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**Temporal Optimization of Attentional Allocation in Expert Football
Performance: An Active Inference Approach**

Department of Neuroscience, Imaging and Clinical
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Coordinator

Prof. Riccardo PALUMBO

Supervisor

Prof. Riccardo PALUMBO

PhD Candidate

Aurélien DEHORNE

Co-Supervisor

Prof. Pierpaolo IODICE

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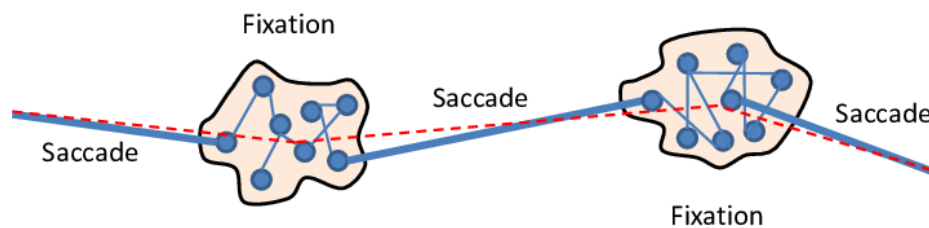
1. General introduction

1.1 General background

In complex and dynamic environments, human performance relies on the ability to rapidly select relevant visual information to achieve a goal. This selection occurs while filtering out distractors present in the environment (Hayhoe & Ballard, 2005a; M. Land & Tatler, 2009). Selective allocation of visual attention becomes particularly critical when multiple tasks must be performed concurrently. This situation frequently corresponds to professional, athletic, and daily activities. Understanding the mechanisms underlying these visual information acquisition strategies constitutes a major challenge for cognitive neuroscience, experimental psychology, and sport sciences.

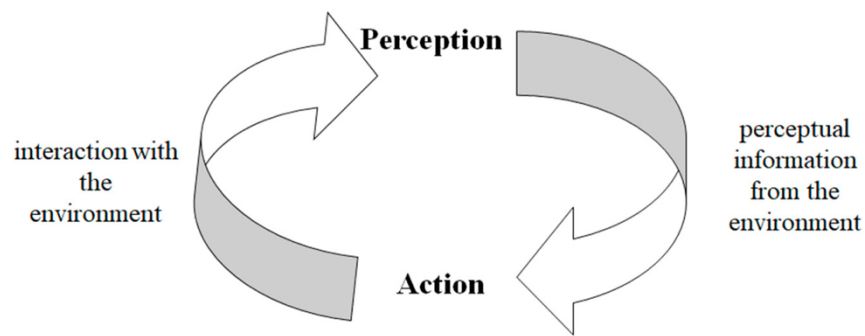
Historically, the study of visual behavior during decision-making has largely relied on the recording of eye movements through oculometry. This work has identified two main types of eye movements: fixations, where gaze is maintained on a specific area of interest, and saccades, corresponding to rapid transitional movements between two fixations (Rayner, 2009).

Figure 1: Illustration of visual fixations and saccades (Krueger et al., 2017)



However, due to technological constraints, most of the previous research has studied visual behavior in static or semi-static contexts, relying on static slides or pre-recorded video clips (Kredel et al., 2017; D. Y. Mann et al., 2007). Yet these experimental paradigms fundamentally differ from natural situations, where individuals act upon their environment and must manage in real time the dynamic consequences of their own actions. This continuous perception-action coupling characterizes natural behavior (Gibson, 1979; Shadmehr & Krakauer, 2008).

Figure 2: Illustration of the perception-action coupling (Hamill et al., 2020)



Recent developments in mobile eye-tracking systems now allow the study of visual behavior in ecological contexts, including during the execution of real motor actions (M. F. Land, 2006; Vater et al., 2020). In the sport domain, several studies have demonstrated that expert athletes develop visual exploration strategies distinct from those of novices, notably characterized by more systematic exploration of the environment and better anticipation of events (D. Y. Mann et al., 2007; Williams & Ford, 2008). These exploratory behaviors, often referred to as visual scans in the sport literature, correspond to rapid head movements, that allow information sampling in different spatial zones (McGuckian et al., 2018). However, despite the importance of this work, the temporal and sequential dynamics of these behaviors remain imperfectly characterized, and the cognitive mechanisms that regulate them in truly dynamic situations also remain poorly understood.

