# A computational account of need states, reward and wanting

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ABSTRACT

Needing is related to deprivation of something biologically significant, and wanting is linked to reward prediction and dopamine and usually has more power on behavioral activation than need states alone. However, it is unclear why sometimes there is association and sometimes dissociation between needing and wanting. The paper aims to clarify their relations using active inference. In this approach needing is related to a deviation from preferred states that living things tend to occupy in order to reduce their surprise, while wanting, i.e. reward prediction, is related to precision over policy leading to rewards. Through a series of simulations, we demonstrate the interplay between needing and wanting systems. Specifically, our simulations show that when need states increase, the tendency to occupy preferred states is enhanced independently of wanting (or reward prediction), showing a dissociation between needing and wanting. Furthermore, the simulations show that when need states increase, the value of cues that signal reward achievement and the precision of the policies that lead to preferred states increase, suggesting that need can amplify the value of a reward and its wanting. Taken together, our model and simulations help clarifying the directional and underlying influence of need states separately from reward prediction, i.e. wanting, and at the same time show how this same underlying influence of need amplifies wanting, i.e. increases the precision of reward cues that lead to the preferred state.

FULL TEXT

## 1. Introduction

There has been a debate around the question of if people, for instance consumers, are driven by their needs or their wants (Campbell, 1998). “Needing” is related to a state of deprivation of something important for life or survival (Bouton, 2016), and increases arousal through interoceptive salience (Craig, 2003); and not responding to a need might lead to some adverse consequence such as physiological or psychological suffering which go beyond mere frustration (MacGregor 1960; Baumeister & Leary, 1995). Rather, “Wanting” is more related to goal

achievement and reward prediction and is more closely related to dopaminergic activity and motivation (Berridge, 2004). Both have some influence, albeit differently, on the motivational value of stimuli. Indeed, motivation can have a directional effect and/or activational effect. The directional effect is linked to choice (preference or action selection) and directs towards or away from stimuli, while the activational effect is related to action and its initiation, maintenance, and vigor or effort (Salamone et al., 2018). Notably, wanting is able to activate and direct motivation

in absence of need states: nonhuman animals tend to respond and "want" food even when satiated (Bouton, 2016), and for humans, cues of M&M or pictures of cigarettes (for smokers) lead to more consumption even after having been consumed to satiety (Hogarth & Chase, 2011; Watson et al., 2014).

However, needing and wanting systems are not segregated but might influence each other reciprocally. Biological needs, such as those related to states of deprivation of a biologically significant stimuli or events (Bouton, 2016), seem to influence the rewarding aspect of biologically relevant stimuli, such as wanting, pleasure and choice. For instance, food is often more wanted, liked and chosen when hungry. Thus, although it has been shown that motivation to pursue rewards depends more on expectations (e.g., reward prediction), than on needs states (Bindra, 1974; Berridge, 2004), need states tend to amplify reward predicting cues that are relevant to such need states (Toates, 1994; Berridge, 2004). Need states can also enhance liking of, and pleasure related to, relevant stimuli that satisfy one's needs (Cabanac, 2017; Berridge & Kringelbach, 2015; Becker et al., 2019). Moreover, a need state has the capacity to give and to control the preference/choice or value of a novel food or drink or of a particular choice or action, in relation to their consequence on the organism (Dickinson & Balleine 1994; Balleine, 1992), and such need related action happens via a system that could be both dependent (Berridge, 2004; Berridge, 2018) and independent of dopamine (Wassum et al., 2011 Salamone et al., 2018). Furthermore, in absence of a reward guiding cue, a need state can (directly) activate relevant actions (Passingham & Wise, 2012) or explorative behavior (Panksepp, 2004). This indicates that biological need states are able to influence certain tendencies towards relevant needed stimuli, hence affecting wanting and goal directed choices (and liking).

At the brain level, needing and wanting systems could map to partially different neural substrates. A recent fMRI meta-analysis compared needing (perception of needed stimuli, i.e. food when hungry) and wanting (perception of a reward cue that leads to reward seeking). It showed that needing seems more related to brain regions implicated in directional motivation/value; whereas wanting seems to be more related to brain regions implicated in both directional and activational motivation/value, and to mesolimbic dopaminergic areas (Bosulu et al., 2022). Furthermore, needing is related to interoceptive predictions and prediction errors as well as cues related to interoceptive states, such as food cues, possibly computed within the mid-posterior insula (Bosulu, et al., 2022; Livneh et al., 2020). Wanting is instead related to exteroceptive (e.g., cue- or reward-related) predictions and prediction errors, with the latter

possibly computed within the ventral tegmental area (VTA) (Schultz et al., 1997; Bosulu, et al., 2022). Hence, needing seems to be more related to the internal environment, whereas wanting seems to be more related to the external environment, although this is not necessarily a strict separation as – for example – wanting could also take into account the internal environment (Berridge, 2004).

To sum up, our previous discussion illustrates that needing and wanting systems could link to different (directional and activational) aspects of motivation and to partially different neuronal substrates and (internal and external) states – but at the same time, they might interact in various ways. Yet, we still miss a comprehensive computational framework that accounts for the findings reported above and that specifically explains (1) how could internal needs exert a directional influence on goal-directed behavior and choice, even in absence of wanting and (2) how could a state of needing amplify wanting (and liking).

The main goal of this manuscript is to provide a computationally-guided perspective on needing and wanting, which helps make sense of the fragmented literature on these topics. In the following sections, we will firstly address the two above questions conceptually, using formal methods from active inference, information theory and reinforcement learning (Parr et al., 2022; Sutton and Barto, 2018). Then, we present two simulations that address the functioning of needing and wanting systems – and their interactions – more formally.

