Cross-Cultural Effects and Attention in Active Inference

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***Abstract*—Earlier behavioural studies have shown a social and cognitive difference between European Americans and East Asian people. Westerners are thought to be more focused on object information, while the East Asians are more sensitive to context or relationship information. We focused on two neural studies and argued that this cross-cultural difference phenomenon could be explained by the attention mechanism. We applied the active inference framework to distinguish two aspects of attention, namely, the gain control and epistemic value. The former is involved in the exogenous, low-level response, and this automatic attention could account for the findings that are culturally favoured, such as change blindness and field dependence-independence distinction. The latter is involved in the endogenous, high-level responses, which is identical to the Bayesian surprise and could be measured by the P3 component. This epistemic value may account for tasks where no behavioural differences were found. Both the exogenous and endogenous value is used to minimise free energy in order to maximise the evidence of the generative model.**

***Keywords*—cross-culture effect, attention, planning, prediction, Markov decision process**

I. Introduction

Social cognition studies found that there is a distinction between Eastern and Western reasoning mode. That is, a holistic tendency of the former and an analytic style of the latter [1]-[7]. This cognitive difference is deemed as the main attribute to the beliefs about the nature of the world and is hypothesised as a cause of allocating attention resources in particular ways. This means that people from different cultural groups may see the world in different ways, which means that our perception is contextually (or culturally) dependent. Behaviour research have listed a series of qualitative distinctions in metacognition, such as the field dependence-field independence distinction [8], which means the degree to which the perception of an object is influenced by the context it is embedded in., or, more simply the ability of disassociating the foreground objects with the background; The hindsight-bias problem which states that people react to prediction errors less surprisingly. However, in comparison to the Westerners, Eastern people are remarkably less surprised by the unusual results of the events than they should be and believed they had predicted the turning at the first place [5]. Besides, research also report the Change-Blindness phenomenon, an attentional effect that influences the perception process for people of different cultures. People failed to recognise marked changes around even when they are asked to find out the changes in the visual filed [9]. Overall, East Asian cultures emphasise the practices of interdependence, resulting in the consequences that they are less likely to distinguish the objects from the background, more sensitive to contextual information changes [10], and more possibly to overestimate the probability they would have predicted the results if they were told the outcome and more field-dependent in the Road-and Frame test [4]. Whereas European Americans emphasise practices of independence, so that they always show big surprise when the prediction is violated [11]; they constantly fixate more on focal objects and they detect object changes more easily than changes in background.

However, in much strictly designed neuronal experiments [12]-[14], no such behavioural differences were found when participants were instructed to do culturally non-preferred tasks, albeit slower and less accurate meanwhile. Researchers from the neuroscience camp argue that culture does influence brain function powerfully by biasing towards certain neuronal pathways and a violation of this bias may lead to an increased brain activity in areas that are associated with attention. This raises the issue of how attention entrains the decision-making process and leads to the overall equally efficient global behaviour. Given cultural practices do facilitate certain decision-making process (i.e., faster reaction time in culturally preferred condition in comparison to culturally non-preferred condition), which mainly unfolds in basal ganglia circuits by computing the difference between the values of the direct and indirect neuronal pathways [15], [16], there may be a unified theorem that mediates the habitual preference and attention. To our knowledge, active inference is the best candidate referring to, since basically, it balances the priors and uncertainty and offers a frame of inferencing optimal future actions which is crucial to the decision-making process. This decision process may lie at the core of the cross-cultural effect. Although the whole theorem may look complex, we can simply take its essence, that is, it emphasises the importance of generative model and prior beliefs agents

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hold such that the world is selectively sampled to fit with the hypothesis in which priors play a role in generating prediction errors [17]. Priors always pair with habitual motor actions, while generative model encodes entropy, which leads to the reduction of uncertainty (i.e., exploration). When planning, the latter offers explanations to the data we perceive, while the former are the beliefs that contextualises our sampling of the world by assigning different weightings to the sequences of actions at the counterfactual level (for example, whether to turn on the light before going home, if the lighting system in your house is controlled by intelligent devices or turn on the light after are different action sequences. What active inference encodes is the beliefs about these sequences, not actions). In the context of cross-cultural effect, we can unpack this phenomenon as people who are equipped with different priors select different policies (i.e., several possible behavioural trajectories) to minimise prediction errors. An example for this is Hedden *et al*.'s work, in which the authors found a dissociation between the habitual behaviour (when doing culturally favoured task) and uncertainty resolving process (when doing culturally unfavored task), but overall equal accuracy and timing. The crucial funding is the equal time the two groups used to make judgements. This means, no matter how biased people are, when they are required to do an unbiased decision-making task, the energy that is used is equal. From the active inference perspective, the minimum expected free energy legitimates the goodness of a policy which balances the exploitation and exploration well. Once these balances are achieved, a motor action will be elicited.

Besides, the planning of actions has a particular relation with attention, in the sense of 'salience' which could be deemed as a property of locations that the highly likely next saccade would target. The evaluation of salience is a process of computing the possibility of different policies in the exploration process. For example, each of the four quadrants of the squared pictures has different information gain that helps to resolve uncertainty [18]. The most salience position is the place that offers the maximal information which could increase the confidence of agents' beliefs about the world [17]. The basal ganglia are thought as a perfect candidate to compute the salience since the dopamine signal is now considered as encoding the imprecision of prior beliefs about policies [19]. It is argued that the prior belief is computed by the direct pathway between the striatum and Globus pallidus internus, while the information gain is evaluated by the indirect, slowly evolving pathways. This seemingly redundant pathways may plausible since they meet the requirement of timing of messages in each pathway [20]. This suits well with the findings of equal time both groups used. The direct pathway has a short latency and could disinhibit a set of policies quickly, while the indirect pathway receives signals from wide range of higher-level cortical areas so that it takes long time to play out its signals. The latter may also account for the relatively long reaction time when participants are required to make the judgement under the culturally non-favoured condition since our brain need to integrate the information into the decision-making process. This evidence accumulation could be reflected by increased activity in dorsolateral prefrontal cortex, and signals from this brain area reveals the weighting of posterior beliefs over prior expectations [21].