Several fundamental questions remain largely unexplored. First, the cognitive mechanisms that regulate the temporal allocation of visual attention between multiple concurrent sub-tasks remain poorly understood, particularly in situations where motor execution and visual exploration must be finely coordinated. In team sports, for example, athletes must simultaneously control the ball, monitor teammates and opponents, and anticipate how the game will evolve. Second, the influence of modulating factors such as mental fatigue on these visual exploration strategies has been little studied, despite the importance of these factors for understanding the limits of attentional capacities and performance degradation in ecologically valid conditions. Third, formal models capable of predicting how attention is distributed quasi-optimally between different information sources are still lacking. Such models should account for the respective value of each source for goal achievement, and explain the differences observed between experts and novices.

1.2 Aims and objectives of the thesis

The ability to perform proficiently in dynamic environments is contingent not only on an individual's visual perception, but also on their capacity to access the relevant information at the opportune moment. In a multitude of real-world scenarios, the process of decision-making transpires under the condition of continuous time constraints, rendering it inextricably linked to the act of action. Individuals must concurrently regulate movement, monitor the environment, select task-relevant information, and predict future events. In such contexts, visual exploration is not merely a passive process of information acquisition; rather, it is an active and temporally organised component of performance. The present thesis aimed to characterize the principles governing visual exploration strategies during decision-making in dynamic and ecological situations involving the joint execution of motor and perceptual tasks. More specifically, it addressed two central questions. First, how is visual attention allocated sequentially between different sub-tasks during a complex activity? Second, to what extent is this allocation shaped by expertise and by the individual's cognitive state, specifically mental fatigue? By addressing these questions, this work sought to move beyond a purely spatial description of gaze behavior, that is, what information is sampled, and to focus instead on its temporal organization: when information is sampled, how visual exploration is coordinated with action, and how this coordination supports decision-making as events unfold.

To address this problem, three specific objectives structure this work. The first consists in identifying the main components that determine visual exploration strategies in athletes in ecological contexts, and in characterizing the differences between experts and novices in the temporal and sequential organization of their visual behavior. Our central hypothesis is that expertise does not translate solely into a quantitative increase in visual exploration, but rather manifests in a more efficient temporal organization, characterized by a concentration of fixations on relevant information sources and increased visual anticipation at critical moments of decision-making.

The second objective aims to examine the effect of mental fatigue on these visual exploration strategies and on performance in a dual task. This analysis aims to better understand which cognitive resources are involved in the coordination between visual exploration and motor execution. We hypothesize that mental fatigue, by reducing available attentional resources, primarily affects the flexibility of attentional allocation, notably

voluntary anticipatory exploration, such as the frequency of explorations preceding decisive motor actions. This would result in more random timing and visual behavior closer to that adopted by novices.

The third objective consists of developing a computational model of attentional allocation during joint tasks. This model aims to formalize the principles governing how attention is distributed between different information sources based on their respective value for the task, and to account for the differences observed between experts and novices.

The theoretical framework we adopt rests on the hypothesis that complex decision-making behaviors can be decomposed into a series of relatively independent sub-tasks, each associated with specific informational requirements (Ballard et al., 1995; Hayhoe, 2000). In this perspective, visual attention is considered to be allocated sequentially between these different sub-tasks, following a principle of quasi-optimal allocation of limited resources. More precisely, we assume that this allocation is flexible and adjusts according to the relative value of each sub-task for achieving the global objective. This value can be conceptualized in terms of expected reward or cost associated with error. Expertise would then translate into an increased capacity to exploit this flexibility: experts would orient their visual exploration toward the most relevant sources at the opportune moment. They would also coordinate more efficiently the exploration and motor execution phases. Conversely, mental fatigue would reduce this capacity for fine adjustment, primarily disrupting the anticipatory and strategic components of attentional allocation.

To test these hypotheses, we developed an ecological experimental paradigm in football. We chose this team sport because it requires constant coordination between motor control of the ball and visual exploration of the environment to make rapid tactical decisions. The setup reproduces a representative situation of real play, involving a dual task requiring ball manipulation and selection of dynamic visual information to choose the appropriate target for a pass. This paradigm allows simultaneous recording of performance measures and fine oculometric data through a mobile eye-tracking system, giving us direct access to the temporal dynamics of visual exploration in representative situations.