## 2. Needing and wanting systems and their interactions: a conceptual perspective

### *2.1 The directional influence of needs on goal-directed behavior and choice*

The goal of organisms is to regulate internal states and keep them within certain very limited boundaries (Barrett, 2017; Sterling & Laughlin, 2015; Friston, 2006). For instance, the average normal body temperature for humans is generally between 36.1°C (97°F) to 37.2°C (99°F), which is a very small range compared to the range of possible temperatures in the universe, from the absolute zero to trillions of degrees. The same is true for levels of glucose or the balance between water and salt in the body. The main idea is that the number of states related to life are really small compared to the very large number of other combinations that wouldn't sustain life. So, in order for these limited boundaries to have a greater probability of occurring and for life to exist, natural mechanisms have set them as so-called (empirical) priors, which might be conceived as (possibly genetically encoded) innate preferred states that the organism always strives to achieve. In other words, living beings strive to occupy very limited, preferred, states (physiological bound), which (from their point of view) have a greater probability, i.e. are less surprising (Friston, 2010). Here surprise (or surprising state), noted h(y), is the inverse of being probable and simply means less probable. Anecdotally, for a fish, being out of water would count as a surprising state. From a formal viewpoint, any self-organizing system must minimize such surprise (Friston, et al., 2006) in order to resist a natural tendency to disorder (Friston, 2010).

Indeed, minimizing surprise allows living organisms to (temporarily) resist the second law of thermodynamics, which states that entropy - or the dispersion of a system - is always increasing.

Formally, the notion of surprise is closely related to the notion of entropy. Entropy, noted H, is the average of the surprise (uncertainty), and it expresses the uncertainty related to which state must be occupied. It is in this sense that the presence of a state with high probability reduces entropy; and that such states can thus statistically be seen as priors (a priori) (Friston, 2010; Parr et al., 2022), or innate preferred states (that we will represent here by p) (Parr et al., 2022; Friston, 2010) as discussed above. It is also in this context that higher probability translates into more preference: living creatures naturally prefer the most probable states that sustain life (Parr et al., 2022). Thus, distancing from those states leads (or equivalently, being in a surprising state) entails an (informational) cost that living beings strive to minimize (Friston, 2010).

Interestingly, the notion of being in a surprising state (or in other words, being far from preferred states) links well to the concept of "needing" discussed in the Introduction. In the same way being in a surprising state entails an (informational) cost, a state of need entails a (biological) cost if a person does not respond to the need (see MacGregor 1960; Baumeister & Leary, 1995). When a creature moves away from the preferred state, needing would amount to a tendency to occupy preferred states (again). Such state of need can be represented as:

$h_n(y) = -\ lnP(y|C)$ Eq. 1;

where $h_n$ represents need related surprise of a sensation or state *y*, which is equal to the negative log probability of being in (or observing) a state *y* given the distribution of prior preferences, denoted as *C*. Note that for simplicity, in this article we will collapse the notions of "state" and of "observation that can be obtained in the state", which are typically distinct in active inference and Partially Observable Markov Decision Systems.

The perception of a need state translates into a "goal" of reducing surprise by reaching the preferred states, e.g., states that represent adaptive physiological conditions (Friston, 2010). Such tendency could activate an action or a policy (i.e., an action pattern or sequence of actions) that compel creatures to seek out the (valuable) preferred states. Note that the actions or policies that resolve a state of need could in some cases correspond to (fixed) regulatory actions, such as autonomic reflexes, as opposed to action courses determined by the circumstances of the external environment (Sajid et al., 2021). The states that the creature occupies when pursuing a policy that resolves a need can become valued per se (Friston & Ao, 2012). In other words, when the creature pursues a course of actions towards the preferred state, all the intermediate states (here intended in a broad sense that encompasses situations, actions, stimuli, etc.) can become valued and needed. For instance, when moving from a state of hunger to a state of satiety, some intermediary states could be the gustatory stimulus associated to having food and the act of eating; and such states would become valued, because they are in the path towards the preferred

(satiety) state (Pezzulo et al. 2015). Through this mechanism, a creature would experience the need for food or the need to eat – and then start to prefer the valued states, stimuli or actions. In other words, the directional motivation effect of need states could come from the tendency to occupy preferred states.

In turn, as noted above, pursuing preferred states reduces "need related entropy" (or simply entropy, from now on) and the surprise associated to occupying non-preferred states. In this sense, the tendency to occupy preferred states confers to need states the possibility to influence – and give value to – stimuli or actions that are either costly states $S(h_n)$ that lead to surprise, or in the path towards the preferred state $\pi(p)$. In other words, in an environment where there are increasingly costly/surprising states, any state (stimulus or action) that is in the path to the preferred state will become valued (needed) because it reduces entropy.

### *2.2 How needing amplifies wanting*

The effect of needing on wanting (and on other phenomena such as pleasure and liking) could be conceptualized by appealing to the formal notion of precision in active inference. Mathematically, precision is a term used to express the inverse of the variance of a distribution which in our context can be seen (loosely speaking) as the inverse of entropy (Friston, 2010; Holmes 2022) – in the sense that the higher the entropy, the lower the precision. In predictive coding and active inference, precision acts as a multiplicative weight on prediction errors, in the sense that prediction errors that are considered more precise have a greater impact on neural computations (Parr et al., 2022).

In active inference, there are different precisions associated with different forms of changes in prediction, such as interoceptive or reward predictions (see Parr et al., 2022). Of particular relevance here is the precisions of policies, which indexes the confidence that we have that by following a particular policy we will reach a preferred (goal or reward) state. Crucially, while we pursue a policy, every cue or information that confirms (reduces uncertainty about the fact) that a policy will achieve a preferred state enhances policy precision. This is the case for example if we are following a route that we hope will lead to a given city (or to a restaurant that we hope is open) and we encounter a traffic sign that indicates that the direction to the city is correct (or a sign that the restaurant is open).

At the neurophysiological level, policy precision, or the confidence that a policy will lead to reward, is typically associated with the dopaminergic system in active inference (FitzGerald et al., 2015; Parr et al. 2022, Holmes, 2022). Therefore, reward cues that enhance our policy precision and our confidence that the policy will lead to reward would trigger dopamine bursts, which will attribute incentive salience to such cues (Berridge, 2007). This is in line with the idea that dopamine is linked with incentive salience and wanting; but also with reward prediction and behavioral activation (Hamid et al., 2016). Rather, precisions regarding hedonic contact with the

reward (is it good?) or the state of satiety (am I well?) might be mediated by the opioid system (Berridge & Kringelbach, 2015) and the serotonin system Parr et al., 2022; Liu et al., 2020; Luo et al., 2016), respectively. In this perspective, when one is in a surprising state, the presence of a cue (e.g., a traffic or restaurant sign) reduces our uncertainty about goal/reward achievement by improving policy precision via dopamine system activity (wanting); the presence of, or contact with, the reward itself reduces entropy by enhancing precision through the opioid system (pleasure/liking); while being directly in a preferred state or towards the preferred state could be related to precision via serotonin (well-being). All of these contexts follow the logic that they serve as information that reduce entropy by signaling (i.e. being in) a path to preferred states ($\pi(p)$) in opposition to surprising states ($h_n$), given some prior preferences.