Armed with these works, the current paper aims to explain the attention mechanism in respect of active inference theorem and then unify all the results with one possible computational model. This paper comprises three sections. In the first, we will focus on two studies that reflect the neural correlates that underlie this cognition problem. In the second, we will introduce the essence of active inference and a recently developed model, namely the Markov decision process. Thirdly, we will reiterate the Lewis *et al.* and Hedden *et al.* experiments in the spirit of this model. We propose that human make decisions according to prediction errors that are transported between levels of the hierarchical generative model. Attention governs precision of prediction errors so that only those precise prediction errors that are weighted by the second-order attention mechanism can be gained to help revise the higher beliefs. Attention could be shaped by culture, resulting in that people with different groups are sensitive to different types of stimuli. However, attention can also be shifted towards the most salient position to resolve uncertainty about hidden cause created by context [22]. The process of human's actively sampling the world and keep themselves within limited states can be explained by the active inference theorem. Behaviour experiments can capture the cultural effect either by manipulating the context which participants usually immerse themselves in, or by showing them cultural preferred and cultural non-preferred stimuli. But overall, these cultural effects are a violation of their causal models that shaped by social demands.

II. Endogenous Components of Cross-Culture Effect

Lewis and his colleagues looked into the neural correlates that reflect this cognitive difference using a three stimuli P3a event-related potential design [13]. In this type of oddball experiments, the target (oddball) will elicit a reliable positive event-related potential peak around 300-400ms after the onset of the target (oddball) stimuli since the ERP technique offers time-lock neural activity recordings. The well-documented P300 signal is thought to be positively correlated with stimulus probability, task demand and attention allocation in processing this less likely appear yet meaningful oddball [23]. In this paper, Lewis et al examined two types of P300 components. The P3a is sensitive to deviations from the temporal stimulus covariance created by the combination of standard and target stimuli, whereas the P3b is a late positive distribution and is thought to signal a context-updating operation [24]. The idea is if East Asians indeed are more sensitive to context and perceptual field, then there would be a significant P3a difference between two groups. On the other hand, if European Americans attend more to focal object, then they should display a relatively larger P3b amplitude. The data proved this hypothesis and their further mediation analysis showed that the relationship between culture and P3a is mediated by interdependent self-construal.

Hedden used functional magnetic resonance imaging technique to locate the place in the brain where these cultural experiences influence judgements [12]. The study was based on the found that the harder the task is, the more attentional effort will be put [25]. Participants from two different cultures are put into fMRI scanner and are asked to make judgements regarding the line lengths. They observed a series of stimuli containing a vertical line inside a box. The task is to judge the stimuli with or without considering the box. Specifically, in the relative instruction part of the task, participants are required to judge whether the proportional scaling of the combination of the box and the line is same with the previous combination. In absolute instruction parts participants judge whether the length of the current line matches the previous one regardless of the box size. In each trial of the block, either the two instructions lead to the same conclusion —policy congruent condition, or the two instructions lead to the opposite conclusion — the incongruent condition. The relative judgement is East Asian-culture-preferred since they care more about the context, environment, and relationships, while the absolute condition is the Western European culture-favored due to their habits of focusing more on individuals. Participants also finished an independent questionnaire which reflects traits of self-identify. The authors found in the congruent trials, participants are faster and more accurate, and no differences are found in culture incongruent trails (i.e., both groups perform similarly). Whereas in the incongruent condition, brain imaging showed that both group members recruited extra cognitive effort when processing cultural non-preferred tasks and the brain areas that are correlated with attention control and working memory are more involved. The culture-identity questionnaire with higher scores for culture-preferred traits correlate significantly with less activation of ROIs in culture-preferred trails.

III. Active Inference and Markov Decision Process

The Hedden et al study pointed out attention plays a crucial role in shaping cognitive differences, whereas Lewis et al argued people with different cultural identity tend to perceive different types of information, the violation of expectations to this type of information induces P300 component — an indicator of surprisal. The latency of the P300 component indicates the level of accuracy the participant evaluated the stimuli [24], and cultural background exerts its influence on the neural processing of context through the mediator of self-construal [13]. These findings imply a prediction model people use to represent the world and some segments of the model are assigned heightened availability. However, these descriptions of attention on the nature of P300 component are not precise. We are expecting a model to code attention, besides, we also need to illustrate how the prediction error produced by this predictive model attracts attention. The answer to this question points to Active Inference theorem since it offers a mathematical approach to explain the importance of how the uncertainty is resolved and how the resolution of uncertainty results in attention. Briefly speaking, Bayesian surprise attracts attention, and this information is the epistemic value of an expected free energy formulation in the active inference theorem. What we are going to explain below is a highly simplified version based on Friston's works [26], [27].

