Advances in Computational Modeling and Mechanistic Studies of Information Integration for Athlete Action Anticipation

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Abstract

Elite athletes must integrate contextual prior information and kinematic information to make accurate action predictions. This paper reviews relevant research on information integration models and their neural mechanisms. Results show that athletes adjust the contribution weights of information sources to action prediction based on the reliability of those sources. The Partially Observable Markov Decision Process (POMDP) model provides a mathematical framework for estimating the weights athletes assign to different information sources during the action prediction process. Furthermore, the brain processing of information integration during action prediction requires further in-depth research. We speculate that CNV amplitude, theta oscillations, and activation of the pMTG and DLPFC are key signals of the relevant neural activity.

Full Text

Preamble

Research Progress on Computational Modeling and Mechanisms of Information Integration in Athlete Action Anticipation

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Abstract

Elite athletes need to integrate contextual prior information with kinematic information to make accurate action anticipation. This paper reviews research on action anticipation based on the information integration model and its neural mechanisms. Results indicate that athletes adjust the weight of each information source's contribution to action anticipation based on its reliability. The partially observable Markov decision process model provides a mathematical framework for estimating the weight athletes assign to different information sources during action anticipation. Furthermore, the brain processes involved in integrating these information sources during action anticipation require further exploration. We hypothesize that CNV amplitude, theta oscillations, pMTG and DLPFC activation are key neural signals.

Keywords: action anticipation, information integration, computational modeling, conflict monitoring, neural mechanisms

2. Development of Action Anticipation Theory

Action anticipation is primarily influenced by two major sources of information: kinematic information and contextual prior information. Early research on action anticipation mainly focused on the impact of kinematic information (Bornstein & Gibson, 1980; Michaels & Carello, 1981). These studies adopted a perception-action interaction perspective, proposing that in competitive sports, perception and action are interdependent dynamic processes rather than independent occurrences (Guo et al., 2015; Oudejans et al., 1999; Williams et al., 2005). This perspective emphasizes that athletes must rapidly perceive environmental information and make corresponding motor adjustments within short timeframes, with the perception process directly guiding and regulating motor behavior (Zhou et al., 2024). The concept of "affordances" proposed by Bornstein and Gibson (1980) suggests that the environment provides multiple possibilities for behavioral actions. In dynamic competitive environments, athletes continuously perceive environmental changes and adjust their action anticipation accordingly (Warren, 2006). Kinematic information refers to perceptual information that emerges during action execution, such as opponents' postures (Savelsbergh et al., 2002), the trajectory of sports equipment (e.g., tennis rackets; Abernethy & Zawi, 2007), or relative movements between players in team sports (North et al., 2009). To investigate the influence of kinematic information, researchers commonly employ the temporal occlusion paradigm, which measures athletes' anticipation ability when only partial kinematic information is available by occluding action video segments at different time points (Cui et al., 2016; Mann et al., 2007). Numerous studies have confirmed that high-level athletes can effectively extract kinematic information to inform their action anticipation (Araújo & Kirlik, 2008). Furthermore, research has found that the action observation network (AON) in the brain plays an important role in processing kinematic information during athletes' action anticipation (Karlinsky et al., 2017; Smith, 2016). The sensorimotor experience accumulated by athletes during action execution is stored as corresponding motor programs, establishing internal motor representations. When observing others' actions, the AON is activated, enabling action anticipation through these established internal motor representations (Balser et al., 2014; Bishop et al., 2013).

In recent years, researchers have begun to examine the influence of contextual prior information on action anticipation (Cañal-Bruland & Mann, 2015). Contextual prior information refers to probabilistic information about event occurrence in specific competitive contexts, including current match scores, opponents' court positions, or opponents' action tendencies (Farrow & Reid, 2012; Gredin et al., 2018; Loffing & Hagemann, 2014). Contextual prior information is typically acquired before kinematic information. In complex competitive situations, athletes usually need to integrate both information sources to make the most accurate action anticipation. For example, in basketball, when anticipating others' (opponents' or teammates') shooting outcomes, athletes combine contextual prior information such as the player's historical shooting percentage and previous shot locations with current kinematic information from body movements to make more accurate predictions (as shown in Figure 1 [Figure 1: see original paper]).

