous elements, whether distorted or contextually inconsistent (Revonsuo & Salmivalli, 1995), as well as adversarial dreaming arising from semantic similarities (Deperrois et al., 2023), provide evidence supporting this parallel. Fig. 1 graphically synthesizes the way LDMs operate.

A pivotal idea in Diffusion Models is the concept of noise: the process of adding and/our subtracting noise to a dataset is the cornerstone of GAI. Deep neural networks in early GAIs dealt with an issue known as *overfitting*. Overfitting occurs when a machine learning model fails to effectively generalize to all data types within its domain, and instead aligns too closely with the training dataset. In other words, when a deep neural network learns to fit one particular dataset, it becomes less generalizable to others. One way to overcome this issue is by injecting noise into the dataset, making it more corrupted and therefore less self-similar. Analogically, a relatively recent hypothesis proposed by Hoel (2021) states that the human brain faces similar challenges when it learns. In this context, dreams serve as a form of biological noise injection that prevents *overfitting* during wakefulness.

3. Consciousness and dreaming

The present model is based on the premise that the configuration of dreams is closely linked to fluctuations across different states of consciousness, analogous to the varying levels of noise introduced or removed from vectorized data in LDMs. These states of consciousness may differ in terms of awareness, arousal, the extent of workspace-like interactions in the brain, and the degree of integrated information. Such variables are examined in detail in the following sections.

3.1. Awareness-arousal continuum

Parallels between LDMs and dream generation ought to be drawn, firstly, on the basis of temporality. There used to be thought that dreams only took place during REM sleep, but it is now known that dreaming can occur during NREM phases as well (Siclari, Baird, et al., 2017; Siclari, Bernardi, et al., 2018). Nonetheless, REM dreams tend to be "longer, more vivid, bizarre, emotional and story-like", whereas NREM dreaming (more specifically during the N2 phase) is "less frequently recalled and, when present, is shorter, less intense and more thought-like and conceptual", and "dis-

plays smaller connectedness" (Martin et al., 2020, p. 1, 17; McNamara, 2023). Sleep cycles are determined by a combination of neurobiological and psychological variables; however, for the purposes of the present article, phenomenological traits associated with different dream phases (i.e., the oscillation of conscious states) are mainly discussed.

The two-component scale proposed by Laureys et al. (2007) is useful in understanding consciousness as a continuum, consisting on two key variables: *arousal* (X axis), which is the "behavioural continuum that occurs between sleep and wakefulness" (p. 723), and *awareness* (Y axis), operationally defined as an "appraisal of the potential to perceive the external world and to voluntary interact with it" (i.e. awareness of environment), and as "self-referential processing, accounting for distinguishing stimuli related to one's own self from those that are not relevant to one's own concerns, to be at the core of the self" (p. 723), i.e. awareness of self. In other words, consciousness requires a combination of awareness, (the contents of consciousness) and arousal at brain level. Given these measures, physiological variations in consciousness result from a positive correlation between perceptual awareness (content of consciousness) and arousal (vigilance, degree of consciousness). This model has received broad acceptance in clinical neurosciences, and variations on its components have been empirically tested (see Lee et al., 2022).

Analogically, dream stages can be also represented along this continuum in relation to the direction, form and degree of the relationship between awareness and arousal (see Fig. 2). NREM stages (i.e., N1, N2 and N3) progress along the consciousness continuum as levels of arousal and awareness both decrease; nonetheless, it is observed that REM
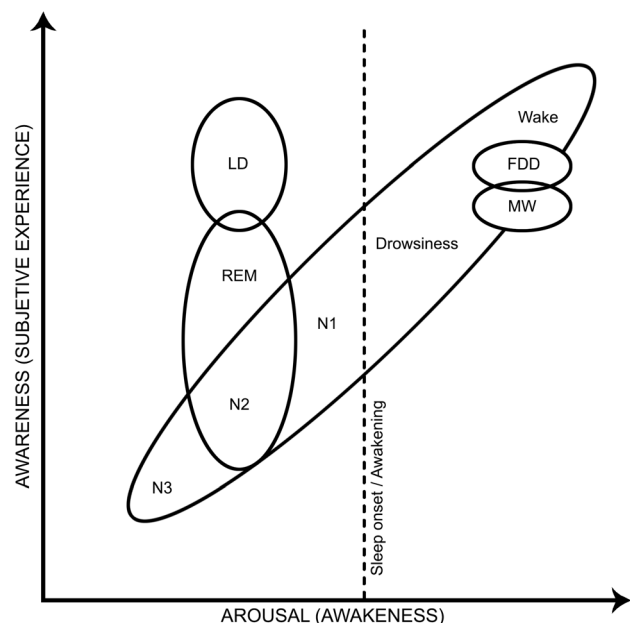
Figure 2. Dream-like experiences throughout the consciousness continuum.
Consciousness can be conceived as a continuum defined by a correlation between awareness (the content of consciousness) and arousal (the degree of consciousness). REM dream is a paradoxical state with increased awareness but low arousal. Lucid dreams (LD) show an even higher level of awareness determined by the dreamer's capacity for volitional control (mental agency). Likewise, focused daydreaming (FDD) is also characterized by purposeful, imaginative mental agency, while mind-wandering (MW) shows slightly decreased awareness (while still awake) as the control of the mental flow is lessened. Modified from Laureys et al. (2007).

sleep peaks and deviates from the correlation with heightened awareness, yet a low level of arousal; this paradoxical state characterizes REM dreams. Even further from the correlation line, lucid dreams (those in which the dreamer is aware of being in a dream) occur with an even increased degree of awareness than REM sleep.