Adaptive agents like humans act to limit the repertoire of physiological and perceptual states in which they can find themselves [28]. The limited repertoire signals some attractors that lead living creatures towards their expected states. Homoeostasis is a perfect example. When core body temperature deviates from the typical temperature range, agents would reason the possible causes and then act accordingly to keep body temperature within homeostatic ranges. The ability to fit subjectively implies that the agent's internal states hold Bayesian beliefs that encode and predict the external causes of sensory information, so that the internal active states reasoning in a way as if the agent ascent on the marginal recognition density over the external states. In other words, to survive, agents need to be able to minimise the divergence between the hypothesis that is currently selected and the true posterior beliefs under the generative model which is fine-tuned over ontogeny [29]. This discrepancy plus surprisal is variational free energy. Briefly speaking, variational free energy is predictive error in nature. Adaptiveness solicits familiar, unsurprising sensations from the environment, this means agents realise themselves by minimising surprise, namely the negative logarithm of Bayesian model evidence $-\ln P(\tilde{O}|m)$, where O denotes observations and m denotes 'generative model'. Variational free energy is an upper bound of log model-evidence. Since model evidence is nearly impossible to compute, naturally, variational free energy measures the approximation of how much evidence provided by the data in terms of the generative model (i.e., the 'm') of the causal process. The states define the observations, because states mirror the causal relationship between the real world and its corresponding mental representations in the brain, and inference (or planning) is an inversion of generative model. Reasoning back from observation to causal states leads to the asymmetry between causation and observation, so that when making decisions (action), to avoid surprise, agents weigh different policies and chose the most possible states (one possible causal state) that maximise expectations with respect to free energy, and actively sample (sensation) observations associated with the minimised free energy. In brief, reducing prediction error (variational free energy) drives perception [30], action [31], attention [32] and motivational value processing [33] mainly because it equips the brain with the function of inferring the causality. In this way, living creatures adapt the fast-changing environment.

The problem is organisms have only sensation data. Active inference thus suggests planning as inference under the energy principle [17], [34], [35]. To find the most approximate posterior belief, generative models like predictive coding or Bayesian decision theory with Markov decision processes are good candidates to equip agents. Active inference takes the latter to account for the creature's belief updating and behaviour as the inversion of a generative model. In this way, the action-sensation loop is linked by expectations, that is, the expectations depend on observations and actions depend upon expectations. This loop shows how agents' internal predictive models communicate with the real world. In other words, agents interact with the world and make decisions of actions as a function of their newly updated expectations. The expectations are updated according to the sensory data agents sampled and are used to refine their beliefs about the states of the generative process, namely the world. We can understand active inference as gathering sensory evidence for an agent's model of its world, and by doing so, the agent realises the so-called self-evidencing. This is a rather subtle statement lies at the heart of active inference that agents adjust their expectations to minimise free energy and they can only realise these requirements when they believe the observations they actively sampled can lead to the minimisation of free energy. For example, I believe I need to keep my body temperature in cold winter, so I would either actively wrap up, or stay indoors because I believe these policies will make sure I will not get cold. This is where the expected free energy plays a role. The expected free energy is the difference between the energy of the counterfactual outcomes and states that generates these outcomes expected under the posterior distribution $Q\ (O_\tau, S_\tau|\pi)$ and the entropy of the posterior predictive distribution over hidden states [36]. $Q\ (\widetilde{S}, \pi)$is a counterfactual posterior distribution over hidden states S_τ under current beliefs, while current beliefs (the priors) about hidden states depend on past observations. The prior beliefs will be the pragmatic (or, extrinsic) value which guide agents towards the goal no matter what policy they choose. When planning or reasoning, to minimise the expected free energy in the future, agents need to choose the policy that could offer more information about 'what the observation I would get' and 'at what state I would be in'. Put simply, agents are in search of a policy that would lead to the maximal mutual information, Bayesian surprise, or information gain. We can also understand this as agents are purposefully navigating themselves to the outcomes that can maximally update their current beliefs towards the expected states. The expected free energy over the ideal policy will then be written as the summation of the pragmatic value offered by prior belief, the epistemic value which tells the reduction of uncertainty of future states offered by possible outcomes and information gain for parameters (i.e., novelty). It is a policy where the power of epistemic value is contextualised by the pragmatic value. This is key to understand the cross-cultural difference since the execution of the culture favoured decision is influenced by the resolution of uncertainty reduction, and the extent to which the agent would explore the environment depends on a precision parameter γ.

The cultural effect is related to attention (i.e., expected precision parameter), a variance that reflects how confident (precise) a model's prediction is. It is the second-order, non-linear inference process which modulates the first-order linear driving connections [37]. Before moving to discuss how this parameter works, it is necessary to formulate the graphic model (MDP) in Fig. 1. to illustrate their relationships. In this model, variables are defined as Table I.