1.3 Structure of the thesis

This thesis is organized into three main chapters, following a progressive logic that articulates state of the art, empirical investigation, and computational formalization. This architecture reflects an integrative approach aimed at combining the identification of behavioral patterns with their interpretation within a unified theoretical framework.

The first chapter establishes the conceptual and methodological foundation upon which the entire work rests. It presents a systematic review and an updated meta-analysis of knowledge on perceptual-cognitive expertise in sport. This work extends and updates the foundational meta-analysis by Mann et al. (2007), which remains the most cited reference in this field. Our meta-analysis aims not only to quantify the overall effect of expertise on oculomotor behaviors, but also to identify the key moderating variables that structure the differences observed between studies. These variables include the type of sport, the stimulus presentation modality, the research paradigm, the response mode, and the expertise classification. The meta-analysis also highlights several recurrent methodological gaps, notably the predominant use of static or semi-static paradigms, the absence of fine consideration of the temporal and sequential dimension of exploration, and the lack of investigations on the impact of mental fatigue in ecological contexts. These elements directly motivate and justify the experimental choices developed in the following chapter.

The second chapter constitutes the empirical core of the thesis. It reports the results of two complementary experimental studies conducted using the representative dual-task paradigm in football. The first study adopts a differential approach by comparing the visual exploration strategies of expert and novice footballers. The originality of this study lies in the richness of the indicators analyzed: beyond traditional oculometric measures such as the number of visual fixations and their durations, we develop specific metrics to characterize exploratory activity in its dynamic and sequential dimension. We pay particular attention to the frequency, duration, and timing of visual explorations of the environment, as well as their coordination with motor execution phases. This analysis of visual behavior allows us to test the hypothesis that expertise translates into a qualitative reorganization of the temporal deployment of exploration, rather than a simple global increase.

The second study adopts a complementary approach by examining the effect of mental fatigue on these visual strategies in expert footballers. To induce mental fatigue in a controlled manner, participants perform a demanding cognitive task with high cognitive load before executing the dual task in football. This study compares performance and gaze behavior patterns across two conditions: in the mental fatigue condition, participants complete an intensive cognitive task for a defined period before the football task, whereas in the control condition, this preparatory phase is replaced by watching an emotionally neutral documentary. This experimental manipulation allows us to test the hypothesis that mental fatigue differentially affects the various components of visual behavior, primarily impacting anticipatory exploration processes that require voluntary allocation of attention, such as the frequency of scans preceding decisive motor actions, while leaving elementary visual processes relatively preserved. Together, these empirical results document in detail how visual attention is orchestrated during complex tasks, and how this orchestration is modulated by expertise and the individual's cognitive state.

The third chapter extends this empirical investigation through a computational modeling approach. We aim to formalize the underlying principles of attention allocation between concurrent tasks. Our objective is not only to describe the observed behavioral patterns, but to propose a theoretical framework that allows their prediction and explanation. To do this, we develop a computational model inspired by Bayesian decision-making approaches and optimal control theory. This model conceptualizes attentional allocation as an optimization process under constraints, in which limited attentional resources must be distributed between different information sources according to their respective value for goal achievement.

Concretely, this model relies on a computational architecture designed to represent the experimental paradigm in football. Simulations allow us to systematically vary model parameters. Specifically, we manipulate the contextualization matrices that encode the relative relevance of different available information, the representations of exteroceptive signals that model environmental perception, and the transition matrices that capture the temporal dynamics of system states. By confronting model predictions with behavioral data collected from experts and novices, we can evaluate to what extent a principle of quasi-optimal allocation accounts for the differences observed between these two populations, while also generating testable predictions for future experimental investigations. This third level of

analysis thus constitutes a step toward the elaboration of a unified computational theory of visual attention in dynamic contexts.

The sequence of these three chapters reflects a progression from state of the art toward empirical discovery, then toward theoretical formalization. The general discussion that closes the thesis synthesizes the contributions of each chapter and positions the results in the broader context of research on visual attention and decision-making. It also identifies the limitations of our approach and proposes perspectives for future work, including possible extensions of the computational model as well as potential applications in other domains involving decisions under temporal constraints.