Not only sleep stages elicit dream-like, subjective experiences, but so do other forms of thought during wake, such as daydreaming. Most researchers utilize the term "daydreaming" when referring to the specific instance of focused daydreaming, and would oftentimes characterize it as being interchangeably with mind-wandering. This can be problematic as it neglects the core differences between both mental phenomena. The term "daydreaming" refers to a supercategory of mental phenomena consisting of two distinct instances: *mind-wandering*, and *focused daydreaming*. Within the stream of consciousness, the segment of mind-wandering is characterized by a fairly unrestrained flow of mental episodes, thoughts, experiences or subjects that switch from one to the other in a rather spontaneous way, whereas focused daydreaming involves a more controlled and purposefully generated course of thought that is structured in a rather narrative flow (Domhoff, 2022; Dorsch, 2014). According to the neurocognitive theory of dreaming, parallels between waking cognition and dreaming could be explained –at least partially– by the role of the Default Mode Network (DMN), which would provide some of the neural substrate that supports both daydreaming (i.e., mind-wandering and focused daydreaming) during wakefulness, and dreaming during the various stages of sleep (Domhoff & Fox, 2015; Domhoff, 2022). According to the conceptual differentiation made by Dorsch (2014), it can be argued that mind-wandering unveils a fairly lessened awareness as oppose to focused daydreaming, in the same way some authors (See Modolo et al., 2020; Jöhr, et al., 2015; Gosseries et al., 2011) locate lucid dreaming above REM sleep in relation to the awareness axis given its volitional nature (see Table 1).

In spite of its shared neural substrate and mutual capacity for internally generated thought, focused daydreaming and mind-wandering phenomenologically differ from dreams during sleep (e.g., lucid dreams and REM dreams). Dreams tend to be more bizarre and fanciful, with decreased executive functions (Hartmann, 1996, as cited in Balgrove et al., 2019), whereas daydreams are usually directed towards a higher number of worries closely related to waking life experiences.

As shown in Section 4, daydreaming could also be accounted by the DDM, given that such experiences operate on certain dynamics similar to those observed in NREM and REM dreams.

3.2. Integrated World Modeling Theory and the Overfitted Brain

Among modern theories of consciousness, one that provides a structured framework for the present model given its sophistication, integration, and relation to computational sciences and artificial intelligence, is the *Integrated World Modeling Theory* (IWMT) of consciousness (Safron, 2020, 2022). IWMT assess the two main aspects of consciousness described by Block (2008) and Pantani et al. (2018): phenomenal consciousness (p-consciousness) and access consciousness (a-consciousness), by drawing upon *Information Integration Theory* (IIT) (Tononi, 2004; Tononi et al., 2016), and *Global Neuronal Workspace Theory* (GNWT) (Baars, 1988; Dehaene, 2014), respectively. A detailed explanation on each of the theories that constitute IWMT, as well as its functional, algorithmic, and implementational levels of analysis, both exceed the scope of this article, yet basic premises derived from them, as well as their relation to the present model, are briefly described.

IWMT attempts to link IIT and GNWT through the lenses of the Free Energy Principle and Active Inference (FEP-AI). FEP-AI states that perception takes place within the context of actions such as "foraging for information and resolving model uncertainty" (p.3), so that persisting systems can minimize prediction error (i.e., free energy) in order to preserve themselves. So as to resist entropy, persisting systems have to entail predictive models by which they make selective decisions among various alternatives. Here, the *Dreaming Brain System* (DBS) plays an important role. In the context of the present model, the DBS is the term coined to refer to the brain enacting as a persisting system with the ability to behave as a self-predicting generative model during sleep, which necessarily takes into consideration the inherent neurocognitive impairments attributed to this state. One could argue that, since dreams are experienced consciously (Kahn & Gover, 2010), the DBS must operate on broadly similar FEP-AI terms. Nonetheless, dreams are characterized by being fairly independent of external sensory stimuli; moreover, it is argued that stimulus-independent thought overlapping with dreaming is phenomenologically different from stimulus-dependent thought (Gross et al., 2020). As Bucci & Grasso (2017) have argued, "brains are sophisticated neural networks that rely on statistical inferences to produce the best prediction of the incoming sensory input and of their own internal states" (p. 3). Based on the Predictive Processing Framework, this distinctive feature of dreaming would require the DBS not only to selectively infer each possible outcome given prior states out of a cluster of events to minimize the amount of prediction error and reach equilibrium, but even recreate such events by retrieving elements from memory in the absence of perceivable external stimuli.