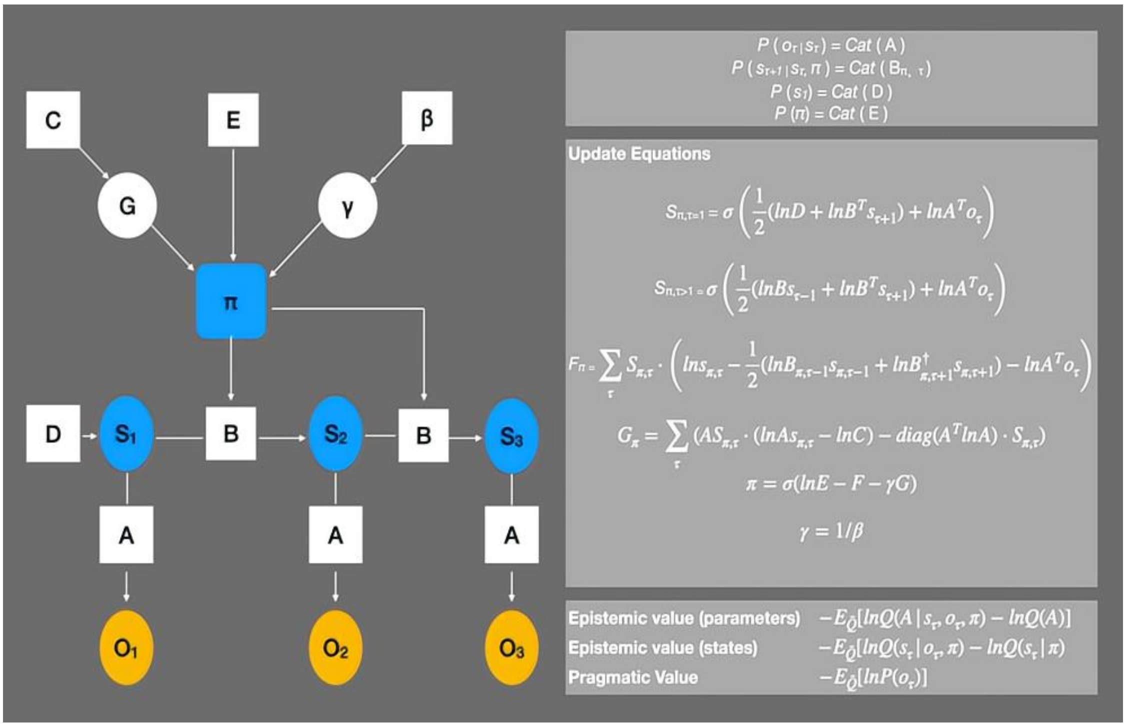


Figure 1. Parameters that are involved in policy optimization.

TABLE I. GLOSSARY OF EXPRESSIONS FOR THE GENERATIVE MODEL

$O\tau$	Outcomes or observations at time τ
$S\tau$	Hidden states at time τ. Often serves as context or choices. For example, in Ponsner paradigm, there are two contexts, namely 'looking at right and looking at left'. In figure-background experiments, background is also a 'context'.
Q	An approximate posterior over hidden and control states
π	A vector encoding the distribution over action policies reflecting the predicted value of each policy. Each policy I a series of allowable actions in a vector U, where actions correspond to different state transitions that can be chosen for each state factor.
A matrix $P(O\tau \mid S\tau)$	A matrix encoding likelihood of the relationship between hidden states and outcomes. It solves questions like which outcomes are most likely when there are multiple hidden states.
B matrix $P(S\tau{+}1 \mid S\tau, \pi)$	A matrix encoding beliefs about how hidden states will evolve over time
C matrix	A matrix encoding the degree to which the observed outcomes are preferred over others. Technically, it is modelled as prior expectations over outcomes. For example, when walking in foggy forest, observations from auditory channel may be improved or outweighed than visual observations.
D vector	A vector encoding beliefs about initial hidden states.
E vector $P(\pi)$	A prior probability distribution over policies, implemented as a vector assigning one value to each policy. Always regarded as habit.

The squares on this map are parameters that map the most possible hidden states to the observed outcomes. Basically, this picture is a road map that can be used to infer the quantities of the hidden states and the relationship between hidden states and outcomes by adjusting different 'square parameter'. The 'D-S_1-A-O_1' pathway shows the basic perception at a single point time, and when policy π is added in, the model generates a temporal time depth. Different cognitive activities can be measured in this time-windows, and we mainly are interested in the attention effect from 100 ms up to 300 ms after the onset of stimuli. The 'D-S_1-A-O_1' pathways means the hidden state (posterior expectations) S_1 can be inferred from sensory evidence O_1 based on the prior beliefs D and a likelihood matrix A. The S_1 can be thought as the best explanation of the observations. The transition from S_1 to S_2 relies on the B matrix layer. It describes beliefs about how state evolves over time, independent of the true future observations. Crucially, B matrix and states of previous time point (i.e., τ-1) function as a temporal empirical prior. A series of B matrix form different policies π, each of which holds different predictions for the future. This is the core of active inference, namely, the policy selection (i.e., planning). Note that, the posterior belief about a policy depends only on the current internal state, that is, internal states can only infer action through its sensory sequelae. This creates a distinction between action and beliefs about its consequences encoded by internal states [36]. Due to this difficulty of licensing correct action but only beliefs about action consequences encoded by internal states, active inference reverses the usual logic of action selection into asking "given the assumption that I achieve my preferred outcomes, what course of action am I most likely to pursue". This means agents need to hold mental representations of outcomes under different policy series, and the dynamics of hidden states over time endow agents with working memory which enables evidence accumulation. The evolution of minimisation of prediction error may lead to the emergence of the best predictors in the higher level. This finessed regularity resists to change since it is good enough to predict the outcomes in a longer time scale. A good example is processing a sentence. The lower level infers single word, and higher level infers categories and the combination of categories of words, while the highest level infers the sequence of the combination of different categories. We can also take clock as an analogy; a ticking of the minute hand corresponds to the lower level. At the end of each circle, the hour hand, which corresponds to the higher level, ticks once [38]. In active inference, this is where the pragmatic value is computed [39], [40]. The γ is an indicator of the sensitivity about how precise the prior beliefs about policies are. The advance of adopting the MDP model is its hierarchical nature enables us to see how the higher-level parameters influence the deep temporal structures. The MDP model can be expended in a nested fashion such that the beliefs about the policy and the first hidden state only depends on the hidden state one level above. That is, the policy, together with its mother and child hidden state node, form a statistical shield that contains all the information that is required to generate certain observations. What we show in the graph is a basic one-level unit of MDP model. We can take it as a whole, and add another state layer upper the π node, such that the chosen of this policy depends on whether its mother node is activated. Further, we can imagine that there are several mother nodes in parallel, each of which generate different outcomes. The active inference suggests that agents can actively sampling the world by activating different state nodes. This possibly is how γ parameter mediates the higher states with the lower levels where the explorative process unfolds. Also, this is where culture exerts its influence on different ways of navigating the world.