Notably, kinematic information and contextual prior information are not independent but rather interact to influence action anticipation performance. For instance, Runswick et al. (2018) required high-level cricket batters to anticipate the delivery location of bowlers in video materials under conditions providing contextual prior information. This study used the temporal occlusion paradigm to occlude the bowler's delivery video at different time points to manipulate the reliability of kinematic information. The later the occlusion time point, the more specific and reliable the presented kinematic information became. Through verbal report data, the study found that when video stimuli were occluded at early stages (run-up phase, low-reliability kinematic information), athletes' action anticipation primarily relied on contextual prior information; when video stimuli were occluded at late stages (close to ball release time point, high-reliability kinematic information), athletes' action anticipation primarily relied on the bowler's kinematic information. Similarly, a baseball batting anticipation task using temporal occlusion technology manipulated the reliability of relevant kinematic information (video materials were occluded 50, 100, and 150 milliseconds after ball release; Gray & Cañal-Bruland, 2018). Additionally, they altered the reliability of the pitcher's action tendency information (e.g., the probability of the pitcher throwing a fastball was 50%, 65%, or 80%; higher probability indicated higher reliability). Results showed that the influence of contextual prior information (i.e., pitcher action tendency) on anticipation performance increased with the reliability of contextual prior information. Moreover, as the reliability of kinematic information decreased, the influence of contextual prior information on anticipation performance also increased.

To further understand how athletes integrate these information sources, researchers have proposed that Bayesian models can serve as an appropriate theoretical framework to elucidate how athletes integrate contextual prior information and kinematic information to make the most accurate action anticipation during the anticipation process (Gredin et al., 2020a). According to Bayesian models, athletes integrate contextual prior information and kinematic information probabilistically to reduce uncertainty in their anticipation judgments. That is, athletes adjust the contribution weight of each information source to action anticipation based on its reliability or precision. When one information source is less reliable, action anticipation relies more heavily on the other, more reliable source. This process implies that the influence of contextual prior information on action anticipation is modulated by the reliability of subsequently presented kinematic information, and vice versa (Vilares & Kording, 2011). However, current support for this theory primarily comes from qualitative speculation based on behavioral results, with a lack of quantitative studies applying computational models to empirical data to explicitly estimate the weights athletes assign to different information sources during action anticipation (Gredin et al., 2021; Helm et al., 2020).

3. Computational Modeling of Information Integration Patterns

Athletes improve prediction accuracy by integrating contextual prior information with kinematic information. However, it remains unclear how the brain dynamically adjusts the weights of these information sources in complex and changing environments to optimize action anticipation and reduce prediction errors. Computational modeling provides us with a quantitative and systematic method to evaluate athletes' information integration strategies across different contexts and to understand how these strategies affect the precision of action anticipation (Harris et al., 2022).

Partially Observable Markov Decision Process Model

Recent studies have attempted to model observed athlete action anticipation responses using the Partially Observable Markov Decision Process (POMDP) model (Harris et al., 2022; Harris et al., 2023). POMDP is a computational model based on Bayesian belief updating principles, comprising state space, action space, observation space, state transitions, and reward functions. When an agent is uncertain about the state of the world, the POMDP model assumes that the agent must infer the likelihood of being in some hidden state based on observations (sensory input) and use this information to select actions (Smith et al., 2016). This model has been widely applied in language, interoception, and visual illusion domains (Arthur & Harris, 2021; Critchley & Garfinkel, 2017; Smith et al., 2020).

In the POMDP model, the variable for time points is t. The circular markers in Figure 2 [Figure 2: see original paper] represent "nodes," where S denotes the hidden state, which is the belief generated internally by the agent based on input information, represented probabilistically and externally manifested as the agent's responses. O represents the information observed by the agent inferred from the hidden state. The square markers in Figure 2 represent mediating factors that exist as matrices in the model. D represents the initial state matrix; B represents the hidden state transition matrix, encoding the probability transition patterns of hidden states across time points; A represents the likelihood mapping between hidden states and observed information.