IIT postulates certain phenomenological axioms (premises about the nature of experience) and then infers the

Table 1. States of consciousness within the dreaming continuum schematized according to low or high arousal and awareness in relation to each other.

State	Arousal	Awareness
Active wakefulness	+ + +	+ + +
Focused daydreaming	+ +	+ +
Mind-wandering	+ +	+
N1	–	–
N2	– –	– –
N3 / SWS	– – –	– – –
REM	– –	+ +
Lucid dreams	– –	+ + +

Note. The plus sign (+) indicates high arousal or awareness in relation to the other dimension (i.e., awareness that is higher than arousal or arousal that is higher than awareness), whereas the minus sign (–) indicates a lower dimension in relation to the other. Equal combinations of +/+ or –/– indicate that both dimensions are equally high or low, respectively. The number of signs describing each distinct state illustrates the degree of such dimensions only in relation to other stages (more than / less than).

properties of physical systems that can account for it. It poses that a physical system is conscious if it is capable to integrate causally effective information. The amount of integrated information in a physical system is denoted by the metric Φ (the "quantity" of consciousness available to a system). According to IWMT, IIT approaches p-consciousness (or subjectivity, experience) by stating that posterior medial cortices and the inferior parietal lobule both play an important role integrating attention schemas, body schemas and visual models of the world in generating conscious experience (Safron, 2020). Moreover, it could be argued that the dreaming continuum (as shown in Table 1 and Fig. 2) covariances with the amount of integrated information, being Φ at its lowest during Slow Wave Sleep (SWS, oftentimes dream-

less sleep), and at its highest during active wakefulness. As Tononi (2014) states, "all indications from TMS-EEG experiments are that (…) information integration is high in wake, collapses in early NREM sleep, and recovers, though not fully, in REM sleep." (p. 216).

On the other end, the GNWT states that "in the conscious state, a non-linear network ignition associated with recurrent processing amplifies and sustains a neural representation, allowing the corresponding information to be globally accessed by local processors" (Mashour et al., 2020, p.776). GNWT is an updated variation of the Global Workspace Theory (GWT) described by Baars (1988), which argues that conscious experience is represented by broadcasted information that becomes widely accessible to local
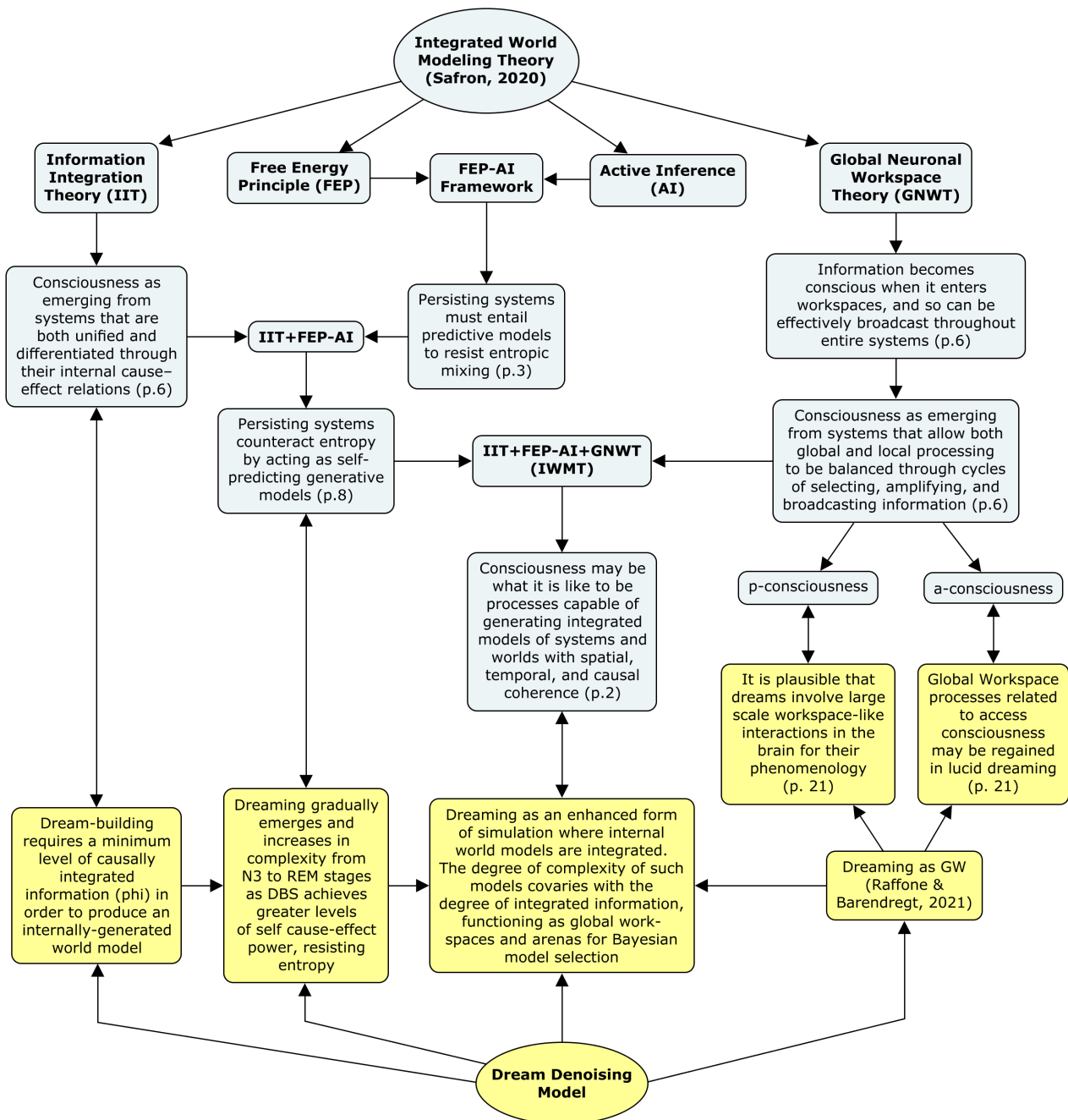