The policies discussed so far depend on exteroceptive cues from the environment. As discussed above, these cues (e.g., cues that signal a reward) can become imbued with incentive salience (Berridge, 2007) in virtue of the fact that they enhance policy precision. This is the key mechanism for wanting.

The increased policy precision that comes from reward cues means more certainty that the state to which the policy leads will be rewarding, and it is this certainty that amplifies wanting. This mechanism could function relatively independent from a state of need. For instance a relatively satiated animal that senses by smell some food, will be motivated to follow the smell because doing this increases the probability of finding food. However, the wanting (and associated dopamine firing) could be amplified if the animal is in a need state. A hungry animal that senses by smell the probability of food will be motivated to follow the smell, not only because there is probability of food, but even more because that food will be very rewarding. That is, the animal will be more certain (enhances its precision) that it should pursue the reward being predicted. It's in that sense that needing amplifies wanting. It is also possible to speculate that the hungry animal will likely have more pleasure while eating food than the satiated one – because it could assign more certainty (precision) to how good food is when one is hungry.

To summarize, we propose that the wanting mechanism is intrinsically related to the fact that cues afford some resolution of uncertainty (e.g., about what policy to pursue) and linked to the dopaminergic system. Indeed, wanting depends on external stimuli that act as pavlovian cues that predict rewards (Berridge, 2018), and the attribution of value to these cues depends on mesolimbic dopamine reactivity which can be enhanced by physiological states (needs, emotions, drugs, etc.) (Berridge, 1996; Berridge, 2004). Furthermore, we propose that the influence of needing on wanting can be conceptualized as a need-induced enhancement of the precision of policies and thus of the saliency of the rewards, stimuli or actions that lead to the preferred state.

### *2.3 Summary*

Our discussion so far has highlighted two important points about needing and wanting systems, and their interactions. First, need states exert a directional influence on choices separately from wanting (and reward prediction). In the perspective offered by our model, need states gain their underlying (motivational and saliency) effect from the tendency to occupy preferred states. When a living system moves away from such preferred states towards "costly" states, a state of need is generated. The model suggests that being in costly or need states automatically increases the probability of activating policies that lead to preferred states. In other words, the mere deprivation/biological cost of 'needing' has an underlying directional effect and influences the tendency to reach rewarding or goal states. This tendency exists irrespective of reward prediction, as conceptualized for example in model-free reinforcement learning systems, which is related to wanting (Zhang et al., 2009; Berridge, 2004).

Second, by the same token, the underlying influence of need amplifies wanting, by increasing the value of reward cues that signal the possibility to reach goal states (hence lowering uncertainty about goal achievement) and the precision of goal-achieving policies. The simultaneous circumstance of being in a need (hence surprising) state and encountering a cue that signals that a goal state is achievable (hence that surprise and uncertainty can be reduced) is the ideal condition to confer goal-achieving policy with a very high precision. By indicating that there is a path to a goal or reward state, the cue renders the organism more confident about what to do - and this is amplified when the gain in reward (or the amount of surprise minimized) is greater, such as when one is in a need state. This is why need states amplify "wanting" (which in itself is reward to cues that signal goal or reward achievement) by enhancing the value of cues and the precision of policies that lead to preferred goal states.

In the next sections, we move from the conceptual treatment offered in this section to a formal implementation of the proposed model of needing and wanting. Subsequently we illustrate the functioning of the model in two simulations, which illustrate how being in need/costly states influence the tendency to reach rewarding/preferred state (Simulation 1), and how the presence of a path to the preferred state determines higher policy precision and reduced entropy in environments with greater costs compared to lower costs (Simulation 2).

## 3. Methods

### *3.1 Simulation environment*

Our simulations regard a very simple situation, mimicking the idea of agents that have to remain within a limited physiological (e.g., food or temperature) bound. For this, we designed a grid-world environment in which only one state is rewarding/preferred, whereas the number of surprising/costly states is much greater (See Figure 1). We can draw a parallel between the grid-world and human physiological states, such as hunger or temperature: the preferred state

corresponds to the optimal interval of sugar level in the bloodstream, or the temperature range (between 36.1°C (97°F) and 37.2°C (99°F)). In the grid-world, each interval of sugar level, or of temperature range, is represented as a specific state in which the agent can be (each state corresponds to a box in Figure 1).

Specifically, we used a 3x4 grid-world containing 8 "costly states" (white boxes) whose value is initially unknown to the agent, 1 "cue state" that is the closest to the rewarding/preferred state (and hence allegorically offers a "cue" about it), 1 "inaccessible state" that cannot be accessed (like a wall) and whose value is always zero, and 2 terminal states (i.e., states that, once occupied, cannot be left by the agent): a "rewarding/preferred" state that gives a reward of 1 and a "death state" that kills the agent.