IV. Attention Mechanism

Attention is established by measuring the precision of probabilistic representations in hierarchical inference about the cause of sensations. Prediction errors that diverse in precision level compete to be explained away, leading to this precision-weighting mechanism [41]. Superficial pyramidal cells are proposed to be crucial in reporting precision-weighted prediction error which has more influence at higher levels [42]. Attention hence is thought to modulate excitability of neuronal populations that generate prediction error and attenuates less reliable prediction error. For example, acetylcholine is supposed to exert its influence on low-level bottom-up auditory processing through boosting postsynaptic gain when stimuli are predictable, resulting in accelerating brain's response to the reliable prediction error [43]. The mirror neuron system is proposed engages in inferring causes of action by observing and minimising the prediction error at all cortical hierarchical levels that are involved in motion-observation. But the precision of this kind of prediction error should be weakened when agents elicit their own actions [44]. A failure of attenuation leads to illusions, which means, physically, agents failed to infer whether the actions are done by themselves or others [19]. Reporting precise prediction error is vital in making optimal inference and balancing internal modal with sensory data at hand [45], [46]. Attention's nature of ascending prediction error and influencing higher level hidden states can be thought as state-dependent. Agents learn state-dependent patterns of noise, and when sampling, this learned patterns are served as prior beliefs to guide perception and action. A change in states of the environment will lead to a change of information-to-noise ratio and change the location where attention will be set. This does not mean attention is always a conscious process [39]. Indeed, sensory data are highly biased both by bottom-up and top-down predictions, and attention can be unaware. A well-studied top-down spatial attention bias, which is also inspiring in understanding automatic culture attentional effect is the Ponsner paradigm. Under this experimental setting, participants are asked to maintain fixation on a central fixation and respond as quickly as possible to the appearance of a peripheral target. The target is cued either by a central arrow which indicates the direction of the upcoming target 80% of time accurately, or a square that shows up around the location the target will show. The valid cue speeded the detection time significantly and researchers argued this is due to endogenous attention facilities the prior knowledge, or the hidden state that generates the observations that are currently processed. Feldman and Friston modelled this task with a 2-level hierarchical model [32]. They demonstrated that the peripheral box, serving as exogenous (overt) cue, attracts attention by augmenting local precision (the right place), so that the spot where the peripheral cue existed gains a boosted precision, which excites the corresponding hidden state. The appearance of the arrow cue solicits a high-precision prediction error, which excites the hidden cause of the higher level that drives the hidden states towards biased location. This bias effect lasts for a while, waiting for a forthcoming target. If the target is the expected one, then a high-precision prediction error will be generated, and stabilises the hidden cause at the second level, which will activate its corresponding hidden state at the first level, results in a perception of a target. If the target is not what is expected, the bias effect will disappear, thus non-activate hidden state fails to generate an invalid target. Note, the hidden state, biased by the hidden cause serves as a temporal prior, and the target is the expected surprise. In short, attention mechanism offers unambiguous perception information that should be boosted when encountered and should be sought when absent. It enhances reliable prediction errors as well as attenuates irrelevant prediction errors. The attenuating function is related to figure-ground recognition process [37], which we can use to explain the figure-ground segregation in cross-culture difference.

The process discussed above is overt attention, meaning the result of attention has been successfully executed, for example, an eye movement. Apart from this automatic overt attention, there is another aspect of attention, namely, the covert attention which is proposed by Posner et al that attention can be reoriented to the non-attended but stimulated space without firstly detecting the signal. This attention is argued as a bottom-up bias [47]. Abrupt-onset stimuli, which pops out from the background as outliers, and thus attracts human attention naturally, even task irrelevant [48], [49]. This type of stimuli offers information in Shannon information fashion because Shannon entropy requires integration of information offered by new outcomes over the space of 'new outcome' of all possible outcomes. Even sometimes, stimuli capture an approximation of surprise, it is flawed sometimes, hence not the best candidate accounts for attention. He also suggested that the programming period of attention is separated from the detection period anatomically. The latter is embedded in the oculomotor networks and responds habitually to the certain type of signal. Once the stimuli deviate from the habitual type, extra effort is needed to detect the stimuli. Some studies imply the overlap of neural networks between attention and oculomotor control can be modulated by dopamine [40], [50], [51], since the disruption of the dopaminergic projection to striatum disrupts normal eye movements [52]. More precisely, the behaviour of phasic dopamine signals reflects the confidence in posterior beliefs about policies [53], [54], and this is the γ parameter introduced in the active inference, which is used to plan the next move. Both overt and covert attention offers information gain agents are searching for. Different from information the bottom-up bias offers, Bayesian surprise requires integration over the model space of the observer and attracts attention in a top-down fashion. Stimuli of this type do not contain information gain themselves but are able to direct attention to the spot that contains information gain [55]. In the language of active inference, this Bayesian surprise is the 'epistemic value'and the level of its salience depends on agents' beliefs about to what extend the sampled data would update the prior belief thus navigate agents towards the true posterior beliefs.