Figure 3. Correlates between the Dream Denoising Model and IWMT.

processors across the brain. GNWT draws upon GWT by including defined networks in the brain as the neural substrate. In the realm of dreams, Global Workspace processes relate to both a-consciousness (lucid dreaming and awareness) and p-consciousness (embodied integrated scenes with narrative structure) (Raffone & Barendregt, 2021). Fig. 3 synthesizes the main premises of the present model and their correlated theoretical framework from IWMT.

Notwithstanding the above, predictive processing approaches face important critiques. Firstly, it fails to explain the "dark room problem" (i.e., why organisms do not universally tend to seek stable environments). Secondly, non-lucid dreams lack the agency that would be required to simulate realistic action-outcome relationships. Thirdly, and perhaps most importantly, the hypothesis that dreams reduce model complexity and improve predictions through progressive optimization does not align with the fact that dreams do not necessarily become simpler or more consistent over time. To address these issues, Hoel (2021) proposed the Over-fitted Brain Hypothesis (OBH), –previously introduced–, which proposes that dreams act as a natural way for the brain to prevent overfitting (i.e., when a model learns the training data *too well*, capturing not only the underlying patterns, but also the noise and irrelevant details specific to the dataset). According to the OBH, the brain faces similar issues of overfitting in its daily learning. Dreams can be very different from our waking experiences ("training data") because of their oftentimes unusual elements. This randomness helps the brain break out of rigid patterns of thought and learning by injecting noise during sleep, enhancing its ability to handle new unfamiliar situations; in other words, "the distinct phenomenology of dreams exists to maximize their effectiveness at improving generalization and combating mere memorization of an organism's day", and "it is the strangeness of dreams in their divergence from waking experience that gives them their biological function" (Hoel, 2021, p. 7). This hypothesis could best explain what Domhoff (2022) refers to as "cognitive glitches" in dreams (referring to bizarre elements); however, the main premise of the OBH is challenged by research suggesting that bizarre, novel or unusual dreams are quite infrequent (Dorus et al., 1971, as cited in Domhoff, 2022). Without disregarding the functionality of dreams proposed by the OBH, this discrepancy could be addressed by (1) expanding the operational definition of *bizarreness*, hypothesizing that any element in the dream that deviates from everyday reality can account, even to a lesser degree, as injected noise; and (2) describing "realistic" dreams, as opposed to the bizarre/unusual ones, through the integrative approach of the IWMT of consciousness. Accordingly, it is argued that the DBS, being a persisting system in itself, resorts to memory to retrieve a myriad of –mainly visual and noise-injected– stimuli-like experiences, to then actively organize such experiences into narratives by means of active inference. This idea also draws upon the Dream-Building System proposed by Barcaro & Magrini (2022), which argues for the existence of a phenomenological retrieving sub-system and a plot-building sub-system.

4. Dream Denoising Model

The present model postulates that the underlying mechanisms of dream building, as phenomenologically described in the previous sections, emulate the basic workings of GAI, specifically LDMs, in the way data is destroyed of "diffused" (noised) and consequently restored (denoised) based upon criteria such as prompt input. This basic idea relies upon the following premises:

1. Memories are the primary source of dream content, particularly autobiographical memory (Malinowski & Horton, 2014), semantic memory (Cavallero et al., 1990) and episodic memory in NREM dreams (Baylor & Cavallero, 2001, as cited in Payne & Nadel, 2004). As the "dream-lag effect" suggests, REM sleep often incorporates events from waking life experienced 5 to 7 days prior to the dream (Van Rijn et al., 2015). Similarly, LDMs in text-to-image GAIs retrieve elements from a dataset in order to generate new images.