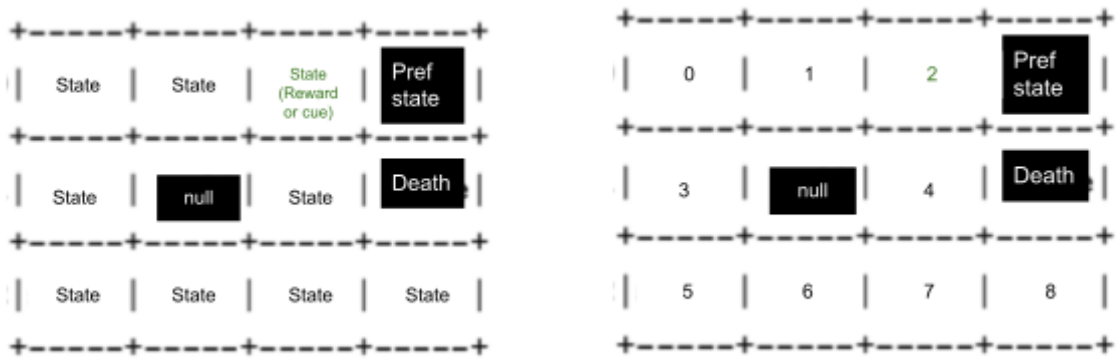



*Figure 1. Grid world environment used in our simulations. Each box represents one state in which the agent can be. These include 8 states ( white boxes) whose value is initially unknown, 1 state that offers a cue about the rewarding/preferred state, 1 state that is inaccessible (like a wall) and whose value is always zero, and 2 terminal states (i.e., states that, once occupied, cannot be left by the agent): a rewarding/preferred state that gives a reward of 1 and a death state that kills the agent. Note that the left and right plots show the same environment, but the left plot shows the types of the states, whereas the right plot shows the numbers associated with these states, which will become important to interpret our simulations later.*

In our simulations below, the only thing that we will vary is the amount of cost associated with the 8 "costly states" and with the "cue state". We will do so by assigning to these 9 states the same negative reward (-1, -2, or -5) representing a significant departure from biological bounds. Note that the agents that dwell in the simulated environments do not know these values and will have to compute the *expected* biological costs, or values by themselves (see below for a description of the agents that we will use in our simulations).

***3.2 Simulation agents***

Our simulations will compare two agents: an active inference agent that embodies our hypotheses about needing and wanting systems and that implements tendencies or prior preferences over policies; and a reinforcement learning agent that computes reward prediction in the form of action values (Parr et al., 2022; Sutton and Barto, 2018).

*Agent 1: active inference agent*

The first agent is a simplified version of active inference, in which the perceptual part is greatly simplified by making all states observable. Technically, this means that we are dealing with a Markov Decision Process (MDP) and not a Partially Observable Markov Decision Process (POMDP) as more commonly done in active inference (see Friston et al., 2009). This simplifying assumption is motivated by the fact that here we are only concerned with action selection and not perceptual discrimination; and it facilitates the comparison with reinforcement learning agents, which commonly use MDP.

In active inference, action selection is the result of an inference process: agents select actions by inferring a distribution over control states or policies (i.e., sequences of control states) (Friston et al., 2017). The preferred or goal states (whose values in our simulation corresponds to the costs or rewards discussed above) are implemented as states that are a-priori more probable; and since the agent expects to be (or to move towards) these a-priori probable states, the prior over states also translates into priors over policies that achieve such states. In other words, active inference agents tend to select policies that lead the agent to achieve goal states - which in Bayesian terms corresponds to maximizing model evidence.

More formally, with the simplifying assumptions discussed above, active inference agents consider the following:

$ln\,[P(y)]$ Eq. 2

with $ln$ for natural logarithm and $(P(y)$ for probability of observing a state. (Bear in mind that here hidden states are observations; hence $y = s$.) Surprise is the negative of the evidence and is given by:

-$ln\,[P(y)]$ Eq. 3

Because need related surprise is so because that surprise is relative to some prior preferences, we add priors (costs and rewards) as condition to such surprise and we get the need related surprise:

-$ln\,[P(y|C)]$ Eq. 4

with C representing prior preferences, i.e. biological costs (or rewards). This equation represents the surprise or negative "value" of an observation/state given the preferences. The latter are defined by costs and rewards as in fig. 2, and they are only relevant because they constrain priors for policies, which define actions that reduce current and expected surprise. In this sense, expected surprise given the preferences (i.e. costs/rewards) is:

$-\ E_{Q(y|\pi)} ln\,[P(y|C)]$ Eq. 5

The $E_{Q(y|\pi)}$ part means that the probability of states/outcomes is averaged over all policies (π). In this equation, $E_{Q(y|\pi)} ln\,[P(y|C)]$ (without the minus sign), which also corresponds to $Q^{\pi}(s, a)$ that agent 2 will compute, is the pragmatic value part that reduces the expected free energy G(π) (un upper bound on expected surprise) and represents prior for policies.

Hence, when there is no information seeking:

$G(\pi) = \ -\ E_{Q(y|\pi)} ln\,[P(y|C)]$ Eq. 6

Under active inference, agents are equipped with a particular prior over policies, noted $P(\pi)$, that assumes policies are inversely proportional to the free energy expected under their pursuit, i.e.:

$P(\pi) = \sigma(-G)$ Eq. 7

where σ represents the softmax function, bounded between 0 and 1, and enforces normalization (i.e. ensures that the probability over policies sums to one (in the given context).
This $P(\pi)$ is what will be used as prior over policies by the agent 1 in order to make decisions and minimize surprise. In our simple grid world environment, policies are identical to actions.

*Agent 2: model-free reinforcement learning*

The second agent makes decisions based on prediction of rewards assessed by state-action values, i.e. each decision will depend on the value of actions given the current states (see Sutton & Barto, 2018). Here the policies depend on the action values, denoted $Q^{\pi}(s,a)$, and given by:

$$Q^{\pi}(s,a) = E_{\pi}\{R_t | s_t = s,\ a_t = a\} = E_{\pi}\{\sum_{t=0} y^i r_{t+i} | s_t = s,\ a_t = a\} \quad \text{Eq. 8}$$

The equation shows the value or "quality" (Q) of the action (a) in state (s) under a policy (π). The function denoted $Q^{\pi}(s,a)$ expresses the expected (E) return (R), which is the (expected) sum of rewards, starting from state (s) and taking the action (a), and thereafter following policy (π). Here the s for agent 2 is equivalent to the y of agent 1.

The agent's decision after learning is based on the optimal policy $\pi_*$, i.e. the one that maximizes the expected return, and therefore the optimal $Q^{\pi}(s,a)$, noted $Q^{*}(s,a)$ is equal to:

$max_a Q(s,a)$ Eq. 9,

where $max_a$ is related to the action that maximizes $Q(s,a)$.