A common way to test attention level is recording saccadic eye-movements. Friston *et al*. proposed that saccadic eye-movements are agents' experiments [56], which are used to change outcomes in hopes of gathering information that explain the perceptual hypotheses best. Statistically, attention can be deemed as an analogy to the 'DO' operator proposed by Pearl [57]. This operator activates certain parts of information networks and blocks others, resulting in a formation of causal Bayesian chain [58], and the best explanation of the hidden states. That is, the 'salience' value guides the sampling towards the unambiguous goal that have not been predicted yet but with a high degree of certainty. Agents' motivation is solving the uncertainty. As can be seen from the graph above that the policy is a functional of variational free energy and precision-weighted expected free energy. It can be written as:

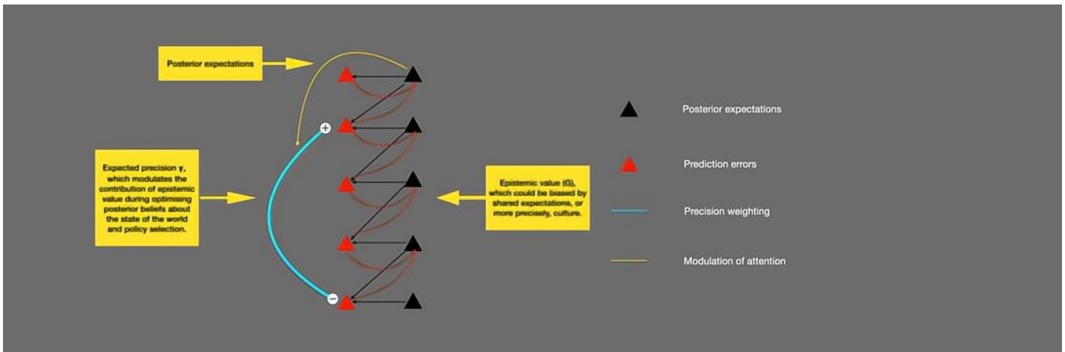
$$\pi = \sigma(ln\, E - F - \gamma \cdot G) \quad (1)$$

With a closer look, this equation means agents need to integrate information of both A matrix and B matrix, and the generative model is dynamic and hierarchical. That is, under each possible policy there are many B matrices that denote transitions of hidden states, and different likelihood encodes in A matrices. Different combination will generate different outcomes, so that the precision is paramount in selecting which pathway agents will select, and which will be inhibited. It is worthy of giving an intuitive example of how the precision of a one-dimensional A matrix and B matrix would influence inference. Normally we rely on binding sensory information of different modalities—vision, hearing, smelling, touching and tasting to make decisions. However, when in foggy forest, a good hunter may need to sharpen his sensitivity to hearing and smelling signals and rely less on other sensory information. In this situation, the precision of olfactory and audile prediction errors are boosted, resulting in a quick response to signals coming from these two sensory channels. If now an olfactory signal reports the possibility of a tiger (the likelihood of A matrix is high) which rarely inhabit this forest (the belief about the precision of A matrix is low), besides, the density of the smell directs the possible location the attention should be directed to (density is a variable of B matrix the change of which represents volatility, a greater volatility shows a less precision of B matrix, in contrast, a lower volatility means the precision of B matrix is high). The more volatile the B matrix changes, the faster the representations of the feature s (e.g., density) are forgotten, the less easy the inference can be made. The combination of A matrix and B matrix can generate a belief about the state — 'how far a tiger is from me'. Once a belief is made, a policy is chosen, this temporal working memory can serve as a context restrains and combine with incoming information which is highly related with the refined past stimuli to predict future information (i.e., whether there is a tiger around or not). In saccadic eye-movements experiment, such as Mirza *et al*. [59], the γ value measures the overall confidence level of a policy. As for the subsets of gamma parameter, they can hold different precisions. For example, the precision of A matrix ζ and B matrix ω (for a visual structure of the distribution of γ which modulates π, and ζ which modulates matrix A) [60]. In a simulation of reading task, Parr and Friston simulated the effects of dopamine modulation on salience using a hierarchical reading task in which a high precision of γ correctly predicted the upcoming word with the minimum eye-movements, whereas the lowest precision of γ led to a random saccade which means a failure in prediction upcoming information [40].

As has been implied above, the saccadic experiments are in search of data that bring about an update of belief to the maximal level, however, they have great uncertainty about the data but only high confidence (precision of expected free energy) in the cause of how the data are generated. Meanwhile, maintaining a representation when distractors are around requires agents holding the execution and believing the incoming data is noisy and useless in updating beliefs. This dilemma offers a chance of biasing the belief updating towards either the current beliefs or the current incoming data from the lower level of sensorium. When it is used in the former way, the posterior beliefs are kept close to the prior belief. This is where the cultural effect influences perception. Given the hierarchical nature of the generative model, when the epistemic value is computed, the higher-level precision modulation determines which expectation would be encoded in the hierarchy [61], and this expectation is shared expectations that formed through shared cultural practices (see Fig. 2 for a summary). The communication between local environments and the associated practices leads to particular patterns of coordinated attention from participants [62], [63]. These patterns have dynamical attractors that guide action-perception loop towards certain states and outcomes rather than others, and these attractors are hierarchically deployed since they are induced by sequence of states which are hierarchically nested. This means that it is possible to generate sequences of sequences. Agents that are equipped with the same generative model synchronised indeed to the same attractors when they are engaged in the communicative setting [64]. This may be how the cross-cultural effect evolved.