2. There seems to be continuity between waking life and dreams (Domhoff, 2022; Schredl, 2010, 2017), meaning that, at least generally, "dream sources are mental contents that directly refer to events in the dreamer's life" (Barcaro & Magrini, 2022, p. 242). Nevertheless, it is important to consider that the continuity hypothesis is more relevant and evident when it comes to emotional reaction, but not so much to behaviour; in other words, what the dream-self (in this case, the DBS) does within the dream is different to how the wake-self would react (Kahn, 2019). In LDMs, elements in a dataset are vectorized in order to be sent into the Latent Space (where forward diffusion and reverse diffusion happen more efficiently), and ultimately decoded back into observable pixels. Generated images are only possible if derived from pre-existing data (i.e., other images) that are reorganized and restructured by the GAI. Likewise, dream content is mediated and/or prompted by some features that can be classified into two broad categories: Stable Traits (ST) –features that are inherently consistent in the individual through long periods–, such as the dreamer's gender (Hall et al., 1982; Schredl et al., 2019), age (Maggiolini et al., 2020) and personality (Parra & Sosa, 2019; Schredl, 2003), and Transient States (TS) –temporary features or recent experiences that are contingent, environmentally-dependent or relatively unpredictable–, such as personal concerns (Domhoff, 2022), mood (King & DeCicco, 2007), environmental stimuli to a lesser degree (Salvesen et al., 2024; Solomonova & Carr, 2019), and some factors that affect continuity, such as emotional involvement (EI) with the waking-life experience, and the type of waking-life experience (TYPE) that is been incorporated into the dream (Schredl, 2003).

3. As shown by dream reports, REM and NREM dreams tend to be qualitatively different from each other, in terms of structure (REM reports show larger connectedness [Martin et al., 2020], as well as a more story-like narrative as opposed to NREM reports, which are oftentimes fragmented and discontinuous [Krishnan, 2021]), and nature (REM dreams are more elaborate, vivid and emotional, whereas NREM dreams tend to be more conceptual and thought-like, and less remarkable in vividness and emotion [Fosse et al., 2004; Purves et al., 2008; Suzuki et al., 2004]); as well as quantitively, with regards to word length (REM reports are longer than NREM reports [Oudiette et al., 2012]), recall rates (recollection of dreams in REM awakenings are significantly higher than in NREM [Krishnan, 2021; Nielsen, 2000]) and frequency (mentation reports are more frequent in REM reports than in NREM reports [Suzuki et al., 2004]).

4. Dreams during deeper NREM sleep, although not impossible, are far less frequent than in other stages and are often blank or short, which indicates a clear reduction in levels of consciousness (Massimini et al., 2005, as cited in Klimova, 2014). As suggested by Tononi (2012, 2014), Φ would be at its lowest during dreamless sleep. It has been argued that (a) the posterior hot zone of the brain may be a core correlate of conscious experience in sleep, (b) local changes in slow wave activity may account for the presence of dreaming, and (c) slow waves disrupt causal interactions between thalamocortical regions, thus impairing information integration (Bucci & Grasso, 2017; Siclari, Baird, et al., 2017; Siclari, Bernardi, et al., 2018). As shown by Banks et al. (2020), disruption of cortical connectivity also contributes to loss and recovery of consciousness. In LDMs, the forward diffusion process concludes when a maximum of entropy X_T is reached, namely, when data cannot be further noised/destroyed.

5. Throughout the night, with each sleep cycle, the duration of REM sleep increases while the duration of SWS decreases (Dijk, 2019).

6. Most dreams are either fictional (possible in real life but unlikely to happen) or bizarre (impossible in real life, e.g., defying laws of physics), whereas a little less than 1/3 of reported dreams are realistic, meaning that they could have happened in the same way during waking life (Schredl, 2010; Schredl et al., 1999). It should be noted that the operational definition of bizarreness used in this model is similar to that of Schredl's (1991) realism/bizarreness scale, in terms of the closeness of the dream action to everyday reality based on the presence of fantasy objects, or connections and actions that are not possible in the real world. By these means, bizarreness should not be confused with structure or connectedness (as it might be if Hobson et al.'s [1987] definition was followed), for dreams can be both *bizarre* or unusual in their context (e.g., the dreamer inexplicably has the ability to fly) and *structured* in terms of narrative continuity or congruence (e.g., the ability to fly is somewhat consistent with the general plot within the oneiric stream). What this ultimately implies is that REM dreams could progressively become more bizarre and structured at similar rates, given that these two characteristics, as defined here, are not mutually exclusive.

Essentially, the DDM postulates that dream-building processes draw upon waking life experiences, which are reorganized by the DBS as an attempt to resist the phenomenological entropy caused by the impairment of information integration. The resulting oneiric experience is mostly prompted by a combination of Stable Traits and Transient States. Fig. 4 schematically summarizes the model.