Our first prediction is that there will be more impact of biological costs on agent 1 which uses prior policies than on agent 2 which only uses the reward prediction. This would illustrate the directional value/motivation related to need, i.e. the tendency/probability to go to (or stay at) the preferred state, separately from reward prediction. So, the assumption is that, the more the biological costs increase (state of need), the more the preference for, and prior policy to go to, the reward state (i.e. the state that leads to the preferred state) will get higher for agent 1 which uses tendencies compared to agent 2 which just uses reward prediction, i.e. state-action values.

### *3.3. How needing can amplify wanting in agent 1*

Our second proposition was only used for agent 1, which is an active inference agent. Indeed, the prediction related to proposition 2 is a specific feature of active inference models, hence we use an active inference agent to demonstrate it. As discussed, the second proposition is about how the conjoint presence of costly (surprising) states and that of the preferred state, as well as a path towards it, reduces entropy and thus increases precision (which can be viewed as a need generated saliency). This results in neural activity that enhances wanting, liking, etc. depending on the context. In order to test our second proposition, we will look at the change in entropy and precision (inverse entropy) that comes from increased biological cost (surprise) when there is a (path to) reward versus no reward. Specifically here we test wanting, but the logic would apply to other processes (e.g. liking).

What we refer to as "need related entropy" (simply as entropy in this paper) can be denoted:

$H_n(Y = S(h_n))$ Eq. 10,

for the case where there is no path to the preferred state, and

$H_{n,p}(Y = S(h_n), \pi(p))$ Eq. 11,

for the case where there is no path to the preferred state; with H for entropy, $\pi(p)$ representing a subset of states that are on the path or policy π towards the preferred state $(p)$, and $S(h_n)$ the states $S$ that lead to surprise $h_n$ given the prior preferences, i.e. the need related surprise (see Eq. 1).

As discussed, the tendency to occupy preferred states bestows to need states their underlying influence on stimuli or actions when there is: 1) costly states $S(h_n)$; and b) states on the path towards the preferred state $\pi(p)$. As discussed, need related entropy is reduced when there is a path towards the preferred state $\pi(p)$, when there are costly/surprising states $S(h_n)$. Thus, we have the inequality below:

$H_n \geq H_{n,p}$ Eq. 12

Defining need related entropy as the uncertainty over which states to occupy given some priors means that surprising states increase entropy, but the presence of a preferred (non surprising) state will decrease entropy if there are surprising states. In other words, if the surprising states are more and more costly, and there is a path to the preferred state, the creature/agent will be more certain about which state to go to, hence the reduction of entropy and enhancement of precision. Mathematically, the probabilities of increasingly costly/surprising states will go further towards 0, while going further towards 1 for the preferred state, which will have much higher probability and thus entropy will be reduced. In this sense, our proposition is that the conjoint presence of costly (surprising) states and that of preferred states, i.e a path towards them, reduces entropy and that is why need (biologically costly/surprising) states increases precision of reward and reward cues, as they lead to preferred state. The precision is given by:

$P_n = H_n^{-1}$ Eq. 13,

when there is no path to the preferred state, and

$P_{n,p} = H_{n,p}^{-1}$ Eq. 14,

when there is a path to the preferred states. Given the inequality in equation 12, we have that, in the presence of more and more costly states, precision gets higher when there is a path to the preferred state, which can be represented by:

$P_n \leq P_{n,p}$ Eq. 12

**4. Results**

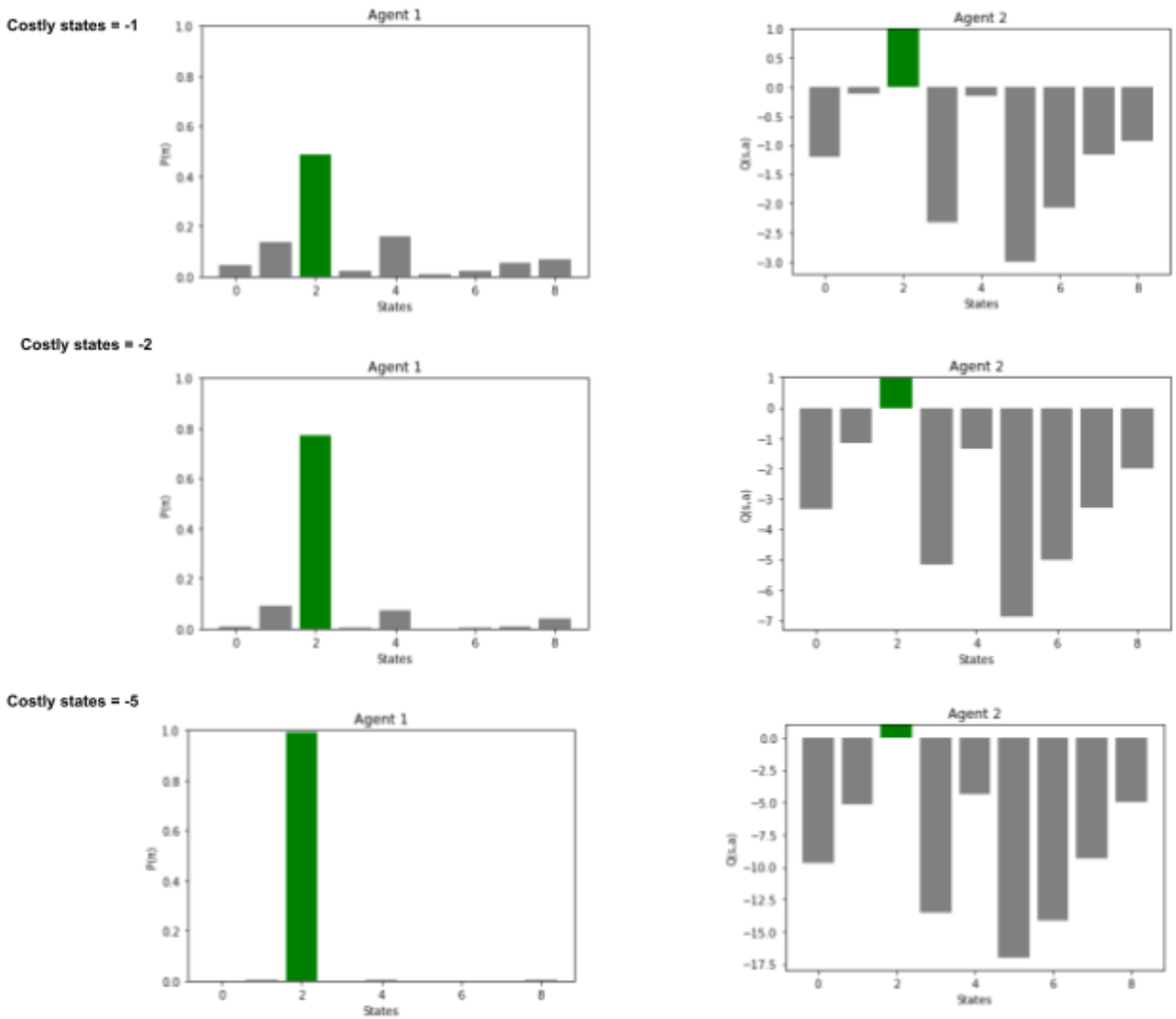
To test the first prediction, that need/costly states influence much more tendency towards the rewarding/preferred state, as compared to reward prediction, we proposed first that the deprivation/biological cost of 'needing' will have more influence on the probability, i.e. the tendency towards the rewarding state, than their absolute or relative values. Second, to test how needing amplifies wanting, we proposed that the conjoint presence of the more costly/surprising state and the path/policy to the preferred state, will reduce entropy, i.e. enhance precision. That is an increasingly surprising state will lead to more probability of preferring the preferred state; and will thus lead to increased precision (reduced entropy) if there is a path to the rewarding/preferred state, because one will be more and more certain about which state to prefer, and thus confident about what to do, i.e. what state to go to. The first proposition will represent the directional influence of need states and the second will represent the fact that need states influence value relevant reward cues because those cues reduce entropy.