Figure 2 shows the Bayesian network for basketball players' action anticipation based on POMDP. Using basketball as an example, assume athletes perform shooting action anticipation under conditions with different prior information ("made shot," "missed shot") (Figure 2). The model input is the initial state D, which is the agent's state at the beginning of the task. At time t=1, the agent is in hidden state S_1, which represents the agent's internal beliefs about different possible outcomes (made shot or missed shot) in the current action anticipation task. The transition matrix B describes the probability of transitioning from one state to another, reflecting the agent's ability to predict future states based on past experience—for example, predicting whether future shots will be made based on past shooting success. At time t=2, the agent is in hidden state S_2, where this state reflects the agent's internal beliefs about different possible outcomes in the current action anticipation task after receiving new information. O represents the kinematic information received by the agent in this state, which cannot be directly observed and does not fully reflect the actual state, but is inferred from the hidden state (e.g., visual noise or uncertainty in action cues). The likelihood matrix A represents the probability distribution from the true state to observations, reflecting perceptual bias—that is, potential inconsistencies between perceived and actual states. This illustrates the agent's perception and interpretation processes when facing incomplete or ambiguous information. Although A is primarily used to describe perceptual bias, its effectiveness can be extended by adjusting the value spaces of states and observations. For example, state S can represent potential hidden states (e.g., whether a shot is made), while observation O can represent specific action representations formed in the brain (e.g., shooting actions). In this case, the content O observed by the agent depends on the agent's current hidden state S, because the hidden state determines the specific form of the action representation in the agent's brain. Matrix A then describes the process by which the hidden state influences the agent's generation of observation information. In this scenario, the psychological meanings of matrices A and B can be extended to describe the relationship between target states and explicit actions.

The detailed process of constructing this anticipation task model is as follows: At $t = 0$, the agent is in the initial state D, a column vector representing from top to bottom the probabilities of the agent being in the start, made shot, and missed shot hidden states. In the initial state, the probability of the hidden state being "start" is 1, and the probabilities of being in other hidden states are 0. Therefore, matrix D is as follows:

D = [1, 0, 0]

At t = 1, the agent is in the initial state, and the information obtained is prior belief. At t = 2, the agent obtains kinematic information from the video material, with two possible cases: made shot and missed shot. In the transition matrix B, each column represents the hidden state at time t, and each row represents the hidden state at time t+1. In the first column vector, the probability of transitioning from the start state to the start state is 0, while the probabilities of transitioning from the start state to the made shot and missed shot hidden states are pB and 1-pB, respectively. pB represents prior belief, reflecting the weight of contextual prior information in the action anticipation process. Values closer to 1 indicate higher prior belief and greater weight of contextual prior information in action anticipation. In the latter two column vectors, the probability of maintaining the made shot hidden state from the made shot hidden state is 1, with probabilities of transitioning to other hidden states being 0, and similarly for the missed shot state. The state transition matrix B is therefore:

B = [[0, 0, 0], [pB, 1, 0], [1-pB, 0, 1]]

In the likelihood matrix A, each value represents the probability of the agent observing kinematic information at time t. SP represents sensory precision, reflecting the weight of kinematic information in the action anticipation process. Values closer to 1 indicate higher sensory precision and greater weight of kinematic information in action anticipation. The probability of the agent observing start state information in the start state is 1, with probabilities of observing other state information being 0, yielding the first column vector. Assuming that when the agent's response (i.e., hidden state) and observed kinematic information are consistent, the agent's sensory precision is SP, the diagonal parameters of the matrix are set to SP; the probability of inconsistency between the agent's response and observed kinematic information is 1-SP. The likelihood matrix A is therefore:

A = [[1, 1-SP, 1-SP], [0, SP, 0], [0, 0, SP]]

Each action anticipation comprises two time steps (t = 1, t = 2). At t = 1, the agent begins observation from the initial state. At t = 2, the agent obtains visual cues (kinematic information) from the video stimulus and combines them with contextual prior information to infer whether they will achieve a certain true state (made shot, missed shot)—that is, the agent generates a hidden state. According to Bayes' rule, belief updating at the two time points t = 1 and t = 2 in an anticipation process is based on the following equations (Equation 6 and Equation 7):

$S_1 = \sigma(\ln(B) + \ln(A) + S_0)$ (6)
$S_2 = \sigma(\ln(B) + \ln(A) + S_1)$ (7)

The function expression in parentheses in Equation 6 indicates that the belief at time t=1 (i.e., hidden state S_1) is influenced by the initial state D, the next moment's hidden state S_2, and the kinematic information observed by the agent at time τ. The function expression in parentheses in Equation 7 indicates that the belief at time t=2 (i.e., hidden state S_2) is influenced by the previous moment's hidden state S_1 and the kinematic information observed by the agent at time t. In Equations 6 and 7, σ represents the Softmax function, with the expression:

σ(x) = exp(x) / Σ exp(x) (8)

In Equation 8, S represents the hidden state function at time t=i: in Equation 6, when t=1, S_1 = ln(B) + ln(A) + S_0; in Equation 7, when t=2, S_2 = ln(B) + ln(A) + S_1. ΣS represents the sum of hidden states across k time points. The Softmax function is used to solve multi-classification problems, aiming to maximize the probability that samples are predicted to the correct classification—that is, to maximize the accuracy of hidden state inference.