Experiences lived, felt and thought during wakefulness provides the raw material, conscious or unconscious, for dream-building. Memories stored in Long-Term Memory (LTM), and particularly those more recent and/or significant, are condensed upon sleeping onset for later usage by the DBS. This is achieved through a retrieval sub-system (R) like the one proposed by Barcaro & Magrini (2022), which creates a cluster of dream sources as an output. When asleep, the first cycle transitions from early stage N1 to N3 and,
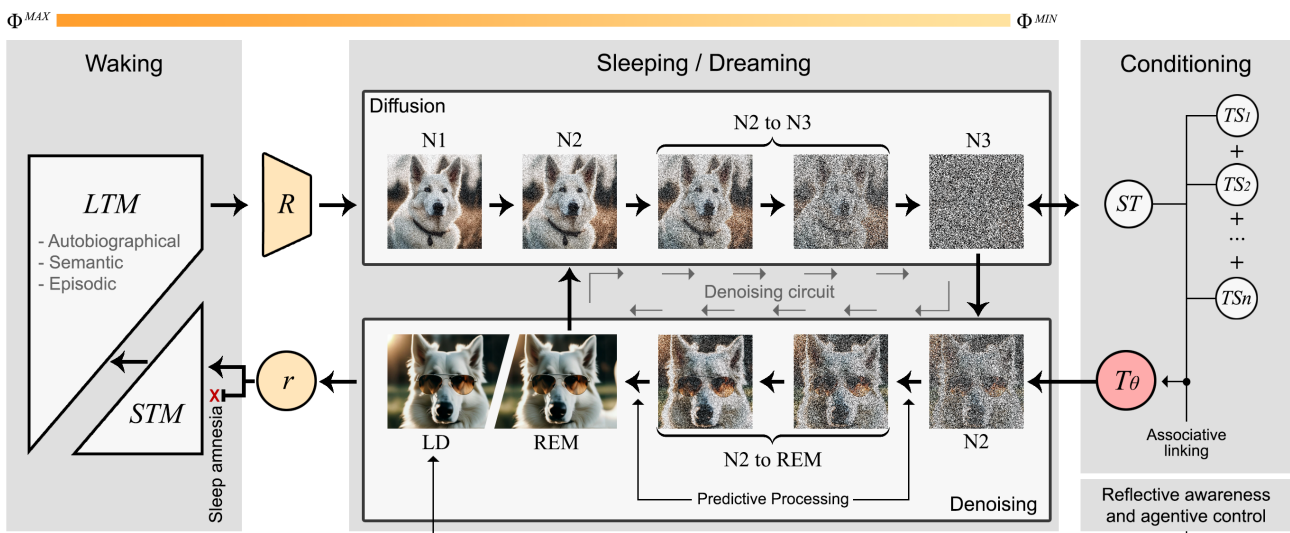

Figure 4. Dream Denoising Model scheme.
The DDM consists of two main processes: dream diffusion and dream denoising. The Dreaming Brain System (DBS) draws upon contents stored in the Long-Term Memory (LTM). Upon sleep onset, the retrieving sub-system (R) works by compressing the input from LTM, that is, the most relevant or readily available contents or experiences, producing a cluster of dream sources. As the cycle progresses from light sleep (N1) to deep sleep (N3), the presence of slow waves increases, thus impairing information integration (, graphically represented along a continuum [gradient] from maximum Φ [left], to minimum). Dreams experienced during this phase tend to be more conceptual and thought-like, as the contents retrieved from memory are still being selected and have not yet been fully integrated with spatial, temporal, and causal coherence. When N3 (and possibly Slow Wave Sleep or dreamless sleep accompanying it) is reached, the DBS counteracts phenomenological entropy by generating an integrated model (i.e., dream) that involves workspace-like interactions in the absence of perceivable external stimuli. The contents constituting this virtual experience are prompted by the dreamer's Stable Traits (ST) and a finite number of Transient States (TS). These conditioners are integrated by the Transformative Sub-System (Tθ), which constantly regulates the stream of events by transforming distributed input into a serial output, and operating through criteria for associativity between two or more dream elements. An extra condition, namely reflective awareness and agentive control, allows for REM dreams to turn into Lucid Dreams (LD) under certain conditions. During the denoising phase, the DBS engages in predictive processing based on Active Inference and Bayesian model selection, constructing an ongoing subjective experience through perception-action loops. At the end of the first cycle, REM stage gradually returns to stage N3, producing a circuit of repeated diffusion-denoising processes. This denoising circuit enables the DBS to access a wider set of elements stored in memory and therefore generate more vivid dreams throughout the night. When awaken, the recall sub-system (r) attempts to store recent oneiric experience into the Short-Term Memory (STM); then, oneiric material can either be sent to LTM for further storage, and later recalled, or fall into sleep amnesia when it is (1) stored in STM, but unable to reach LTM (i.e., shortly remembered upon awakening but quickly forgotten thereafter), or (2) lost before awakening or immediately after, unable to even reach STM. *Note*. Images generated using the prompts "White Swiss Shepherd" and "White Swiss Shepherd with sunglasses" respectively, by Stability. ai, *Stable diffusion online*, 2023. (https://stablediffusionweb.com).

hence, from alpha waves to SWS, according to EEG. This shift impairs information integration (required for vividness, coherence and structure in oneiric experiences), causing dreams in these stages –if recalled– to be thought-like and lacking the richness that characterizes REM dreams. When N3 is reached, the DBS counteracts the impairment caused by SWS (hereby understood as phenomenological entropy) by attempting to reach a previous state of higher consciousness (i.e., active wakefulness), yet outstretching no further from REM sleep or Lucid Dreaming in normal conditions, as this would otherwise cause a premature awakening or maintenance insomnia. In terms of information integration, it could be argued that $\Phi_{wake} > \Phi_{REM} > \Phi_{NREM}$, as electroencephalographic responses evoked by transcranial magnetic stimulation studies suggest (Massimini et al., 2010). During REM (and, more indirectly, NREM), dreams are prompted by two categories of conditioners: Stable Traits, which are relatively consistent in a dreamer's lifespan and/or developmental stage in life, and a finite number of Transient States, which are recent-experience dependent and vary in a mostly daily-to-weekly basis. These various conditioners influence the way memories are reorganized, reinterpreted and reintegrated into a structured oneiric experience by a Transformative Sub-System T_θ, which would be the counterpart of the Plot-Building Sub-System described in Barcaro & Margini's (2022) model.