### *4.1 Directional aspect of needing separately from reward prediction*

Our first proposition is that, with increases in biological costs, $P(\pi)$ will be higher for the state that leads to the preferred state (state 2); and lower probability for (biologically) costly/surprising states. This would illustrate need related directional value, i.e. the tendency to go to the preferred states, when there are, or we are in, need (i.e. costly) states.

We show that expected biological cost influences the tendencies of behavioral patterns more than action values. That is, biological costs do not control or constrain values directly, but directly control probabilities, i.e. policies or tendencies, to be in (or go to) the preferred states.

Fig. 3



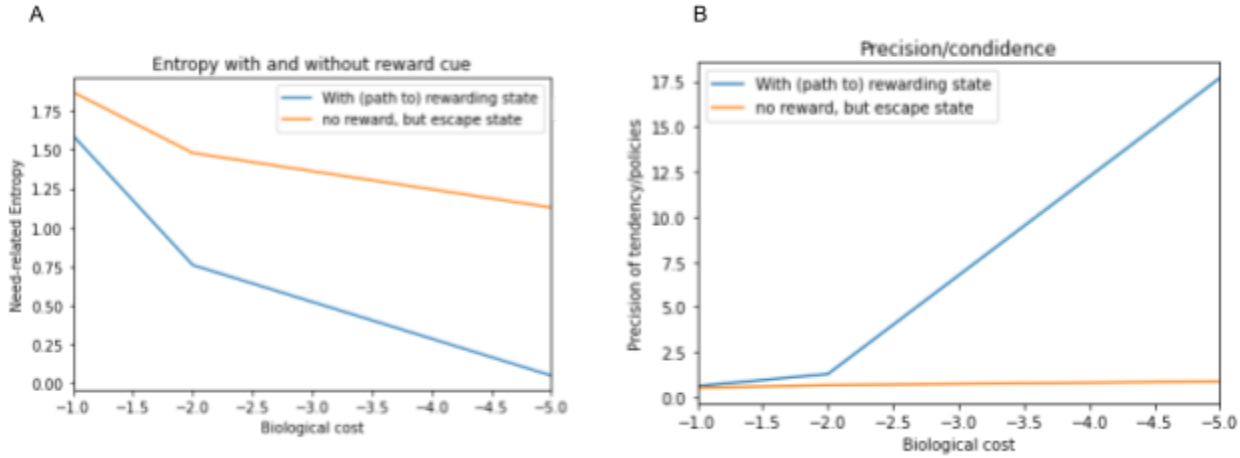
*The results show that increasing (biological) costs have more positive impact on the probabilities of going to the rewarding state (state 2) leading to the preferred state (computed by agent 1), as opposed to other states, whereas this effect is absent when looking at reward prediction (computed by agent 2). This is consistent with our proposition that need (directionally) influence tendencies (i.e. probabilities) more than reward prediction.*

### *4.2 How the directional aspect of needing can amplify wanting*

Our second proposition was that the need-related entropy will be reduced/low with increasing biological costs if there is a path to the preferred state as compared to no preferred state. Such entropy reduction will be related to increased precision. The logic being that, because entropy represents the uncertainty about what state (is more probable) to occupy; the more costly the surprising states, if there is a path to the preferred state, the more the probability of the creature/agent going to (or staying at) the preferred state ; hence the reduction of entropy and enhancement of precision.

Our results show that conjoint presence of increasingly (biologically) costly states and path to preferred state reduce entropy and increase precision (certainty over which state to occupy), and that the more the surprising states are costly, the more the agent is certain that he/she wants to be in, or to go to, the preferred state. (Here no reward state means all states are (biologically) costly, and hence there is no real preferred state.)