V. An Explanation for the Previous Experiments

In this part, we aim to reexplain the two neural studies by using the active inference framework introduced above. Before doing so, it is helpful to look back on the studies we discussed at the beginning. Hedden assessed the fMRI responses when participants were doing both absolute (ignoring the visual context) and relative (considering the visual context) judgements under different conditions (congruent and incongruent) [12]. Participants were either from Western cultural context or East Asian community. This probably is the first neural study of the cross-cultural phenomenon, the results of which denied the existence of significant behavioural effects. The authors found no behavioural culture effect for accuracy or reaction times, albeit faster reaction time and more accurate judgements in congruent trails in comparison to the incongruent trials. However, they did find the above-threshold activities at the neural level in higher-order cortices (frontal, parietal, temporal) that are involved in cognitive control, attention and working memory when participants were doing culturally non-preferred judgements, they hence concluded the cross-cultural effect is involved in the simplest activities by endorsing attention. These findings could be explained in two aspects: the first is how attention mechanism selectively responds to culture favoured stimuli; and how participants actively resolve the uncertainty while holding the execution to the culturally favoured stimuli.



A simple cortical hierarchical model with ascending prediction errors generated by superficial pyramidal cells (the red triangle) and descending predictions generated by deep pyramidal cells (the black triangle). The gain control (attention) decides the power of influence the prediction errors on posterior expectations. However, at the higher level, the expectation controls the attention and in current paper this is shared expectations. Differences in the development of attention lead to different confidence in salience or epistemic value, resulting in the cross-culture effect discussing in current paper. The graph is based on Friston et al.(2014). As for this **precision** parameter, it is easy to understand. 'Engaging in predictive inference without taking account of precision would be as precarious as engaging in statistical comparison of means without taking the variance about the means into consideration' (Hohwy,2013). It quantifies the confidence level of a given distribution. For example, the higher the precision of the prior belief is, the more dominant this prior belief would be in computing posterior belief. There is a set of precision parameters. γ is the precision of prior beliefs, ω is that of the B matrix and ζ of A matrix. There are also some neurotransmitters that are argued to correspond with this set of precision parameters. For example, Acetylcholine may be involved in modulating the precision of the A matrix that encodes the likelihood mapping (Marshall et al.,2016); noradrenaline is associated with the level of precision of the transitions of B matrix (Marshall et al.,2016) which signals how volatile the world is , and dopamine which is well studied as encoding the precision of policies (Schwartenbeck et al.,2015).

Figure 2. A simple cortical hierarchical model with ascending prediction errors and descending predictions.

Neurobiologically, the precision weighting (attention) is a parameter that does not change with time and is highly experience-dependent. This means, the updating of γ resembles associations between short and long term changes in synaptic connections [64]. It is an emergent phenomenon and signals that the generative model contains prior beliefs, and the log-precision of these prior beliefs is redistributed in context sensitive fashion. Given the state-dependent nature of posterior beliefs, we could thus state that different priors select different types of sensory information. That is, agents tend to actively sample certain types of outcomes with respect to their prior expectations shaped by different culture niches and visit the most familiar sensory states again and again [65]. The prior, or hidden cause generates expected information gain (i.e., Bayesian Surprise), such that only the targets that can induce high-precision prediction errors that could be perceived.

In behavioural experiments investigating the cultural effect, with the absence of cues, the precision information is encoded in the probabilistic contexts (or states) generated from the task requirements, in which two causes are expressed. The judgment task carried out by Hedden et al introduced two sets of hidden states, namely Rule and Categories. A scene can be perceived in two ways, according to rules, either by focusing on the object or the combination of the objects and the peripheral box. The two categories correspond to objects (i.e., S_{line}) and the combination of the objects and the peripheral boxes (i.e., $S_{line+box}$). These two outcome modalities generate 4 outcome possibilities in total that deviate from participants' normal expectations. The first outcome modality Rule unambiguously cues the context. This process is exactly as same as how the endogenous and exogenous cues excite the hidden causes in Posner Paradigm and then hidden causes drive two hidden states bias the precision towards the most favourite (valid) information. These causes are shaped by encoding the affordance of culture niche in real social life into tonic dopamine firing levels [56], [66], since consistent results of certain actions in certain culture communities furnish reliable prediction errors, and this attracts the actions towards the most revisited repertoire of hidden states. Put in other words, the hidden cause shows a long-term persistence that shortens the reaction time and requires extra evidence accumulation to be reversed. The active sampling action reports participants' beliefs about the category of the scene categorised under the precision of the Rule. Further, Rule category exists at the higher level of the hierarchy of the MDP model since it governs how other modalities generate outcomes and the real perception result is a function of

Rule hidden states (e.g., sampling the length of the line when the rule is *Focus Object* will get a *right feedback*). Modulating the precision of rules leads to a change in perception outcomes. Mirza et al simulated a colour/shape task in which both colour and shape features can be used to sample a scene [59]. When increasing the precision of one rule to the maximal level (i.e., the colour rule) while decreasing that of the other to zero (i.e.,the shape rule), participants selectively percept the outcomes generated by the high-precision rule (i.e.,colour) and neglect the shape outcomes totally. However, when the precision of both rules is increased, participants attend two targets generated by the two hidden causes without neglecting any targets. Similarly, we can assume that simply by changing γ values, the behaviour differences could be captured. For westerners, γ value for R_{line} may relatively higher than that of $R_{line+box,}$ which means participants have a high posterior confidence over current policy, namely focusing on object information. For Asians, the other $R_{line+box}$ has higher γ value that drives them in search of information from the combination of object with others. This analysis may indicate the substantial cognitive differences across cultures is objective and significant behavioral differences could be observed. However, it is important to notice that the behavioral indices of cultural effect for accuracy and reaction time are similar across Westerners and East Asians, besides, participants were faster and more accurate in congruent trials in comparison to the incongruent trials. That is, when the cultural expectations are violated, the reflexive did not slow down the reaction time albeit some costs of accuracy were paid. This may because the extra attentional load is recruited to reduce prediction errors. In the incongruent condition, participants were required to make judgements to the stimuli they did not habitually attend to. So, participants need to retain habitual responses to the cultural favoured stimuli while planning movements by reducing the epistemic value. The appearance of the stimuli in the non-expected direction induces a shift of attention and rearrangement of the ocular motor program, leading to redirect fovea to the place the attention beam light is shifted to [67]. This change could interfere with the habitual system, thus slow down the reaction time. As what has been implied above, the neural networks of attention and salience are different anatomically. The salience is thought to be mapped in the superior colliculus and relies on motor control which interacts with attention system and elicits actions according to the affordance the salience has offered [68], [69]. It is possible that the messages from cortex (attention) to colliculus (salience) are prediction errors [40]. Given both groups were undergoing the same process, that is to minimise the expected free energy, this may result in overall the same reaction time yet increased errors (since retaining the response is hard according to Ponsner *et al.*) [47].