How does the Transformative Sub-System predict the relation between those elements retrieved from the memory storage, upon which such elements are retroactively chosen? AI Text Generators typically use a technique called Word2Vec that allows them to obtain vector representations of words. The vectorization of words permits to capture information about the meaning of a word by analyzing the context provided by the surrounding words. For instance, a vector for the word "dog" would be more likely to be closely related to the word "wolf" than it would be for "fish" (See Fig. 5). By this means, for instance, AI Text Generators can efficiently construct grammatically accurate bodies of text that somewhat resemble human writing. Word-embeddings have even been used in the study of dream reports (See Altszyler et al., 2017). Similarly, it has been proposed that dream sources could be linked to one another following certain criteria. A robust number of studies regarding the causally associative nature of dream sources has been made mostly on the basis of hermeneutic –and, more specifically, psychodynamic– approaches; nevertheless, the empirical evidence does not provide systematic support for such explanations (see Domhoff, 2022, chapter 5, for a thorough review on the evidence for symbolism in dreams). Although the causally associative nature of the building blocks of oneiric experiences remains largely unknown to the neurosciences, research has suggested that the link between different dream elements can be justified in the processing of the DBS through:

a) Dreamer's cognitive social networks, which are mirrored by characters appearing in dreams (Schweickert, 2007a; 2007b; 2007c). This means that dreaming social networks (as well as waking social networks) include short paths to other people, a tendency for connected individuals to be paired as characters in the dream, and a strong likelihood for a large number of characters to be connected in a large central component; also, people who are closer to the dreamer (e.g., relatives, significant other…) in waking life tend to ap-

pear more often in dreams than other individuals (Han et al., 2015, as cited by Domhoff, 2022).

b) Semantic similarity between inputs, as noted by Deperrois et al. (2023). During REM sleep, different representations of observed stimuli from waking life are retrieved and generate a creative dream through feedback pathways. In essence, in REM sleep "several independent memories are replayed from the hippocampus and combined in high-level areas" (p. 6), given their semantic similarity.

c) Pre-existing cognitive categories, reinforced by previous experience (see Beck, 2002). Cognitive entities and experiences organized in categories allow for better predictive processing; for instance, it would be more likely to dream about a car being driven by an adult human on a highway (given the semantic and categorical relationship between "adult human", "drive", "car" and "highway"), than by a cat on the moon. Even though the latter is still possible (as studies on bizarreness during REM sleep have shown), even such randomness could also be accounted for by a myriad of other links and conditioners (e.g., having recently watched a sci-fi movie involving anthropomorphic animals).

When base memories (and the basic relations among them) are selected and elicited, the sequence of events (i.e., the stream of information) within the dream experience is then guided, on the one hand, by the active and ongoing influence of the conditioners, and, on the other hand, by means of the FEP-AI (i.e., the DBS 'best guess' to minimize prediction error), enabled by the amount of Φ available at a given stage. This notion is fundamental for understanding the qualitative differences between REM and NREM dreams. NREM dreams, in the light of a lessened Φ value, are experienced with little to non apparent causal relation between its constituent elements; they lack structure and a story-like narrative given the diminished capacity for the DBS to make ongoing and more complex predictions. Isolated images and other discontinuous elements experienced in NREM dreams would be the result of direct retrieval of waking memories that are yet to be causally integrated, modelled and predicted by the DBS in a higher Φ state; that is to say, "more sparse activations [in the brain] during NREM stages would result in segregated information, but the local maxima might still be sufficient for static, non-narrative perceptual-like mentation" (Bucci & Grasso, 2017, p. 10).

From the second sleep cycle onward, the gradual shifting between stages REM and N3/SWS, back and forth, repeats approximately 5-6 times before awakening (Weiner & Craighead, 2010), producing a cycle in itself (namely, *denoising circuit* by the DDM). Throughout each cycle, REM stages become longer while SWS becomes briefer. Although little research has been conducted about the phenomenological differences and changes throughout the sleep cycle, Carr & Solomonova (2019) report that attributes such as bizarreness and perceptual vividness increase as the night progresses for both REM and NREM sleep reports. This singularity could be explained as the result of the denoising circuit; throughout the night, with each denoising cycle, the DBS deals with fewer degrees of injected noise (as SWS stages become shorter), allowing the system to access a wider variety of waking experiences and elements stored in memory to build the dream itself. This amplified accessibility is what would cause REM stages to elicit progressively more vivid and bizarre experiences, as links and associa-

tions can become more numerous and complex. The capacity for active inference in internally-generated world models, although not necessarily becoming better or more precise during the sleep cycle, would account, even in non-lucid dreams where agency is somewhat lacking, for the *narrative* property of dreams, in which sequences of events are ordered with temporal consistency, that would most likely also include spatial and causal coherence. If this was not the case, dreams would elicit internal extro-science world models (Meillassoux, 2015), characterized by a regime lacking guiding laws of existence and, therefore, too chaotic to be causally conceivable. By contrast, NREM dreams are usually less narrative and more conceptual since incremental noise injection, at least during the first sleep cycles after sleep onset, restricts access to waking experiences and, therefore, to more complex links among retrieved dream elements.