Each subject's final estimated parameters include pB in the transition matrix B and SP in the likelihood matrix A. The parameter estimation method uses Bayesian inference at two levels: first, using the above Bayesian network to model each subject's responses, and then using Bayesian optimization algorithms (variational Bayes) to estimate each subject's parameter values. Variational Bayes achieves parameter estimation by introducing the similarity between the approximate posterior distribution q(s) of hidden states and the posterior distribution p(s|o) in the Bayesian generative model:

F(p, q) = -ln p(o) + KL[q(s) || p(s|o)] (9)

In Equation 9, q(s) is the assumed approximate posterior distribution; KL represents KL divergence, a measure of the difference between two distributions. KL[q(s) || p(s|o)] represents the difference between the approximate posterior distribution and the true distribution—that is, model complexity. -ln p(o) represents the deviation between observed results and model predictions—that is, model accuracy. By minimizing model complexity and maximizing model accuracy, optimal solutions for pB and SP are obtained, thereby explicitly estimating the true weights athletes assign to contextual prior information and kinematic information during action anticipation, and revealing from a quantitative perspective the integration patterns of kinematic and contextual prior information in basketball players.

Other Computational Models

In the field of decision-making behavior, other commonly used computational models include the Drift Diffusion Model (DDM) and the Bayesian Belief Updating Model. DDM is a classic model for explaining binary decision tasks. This model describes the decision-making process as continuous accumulation of decision-relevant evidence, triggering a decision output when the accumulated evidence reaches a certain threshold or boundary (Ratcliff & McKoon, 2008). In the context of action anticipation, DDM might be used to describe how athletes make rapid decisions based on observed kinematic information. The DDM includes several key parameters. Drift rate (v) reflects the strength of evidence or preference for a decision option; in action anticipation, drift rate can reflect athletes' sensitivity to specific actions or situations. Starting point (z) represents the initial position of evidence accumulation, reflecting individuals' initial tendencies or preferences at decision onset. If the starting point is closer to a decision boundary, it means the individual has a stronger prior preference for that choice; in action anticipation, the starting point may be influenced by prior knowledge or experience. Decision boundary (a) defines the amount of evidence required to make a decision; wider boundaries require more evidence accumulation before decision-making, typically manifesting as a trade-off between higher decision accuracy and longer reaction times. Non-decision time (t) includes time unrelated to evidence accumulation, such as perceptual processes and motor response time; in action anticipation, this may reflect athletes' response speed and efficiency in preprocessing stages (Bogacz & Gurney, 2007; Ratcliff et al., 2016). The advantage of DDM lies in its parametric characteristics, allowing researchers to parse different stages and potential influencing factors in the decision-making process. It can efficiently apply to simple decision tasks under laboratory conditions by parsing reaction time and decision accuracy. However, DDM assumes that the evidence accumulation process is fixed, moving from the initial point to a decision boundary at a fixed drift rate. This fixed nature means the model cannot adjust accumulation rate or path during the decision-making process. In many real-world situations, decision-making processes are not fixed but continuously adjusted based on new information and situational changes. For example, athletes may dynamically adjust their extraction of kinematic information and decision strategies as opponents' actions unfold. DDM's fixed accumulation path cannot capture these dynamic adjustment processes (Koul et al., 2019).