Fig. 4




*Graphs showing the impact of biological costs on the entropy (graph A) and on the precision/confidence (graph B), when there is a reward, i.e. path to the preferred state compared to no reward/no preferred state. Entropy reduction (or increase in precision) means that there is*

*more probability that the agent will occupy the less costly, i.e. the preferred, state; given the increasing costs on other states. In this case, the more the biological costs, the more the agent is certain about in what state to be or to go to. Precision increases faster when entropy gets closer to zero. It should be noted however that the reduction of entropy in the no reward is due to the fact that it is still better for the agent to go to the terminal state, i.e. to go to "death", than stay in the environment with increasing biological costs.*

## 5. Discussion

Our goal was to look at the computational way in which need states enhance tendencies that direct actions and choice, and result in enhancement of wanting (and liking). Our first prediction concerned how need states direct action/motivation: for living creatures, there are very limited physiological bounds, i.e. preferred states, as opposed to surprising states, and living creatures have a tendency to go to or stay at the preferred states. Need states are related to biological costs of being in surprising states, and enhance the tendencies or policies that lead to the preferred state. The second prediction was that, if one takes into account both the limited preferred state and the surprising states, the entropy would be reduced and the precision enhanced the more the biological cost on the surprising states, if there is a path to the preferred state. To test these predictions, we used the active inference framework concepts and models. In order to test the first prediction, we compared two agents that are making decisions, a simple active inference agent that computes prior policies to go to the preferred state (i.e. tendencies); and compared that to a simple reinforcement learning agent that computes only reward prediction (action values). For the second prediction, we measured the variation of entropy or precision with regard to increasing biological costs of surprising states when there is a path to reward versus when there is no reward. With regard to the first prediction, we show that biological costs influence tendencies, i.e. prior policies, positively towards the preferred states; as shown for the agent 1 that computes such probabilities compared to the agent 2 that only computes simple reward prediction through action values. This explains the directional effect of need states, in the sense that states within the path/policy trajectory that lead to preferred states become rewarding and preferred as so it can direct motivation. Concerning our second proposition, our results show that the conjoint presence of biologically costly states and preferred state leads to a more reduced entropy and greater increase in precision, and this can be viewed as the more the costly (surprising) states are, the more the agent is certain that he/she needs to go to the preferred state. This explains how need states amplify wanting or liking of stimuli: they reduce entropy or more clearly, they precise the path/action to take/do.

### *5.1 Need related directional motivation*

Our results confirmed our prediction and showed that the presence of the biological costs (surprising states), i.e. need states, influence the tendencies (prior over policies) positively towards the preferred states and negatively for the surprising/costly states; and this tendency (computed by agent 1) is not dependent on the prediction of reward (computed by agent 2). This result could be used to explain the directional and underlying effect of need states: need controls directional motivation, because of the tendency of living beings to move towards preferred states ; and such tendency activates policies that lead to the preferred states. In doing so, states within the trajectory of those policies become preferred, i.e. valued, in the presence of costly/need states. This tendency is mediated by homeostasis or its more general form allostasis (Sterling, 2004; Barrett, 2017; Holmes, 2022; Demekas et al., 2020), processes that help animals reverse or resist entropy (Sterling, 2004; Holmes, 2022) both physiologically and behaviourally (Holmes, 2022). In other words, preferred states, likely evolutionarily defined (Friston, 2010), are maintained by homeostatic or allostatic regulation via behavior (Parr et al., 2022), at the somatic, autonomic and neuroendocrine levels (see Swanson, 2000) ; and act as drives or goals that, through homeostasis and allostasis, direct action (Barrett, 2017); hence the directional effect of need states. Such directional influence, dependent on tendency to occupy preferred states, is also responsible for the underlying effect through which need states amplify wanting, pleasure, interoceptive prediction, choice, etc.; by enhancing precision of their related stimuli (or actions) that are in the path towards the preferred state, in an environment of costly/surprising states. This will be discussed below.

### *5.2 The path towards the preferred state*

The second simulation showed that when the surprising states (need state) that create entropy become more and more costly, this entropy is more reduced, and precision is much more increased, if there is a reward or a cue, i.e. a sensory signal, that indicates a path to the preferred state, compared to if there is none. This confirms our prediction that the formula of need related entropy reduction is conditional to a path towards the preferred state. In that sense, any stimuli, cue, or action that is on such a path will reduce need related entropy, and enhance precision because the animal or his body will know what to do to go to the preferred state. It should be noted however that in our results, there was a slight reduction of entropy when there is no reward. This is due to the fact that it is still better for the agent to go to the terminal state, i.e. to go to “death”, than stay in the environment with increasing biological costs. However, when there was a reward, i.e. a path to the preferred state, the reduction of entropy and especially the increase in precision were still greater. This might further explain the underlying effect of need states on actions and stimuli that lead to the preferred state. When in need states, the precision of relevant stimuli and actions is increased as they reduce entropy ; and such increase in precision can be viewed as a need generated saliency. In that sense, our result might explain how need states amplify wanting, i.e. amplify value of reward cues. We know that wanting is related to

both reward cues that activate dopamine, which is linked to precision of a policy leading to reward (Parr et al. 2022, Holmes, 2022), and to physiological states such as need states. In that sense, need (surprising) states can amplify such precision signaled by reward cues, i.e. make them more salient (e.g. via need induced higher dopamine reactivity), because they lead to preferred state and reduce entropy.

### *5.3 Needing vs wanting*

Our model is coherent with previous reinforcement learning models for incentive salience. The first is the model by Keramati and Gutkin (2014), who argued that any behavioral policy, π, that maximizes the sum of discounted rewards also minimizes the sum of discounted deviations from a setpoint. In other words, the maximization of a needed reward also minimizes the deviation caused by such need (Keramati and Gutkin, 2014). Here such deviation is related to the biological cost of surprising states, and our result shows that being in such states maximizes the reward that represents the path to the preferred state. Another model is the one by Zhang and colleagues (2009) who discussed wanting. Zhang et. al. (2009) provided a computational model for incentive salience 'wanting', suggesting a physiological variable, k (more specifically representing dopaminergic state), that changes the value of reward, r, that contributes to the value of states, V(s), resulting in an amplified value where $\overline{V}(s_t) = \overline{r}(r_t, k) + \gamma V(s_{t+1})$. (With γ representing a discount factor, t for time step, and $V(s_{t+1})$ the value of the next state). Hence, the value of a reward cue depends on the synergy between the reward value $r$ and the dopaminergic states $k$. If r can be a proxy of reward that assigns state values, and *k,* is influenced by the physiological need states, and in this case surprising state (hunger or thirst, etc) then $\overline{r}$ , which is the function of the combination of r and k reduces entropy. In this sense, the state value $\overline{V}(s_t)$ is enhanced because of both the physiological need state k (surprising state) and the value of the reward r, that signals the path to the preferred state ($p$). The amplified variation of reward is a function of the reward itself and k, that is: $\overline{r}(r_t, k)$. Here the reward is (on) the path to the preferred state. Hence, replacing the path/policy to preferred state, that is the reward r, by $\pi(p)$, and the physiological state k by the need state that lead to surprise $S(h_n)$, we have that the function of the enhanced reward $\overline{r}$, which is encoded as confidence by dopamine, is related to precision over policies leading to reward; that is the inverse of need related entropy, i.e. inverse of the function $H_{n,p}(Y = S(h_n), \pi(p))$, or in other terms: the function $\overline{r}(r_t, k) = H^{-1}_{n,p}(Y = S(h_n), \pi(p)) = H^{-1}_{n,p} = P_{n,p}$ ; showing a direct equality between our model and Zhang's (2009) model. Our model is different and allows a more general treatment in that it expresses that relation in terms of information and uncertainty.