Regarding daydreaming experiences, particularly mind-wandering, the unrestrained flow of mental scenes could also be the result of noise injection during wakefulness, but perhaps to a lesser degree than that implicated in dream mentation. The numerous overlaps, both phenomenologically and neurally, between dreaming and mind-wandering (Fox et al., 2013) seem to indicate that this is a plausible hypothesis.

5. Limitations and discussion

The aim of the DDM is to serve as a descriptive model accounting for phenomenological occurrences and variances across different sleep stages, synthetizing previous findings regarding the qualitative differences between REM and NREM dreams, the continuity hypothesis between experiences in waking life and oneiric material in dreaming life, the unlikeliness of dream experience while in SWS, and the main ideas proposed by the IWMT extrapolated to dreams as altered states of consciousness. The guiding principle is the notion that LDMs and dream-building mechanics share core processes when generating output. Because of this mainly descriptive proposition, the DDM does not attempt to explain a well-defined causal relation between waking-life indicators and dream content, nor does it claim to improve dream predictability. Quite on the contrary, it suggests that the complex mechanisms of the dreaming brain, although seemingly arbitrary, rely on a myriad of waking-life experiences and complex conditioners by which it attempts to generate virtual models and make ongoing predictions under cortically impaired conditions (phenomenologically expressed in noise injection).

Perhaps the most robust limitation of the DDM is that it is mostly supported by studies made in Western societies with fairly homogeneous samples. This cultural bias crosses most theoretical models of dreams since cultur-

Figure 5. Distance between word vectors.
The vector representing the word "dog" is shown in a three-dimensional space along with its neighbouring context words. Source: Embeddings Projector, Word2Vec 10K model.

ally, ethnically and idiosyncratic heterogeneous samples are somewhat lacking in the current oneiric literature. In spite of that, research also suggests that there seem to be no significant differences in dream content based on nationality and cross-cultural differences, except in terms of aggressive elements (Domhoff, 2022). Whether current studies about dream phenomenology can be generalized to all cultural contexts remains unclear, and it raises questions about the degree to which contextual or contingent conditioners shape dream content.

It is also worth considering that cortical connectivity associated to loss (and recovery) of consciousness in certain sleep stages may not be as discrete as the scheme of the model might graphically suggest; instead, sleep stages have a great deal of overlapping when shifting from one another, as Banks et al. (2020) have pointed out. φ-coefficient is useful in understanding consciousness fluctuations, but empirical research testing DDM's hypothesis on these values would be of great utility.

Given its descriptive nature (i.e., *how* dreams come to be), DDM can engage with multiple causal theories of dreaming (i.e., *why* do people dream). Biologically, The Defensive Activation Theory ([DAT], Eagleman & Vaughn, 2021) argues that dreams are predominantly visual to prevent the plastic takeover of the otherwise inactive visual cortex during sleep; given the intrinsically visual emphasis of the DDM, it could be argued that these hypotheses can complement each other. However, empirical evidence supporting this theory is still needed. Cognitive-wise, the Neurocognitive Theory of Dreaming ([NTD] Domhoff, 2022), strongly emphasizes the role of the Default Network Mode (DNM) and its activation in the generation of dreams as embodied simulations, and the idea that dreams are the by-product of waking-life cognitive capacities that are of great value for adaptation and survival. These dreams would mostly enact personal concerns, which "usually relate to important people and avocations in the dreamers' lives" and "dramatize the dreamers' conception of themselves and their relationships with other people" (p. 3). Taking this into consideration, one could argue that personal concerns are of great importance for dream-building and have a greater degree of influence among other conditioners; likewise, these concerns could be categorized into ST concerns (those that are normative within certain stages of the psychological development, like choosing a career path or having children) and TS concerns, regarding daily-basis worries. These theories, along with some predictive hypotheses such as that from Deperrois et al. (2023) or the OBH (Hoel, 2021), seem to be more prominent and best fitting for DDM implementation, as they work within the paradigmatic frameworks of neurosciences and/or computational sciences.

Further research oriented towards the neural substrates supporting or challenging the premises of this model is required. Implications of the DDM in psychopathological states and other altered states of consciousness ought to be thoroughly examined, as well as the extent to which ST and TS each act as conditioners influencing dream building. It would also be of great importance to explore how specific criteria, such as time, can be accounted for to include certain conditioners in either ST or TS categories. Finally, it is worth exploring what functions noise injection underlies in daydreaming, given the notion that the same mechanisms governing dream mentation are at work.

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