The Bayesian Belief Updating Model is also based on Bayes' theorem, providing a dynamic framework for integrating prior knowledge with new observational information. This model reflects new information through continuous updating of existing beliefs and optimizes these beliefs during decision-making, making it particularly suitable for situations with high uncertainty (Knill & Pouget, 2004). The Bayesian Belief Updating Model updates posterior probabilities by calculating prior probability and likelihood function (Knill & Pouget, 2004). Prior probability represents individuals' beliefs or expectations about a hypothesis before new evidence emerges. The likelihood function reflects the probability of new evidence occurring under different hypotheses, helping to adjust belief strength after new information appears. Posterior probability is the updated belief calculated by combining prior probability and new evidence, reflecting individuals' latest judgments after obtaining new information. This Bayesian belief updating process enables the brain to make more accurate predictions and adjust its internal representations to adapt to constantly changing environments (de Lange et al., 2018; Zénon et al., 2019). In the context of action anticipation, the Bayesian Belief Updating Model can be used to explain how athletes anticipate specific actions or situations based on past experience (prior probability) and dynamically update posterior probabilities based on newly acquired kinematic information, thereby quickly adjusting expectations of opponents' behavior during competition. The advantage of this model lies in its flexibility and dynamic updating capability, enabling effective integration of information from different sources (Ma, 2019). However, in the process of information integration during action anticipation, how to precisely define the likelihood function and how to quantify prior and posterior probabilities remain issues requiring further research and understanding.

Overall, existing research indicates that POMDP has important application value in describing information integration and decision-making processes in action anticipation. POMDP can estimate the weights of information sources in uncertain environments, providing a powerful framework for understanding how athletes optimize decisions in complex situations. However, POMDP is not the only model applicable to action anticipation research. DDM and the Bayesian Belief Updating Model also have unique advantages and potential application value. Future research should further explore the applicability and limitations of these models in information integration during action anticipation, compare their performance in different decision-making contexts, and select the most appropriate model based on specific research questions and experimental conditions. Additionally, combining multiple models may provide a more comprehensive understanding, revealing how athletes effectively integrate and utilize various information sources during the action anticipation process.

4. Neural Basis of Contextual Prior and Kinematic Information Integration

Although some studies have explored the integration of prior knowledge and kinematic information in action anticipation, the neural mechanisms underlying this process remain poorly understood. In recent years, researchers have used electroencephalography (EEG) and event-related potential (ERP) techniques to reveal the neural basis of how situational prior information and kinematic information influence athletes' action anticipation. Wang et al. found that in a task requiring professional soccer goalkeepers to anticipate penalty kick directions, cues providing contextual prior information elicited smaller contingent negative variation (CNV) amplitudes compared to neutral cues (Wang et al., 2019). CNV is a negative wave appearing after cues, typically reflecting preparation and anticipation during the pre-stimulus phase (Kononowicz & Penney, 2016). This result suggests that contextual prior information affects the processing preparation for upcoming kinematic information, reflecting athletes' integration of different information sources during anticipation. Specifically, when contextual prior information is available, athletes allocate less weight to kinematic information and invest fewer cognitive resources, resulting in smaller CNV amplitudes in brain activity. This inference remains to be further experimentally confirmed.

In time-frequency analysis studies, Simonet et al. (2019) found that when stimuli related to contextual prior information were provided (e.g., current score, opponent tendencies), high-level athletes showed stronger alpha band desynchronization in frontal and temporal regions compared to novices. Frontal and temporal alpha band activity is associated with action observation, sensorimotor processing, and visuospatial attention. Increased desynchronization in frontal and temporal alpha bands represents increased cortical excitability, reflecting that high-level athletes associate contextual prior information with episodic and semantic information from long-term memory during the preparation phase. However, they did not explore the relationship between different information conditions (contextual prior information only, kinematic information only, and both) and motor experience, which may overlook differences in information integration strategies between experts and novices. Additionally, in spectral power analysis, Gredin et al. (2020b) found that in a soccer field simulation-based anticipation task, the energy ratio of frontal theta band to parietal alpha band was higher when contextual prior information was provided compared to when it was not. This ratio is positively correlated with working memory involvement and workload (Jaquess et al., 2017). They suggested that this result reflected increased cognitive resource involvement during action anticipation when contextual prior information was provided, indicating increased cognitive resource demands for information integration. However, EEG spectral power analysis sacrifices temporal resolution to some extent, making it difficult to conduct fine statistical analyses of temporal dynamics across different experimental conditions. Furthermore, the action outcomes indicated by contextual prior information and kinematic information are not always consistent (Chen et al., 2024; Wang et al., 2019). When the two information sources indicate inconsistent action outcomes, athletes need to process conflicting information, which triggers enhanced processing of kinematic information and inhibition of invalid contextual prior information processing, thereby achieving conflict resolution or control. This process requires relatively more cognitive resource investment. Gredin et al.'s (2020b) EEG study only compared brain activity features between conditions with and without contextual prior information, without further discussing the consistency of action outcomes indicated by the two information sources, which may lead to erroneous conclusions. Previous studies have demonstrated that frontal theta band is involved in numerous conflict-related cognitive processes. In conflict monitoring, when conflicting stimuli appear, theta band oscillations strengthen, assisting the subthalamic nucleus (STN) responsible for inhibitory processing to initiate optimal solutions to cope with conflict (Zavala et al., 2013). Additionally, research has shown that the strength of theta oscillations is related to effectively reducing reaction time under conflict conditions (Cohen, 2014). In relatively complex table tennis scenarios, cognitive processing links involving conflict induce enhanced frontal theta oscillations (Lu et al., 2019). Therefore, the increased energy ratio of frontal theta band to parietal alpha band may be caused by conflict processing of inconsistencies between contextual prior information and kinematic information, rather than simply increased cognitive resource involvement due to providing contextual prior information.