The same analysis could account for the three-stimulus oddball task carried out by Lewis *et al.* To recap briefly, the authors investigated neural responses to targets and novel stimuli by using a 3-stimulus novelty P3 event related potential design. Participants were required to respond to the targets '6' while being distracted by novelty stimuli whose possibility is the same as that of the targets. No main cultural effect was found in this experiment. However, culture significantly interacted with the condition, and condition interacted with Electrode. The relationship between culture and Electrodes is mediated by self-construal. That is, westerners attend to targets more easily while Asians tend to pay more attention to contextual information. Different from the Hedden et al' paper, in which participants need to respond to both the typical and atypical stimuli, participants in oddball task were required to respond only to the target number. For Westerners, this type of target easily activates the hidden state of S_{target} which generates the objects, leading to their accurate responses to the targets. Whilst the precision of hidden state S_{target} is lower than $S_{target+deviate,}$ resulting in a consistent attention to the relationship between the current and upcoming stimuli to minimise the expected fee energy. The different amplitudes of P300 component are a piece of evidence.

According to Donchin and Coles [24], agents are waiting for certain types of information that are expected according to the current context created by the task. We now know this information is the type of targets that is able to induce high-precision prediction errors. The P300 component is a sign of the appearance of this type of stimuli. It is a sign of Bayesian surprise, the epistemic value that is expected to gain, but the certainty about the data is low. It manifests the changes in the environment that help to update the current context to adjust the changes. Not all odds in the environment induce this event-related potential. Only the segments of the context that are meaningful to the tasks are likely to induce the revision of the generative model [70]. To test how responses to the invalid targets change when jointly put together with attended targets, Feldman and Friston presented valid (stimuli that are easily captivated by attention around 100 ms after the onset of stimuli) and invalid targets in conjunction and found that the response to the invalid targets is half of that of valid ones [32].

The valid targets will lead to the increased N1 amplitude due to their ability to win the attention resources by attenuating the invalid targets, but a reduced P3 amplitude, since no prediction error needs to be explained away. On the contrary, the invalid targets generate decreased N1 and increased P3, meaning the prediction error needs to be reduced and the higher order context should be updated [71], [72]. This explains well the Lewis *et al.*'s results that the European Americans have a higher P3b amplitude singling their attention on changes of objective targets which are expected to update their posterior beliefs, while East Asian Americans' greater novelty P3a component shows their generative models encodes high precision of relationship information and thus easily attend to targets that may bring changes to this relationship information. This has been proved by Wright *et al.* by using a Hierarchical Gaussian Filter [14]. East Asian's higher probability learning rate shows a faster updating of beliefs about probabilistic relationships thus a high precision (or covariance) of context. Ji *et al.* also showed that Asians are more confident in differences in covariation and have a high road-field dependence [4].

VI. Conclusion

Early research on cross-cultural effect focused on sensitivity to social cues and conditional context, and the cognitive studies mainly emphasised attention to the perceptual field. But these behavioural studies are not well-controlled, nor well replicated. The two neural experiments mentioned in the body part studied the neural correlates that underpin these cognitive differences and limited the cultural effect to the attention mechanism. We tried to give a computational model to explain how attention affects the way people sampling the world. We argued that the hierarchical nature of human inference leads to nested network, the plasticity of connections between levels is modulated by the γ value, which is basically ‘attention’. However, there are two aspects of attention, namely gain control and salience, the former lies at the highest level, and is formed through coordinating with people living in the same community. This value resists to change and accommodates many cross-cultural phenomena. The latter can be found in low level task relevant inference processes, such that people can change their expectations according to changes in the environment. This is why no behaviour differences were found in neural experiments. The communication between these two aspects of attention forms the paths of minimising expected free energy.

Abbreviations

MDP: Markov decision process

P300: A component of the event-related brain potential which is controlled by the subjective probability and task demanding. It signals agents’ model of the environment needs to be revised. In this article, the appearance of P300 component means the context, which is encoded by hidden states of the observation, is being updated.

P3a: The novelty-related component which proved particularly sensitive to deviations from the immediate stimulus context that is created by the standard and target stimuli in the three-stimulus variation of the oddball task. The more perceptually discrepant the stimulus is compared to the standard and target stimuli, the greater novelty P3a amplitude will be elicited. For example, car horn is perceptually salient than target stimuli which forms a temporal context.

P3b: A late positive component which reflects the revision of the long-lasting probabilistic context encoded by inferred hidden states.

Conflict of Interest

The author declares no conflict of interest.

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