Needing and wanting can happen both together and separately (see Bosulu et al., 2022). First need can happen without wanting, because wanting relies on reward prediction and our first results show that need is related to the tendencies to occupy the preferred states, and can influence preference of reward that lead to preferred state even when such influence is relatively low or absent in reward prediction frameworks. When needing and wanting for a stimulus (or action) happen together, need states tend to amplify wanting (Berridge, 2004 ; Toates, 1994) by increasing precision, or saliency, of wanted cues as shown in our second results.

Furthermore, although here we are mainly concerned with the precision of policies, as discussed there are different precisions associated with different forms of changes in prediction (see Parr et al., 2022). So our result lets us speculate that needing can increase different forms of precision, or salience, such as those related to wanting, i.e. “incentive salience” (see Berridge 2004), but also to liking or pleasure, etc. as long as they are on the path to the preferred state. In the same way, needing increases precision of stimuli or actions only if they are available and fulfill their role. For instance, for need states to amplify pleasure, the agent must come into contact with the reward (e.g. have food in the mouth when hungry). In the same sense, for the need states to amplify wanting, there must be the presence of a cue that predicts that the policy (sequence of events) will lead to reward. In that sense, Bosulu and colleagues (2022), who conducted a fMRI meta-analysis on perception of needed stimuli in absence of wanting, found that need states did not sufficiently and consistently activate the dopaminergic system, which is related to wanting. This might be due to the fact that the perceived needed stimuli did not sufficiently indicate that, in the sequence of events, they would be obtained ; and need states can not enhance precision of nothing. It's in this sense that needing can happen independently of wanting. However, the same study showed consistent activity within the mid-posterior insula in the perception of needed stimuli (Bosulu et al., 2022), which might be interpreted as that needing can amplify the precision regarding change in interoceptive prediction, even in absence of a “true” reward prediction (see Bosulu, et al., 2022). Also, wanting can happen without needing as it is generated by reward prediction, which is related to precision over policy and is technically independent of need (Bindra, 1974; Berridge, 2004). In addition to this, the wanting can be amplified by internal states other than the need states, such as emotions, stress, drugs, etc. (Berridge, 1996; Berridge, 2004). This likely means that those non-need related internal states can amplify wanting related precision, and that need states are perhaps not the only ones to generate entropy or influence the reactivity of the dopaminergic system. Thus there can be needing without wanting, and wanting without needing, and there can both happen synchronously.

Furthermore, our study showed that tendencies could be much more influenced by need states than reward prediction suggests, and that in case of need states the policy comes first and determines reward. Whereas wanting, being related to reward prediction, is determined by reward, i.e. reward cues. This difference in precedence between policy and reward may be due

to the fact that in the case of need, it is a prior and internal policy, i.e. preferred state transitions (likely genetically encoded) related to the functioning of the organism, possibly through homeostasis or allostasis. While wanting is related to learned and external policies, i.e. changes in the environment related to prediction of reward which can be attained by the behavior (likely related to the somatic motor system (see Swanson, 2000). This is one of the reasons why wanting has more control over the behavioral activation portion of motivation than needing (Bosulu et al., 2022; Salamone et al., 2018; Berridge, 2004). Moreover, this also gives another perspective on our second results which showed that need states increased precision when there is a reward leading to the preferred state. In that sense, if the reward determined by the need states, i.e. by the prior (internal) policy, is the same as the reward predicted by a signal of reward which specifies the external policy; then the precision will be enhanced and needing and wanting will be synchronized.

## 6. Limits and strengths

This study aimed at providing a model that defines the difference, independence and interaction between needing and wanting. However, some of the notions discussed here might be difficult to define experimentally, for instance it can be challenging to define “need related entropy” in the brain. Also, here we relate needing to biological cost, but one can wonder: are all needs linked to a biological cost if they are not met? Hence, this paper has several limitations that could be addressed in future research. Nevertheless, the propositions discussed in this paper have grounded roots in brain and behavior related literature. Also, the paper introduces the notion of, and explains, the underlying effect of the need states. This idea leads to the suggestion of the distinction between internal (prior) policies and external (inferred or learned) behavioral policies. This latter idea makes it possible to explain why wanting has more control on behavioral activation (Berridge, 2004; Salamone, 2018), but that need can modulate wanting (Berridge, 1996 ; 2004) just as it can modulate liking (Berridge, 2007), preference (Balleine, 1992), etc. trough need generate saliency that we described here mathematically as need related precision. This also explains the directional effect of need and both the activational and directional effect of wanting (see Bosulu et al., 2022). Furthermore, the independence between needing and wanting, and the possibility that there are other phenomena which could cause effects similar to need related entropy, and amplify wanting explains how dopamine reactivity such as related to stress, emotions, etc. can amplify wanting even in absence of need states (Berridge, 1996; Berridge, 2004).

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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AUTHOR CONTRIBUTION

**Juvénal Bosulu**: Designed the study, performed the experiment, data analysis, interpretation, and wrote the manuscript. **Giovanni Pezzulo**: revised the manuscript and provided critical feedback. **Sébastien Hétu**: revised the manuscript and provided critical feedback. All authors contributed to and approved the final manuscript version.

DATA AVAILABILITY STATEMENT

All Data are available upon request.

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