Moreover, previous studies using functional magnetic resonance imaging (fMRI) technology have only explored the impact of kinematic information on action anticipation and are relatively dated. Therefore, existing research cannot fully explain athletes' integrative processing of the two information sources during action anticipation, and the underlying brain mechanisms require urgent in-depth study. The brain network primarily related to action anticipation is the action observation network (AON). The AON plays a crucial role in perceiving others' actions, involving not only action perception but also action prediction. It reduces anticipation errors through information transmission between brain regions to make accurate action judgments (Cross et al., 2009). The AON is a widely distributed sensorimotor cortex, mainly including the inferior frontal gyrus (IFG), inferior parietal lobule (IPL), superior temporal sulcus (STS), premotor cortex, and other frontal regions (Caspers et al., 2010; Hardwick et al., 2018). These regions jointly participate in action perception, understanding, and anticipation (Stehr et al., 2021). Among them, IFG and IPL contain mirror neurons, which we typically consider the basis of action understanding. They are activated when observing or executing a specific action and exhibit similar response patterns during both observation and execution of that action (Molenberghs et al., 2012). Furthermore, the activation degree of mirror neurons is related to observers' familiarity with the action (Calvo-Merino et al., 2004). During action observation, activation of the mirror neuron system (MNS) is considered simulation of the action (also called "motor resonance"; Fadiga et al., 2005), which plays a key role in many cognitive functions, including action understanding and anticipation of action outcomes (Balser et al., 2014; Bishop et al., 2013). The STS is responsible for visual information input, with the posterior superior temporal sulcus (pSTS) playing an important role in the action observation network, participating in observing and understanding others' actions, intentions, and goals. The pSTS is not only responsible for perceiving and encoding body movements but is also modulated by high-level contextual factors (e.g., observers' expectations, goals; Stehr et al., 2021). The predictive coding model proposed by Kilner (2011) describes information transmission between various brain regions in the AON, providing richer theoretical support for AON function (Cai & Padoa-Schioppa, 2014). The predictive coding model emphasizes the predictive role in perception processes. According to this theory, observers' predictions of future actions affect perception of current actions. This predictive information comes from internal models that help adjust perception when observing actions to improve understanding of intentions and behavioral goals (Kilner, 2011; Koster-Hale & Saxe, 2013). This model suggests that the AON processes familiar actions through stored motor representations in a top-down manner, transmitting information from the inferior frontal gyrus to parietal and occipitotemporal regions (IFG→IPL→STS). Unfamiliar actions, however, require a bottom-up, data-driven approach, transmitting information from occipitotemporal to parietal to inferior frontal regions (STS→IPL→IFG).

In the process of information integration, it remains unclear which brain regions process contextual prior information and generate corresponding action outcome expectation representations, and which brain regions are involved in conflict resolution processing when contextual prior information and kinematic information indicate inconsistent action outcomes. Some researchers have proposed that the ventral pathway connecting the posterior middle temporal gyrus (pMTG) and anterior inferior frontal gyrus (aIFG) is responsible for retrieving action-related semantic information and selecting the most likely action representation in a given context. The selected action representation will influence the AON's encoding of specific kinematic information. Therefore, we speculate that the pMTG may participate in processing contextual prior information and generating corresponding action expectation representations. In primate studies, the dorsolateral prefrontal cortex (DLPFC) has been found to influence action selection in the premotor cortex (Cai & Padoa-Schioppa, 2014b; Saleem et al., 2014; Takahara et al., 2012). Furthermore, action selection theory suggests that during competition among different action representations, the DLPFC biases action selection toward actions consistent with current context-relevant information (Cisek, 2006, 2007). Evidence indicates that the DLPFC may play a top-down regulatory role when detecting mismatches between action representations and the current semantic environment (Balconi & Vitaloni, 2012, 2014). Therefore, we speculate that the DLPFC participates in conflict resolution processing when the two information sources are inconsistent (Figure 3 [Figure 3: see original paper]).

Figure 3 shows a schematic diagram of the neural basis for integrating contextual prior information and kinematic information. The action observation network (AON) participates in processing kinematic information, the posterior middle temporal gyrus (pMTG) participates in representing contextual prior information. When contextual prior information and kinematic information are inconsistent, conflict monitoring and increased cognitive resources are triggered, with theta oscillations and dorsolateral prefrontal cortex (DLPFC) activation being key signals of related neural activity.

The aforementioned POMDP and other computational models provide us with a quantitative framework for describing how athletes dynamically integrate contextual prior information and kinematic information during action anticipation. However, relying solely on computational models cannot reveal the underlying neural mechanisms. Neural basis research can verify hypotheses in computational models by probing brain activity patterns and provide understanding of the biological basis of information processing. For example, based on parameter settings in the POMDP model, we expect that key parameters prior belief (pB) and sensory precision (SP) can be validated through different neural activity patterns. Specifically, prior belief reflects athletes' dependence on contextual prior information and is related to CNV amplitude changes. When pB values are higher, indicating that athletes rely more on prior information for decision-making, smaller CNV amplitudes will be exhibited, possibly reflecting reduced brain preparation for upcoming events. Meanwhile, increased contextual information processing demands related to pB will cause significant activation in the pMTG region responsible for representing contextual information. On the other hand, SP reflects athletes' perceptual precision of kinematic information and is related to activation of the action observation network (AON). When SP values are higher, indicating higher sensitivity when perceiving and processing precise motor information, neural activity in AON-related regions will be more significant. By mapping computational model parameters to neural activity patterns, we can use the POMDP model to predict brain activation patterns under different conditions, further clarifying the neural mechanisms of information integration. This approach not only validates the model's predictive power but also provides a new perspective for understanding how the brain integrates information during athletes' dynamic decision-making processes.

5. Summary and Outlook

Accurate action anticipation helps athletes plan their subsequent actions and ensures excellent sports performance. Athletes typically integrate contextual prior information with kinematic information to make accurate predictions of action outcomes. This paper reviewed relevant research on information integration models and their neural mechanisms during athletes' action anticipation processes. Findings indicate that the integration of contextual prior information and kinematic information plays a key role in action anticipation, with effective integration of the two significantly improving anticipation accuracy and response speed. Additionally, this paper explored the application of computational modeling, particularly the Partially Observable Markov Decision Process (POMDP), in action anticipation processes. By applying POMDP to research on athletes' action anticipation, we preliminarily constructed a model capable of simulating athletes' anticipatory responses in different contexts, revealing the weight allocation and changing patterns of different information sources during anticipation. However, it must be emphasized that POMDP is not the only model applicable to action anticipation research. This study also deeply explored the cognitive neural mechanisms of information integration during anticipation.

Although a preliminary research framework for action anticipation information integration models exists, the cognitive neural mechanisms of information integration and the application of computational modeling still face certain limitations and challenges: (1) Expanding empirical research. Although computational modeling has been incorporated into psychological research, with limited results supporting the applicability of POMDP for constructing athletes' action anticipation response models, empirical research remains scarce. Future research needs to apply computational models to empirical data, using the mathematical framework provided by POMDP to explicitly estimate the weights athletes assign to different information sources during action anticipation. (2) Verifying and improving the theoretical construction of information integration models. Although existing research provides preliminary neurophysiological evidence for the impact of contextual prior information and kinematic information on action anticipation, the brain processing involved in integrating the two information sources during action anticipation, particularly when contextual prior information and kinematic information indicate inconsistent action outcomes, requires further in-depth exploration. We speculate that CNV amplitude, pMTG activation, and theta oscillations may be key signals involved in processing contextual prior information, while the DLPFC may be a key brain region for coping with situations where the two information sources indicate inconsistent movement outcomes.

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