2. Chapter 1: Theoretical Framework, Literature Review, and Research Positioning

In this first chapter, we present the theoretical foundations upon which this entire work rests. Through structured argumentation, we demonstrate the relevance of our research questions by highlighting various gaps in the existing literature. This chapter consists of three main parts. First, we present the theoretical framework in which our approach to attentional allocation in dynamic contexts is situated, integrating recent computational models with the specificities of the sporting context. Next, we present quantitative results from recent literature on perceptual-cognitive expertise in sport, highlighting gaps in the complete understanding of mechanisms underlying expert performance. Finally, the third part addresses our positioning in view of these gaps, justifying our methodological choices and formulating precise hypotheses derived from the presented theoretical framework.

2.1 Theoretical Framework: From Selective Attention to Optimal Allocation in Dynamic Contexts

The study of visual perception strategies rests on a fundamental question: how does our cognitive system efficiently explore a 360° environment saturated with information, despite our limited capacity to process it?

Early models established that attention functions as a selection mechanism that prioritizes certain information over others. Broadbent's (2004) attentional filter model, later updated by Treisman (1988), constitutes a foundational example. However, these initial works were conducted in highly controlled laboratory conditions. They used dichotic listening tasks without motor response execution. Yet, in natural and dynamic contexts that we continuously encounter, attention cannot be interpreted independently of the action it serves to guide.

2.1.1 From Selective Attention to Active Exploration

It is precisely this ecological context that has driven the evolution of attentional models. This evolution notably occurred through the work of Gibson (1979), and, more recently, Hayhoe & Ballard (2005). According to this ecological approach, the individual is an actor who explores their environment according to their objectives, in a continuous perception-action loop where visual perception serves a motor or cognitive intention.

Visual attention is thus no longer conceived as a simple passive filter responding to stimulus salience, but as an active mechanism oriented by the task to be performed. The problem around visual attention transforms radically: the question is no longer about which information attracts our attention, but which relevant information we actively search for in our environment in order to accomplish our objectives.

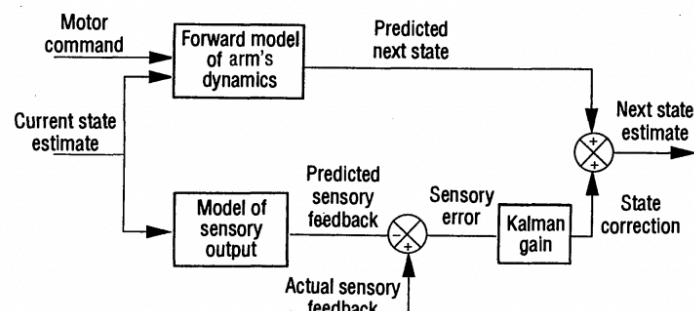
This conceptual evolution has profound methodological and theoretical implications. At the methodological level, this implies that attention must be studied during tasks representative of real situations, tasks that include both the execution of motor actions having consequences on the environment, and temporal pressure constraints. At the theoretical level, it requires models capable of predicting where and when attention will be allocated, depending on the current state of the environment as well as the individual's goals and objectives.

2.1.2 The Predictive Brain and Computational Formalization

More recently, the allocation of visual attention in dynamic contexts has been mathematically formalized through computational models. These models postulate that the brain functions as a “Bayesian brain”: rather than merely processing incoming sensory information passively, it maintains a generative model that continuously creates predictions about future states and uses these predictions to guide attention allocation according to its needs.

This view of the brain as an active, predictive system was notably developed by Wolpert et al. (1995) in the context of internal models for motor control, and later extended by Friston through his theoretical framework of active inference (K. Friston, 2010; K. Friston et al., 2012, 2015, 2017).

Figure 3: Internal model for sensorimotor control (Wolpert et al., 1995)



This predictive model corresponds to an internal representation that the nervous system constructs to anticipate the consequences of its own actions and the future evolution of the environment. For example, in the football context that we address in Chapter 2, when a player prepares to receive a pass from a teammate, their nervous system constructs in real time a prediction of the ball's trajectory, the pass arrival point, and the optimal moment to initiate the action allowing control of the ball.

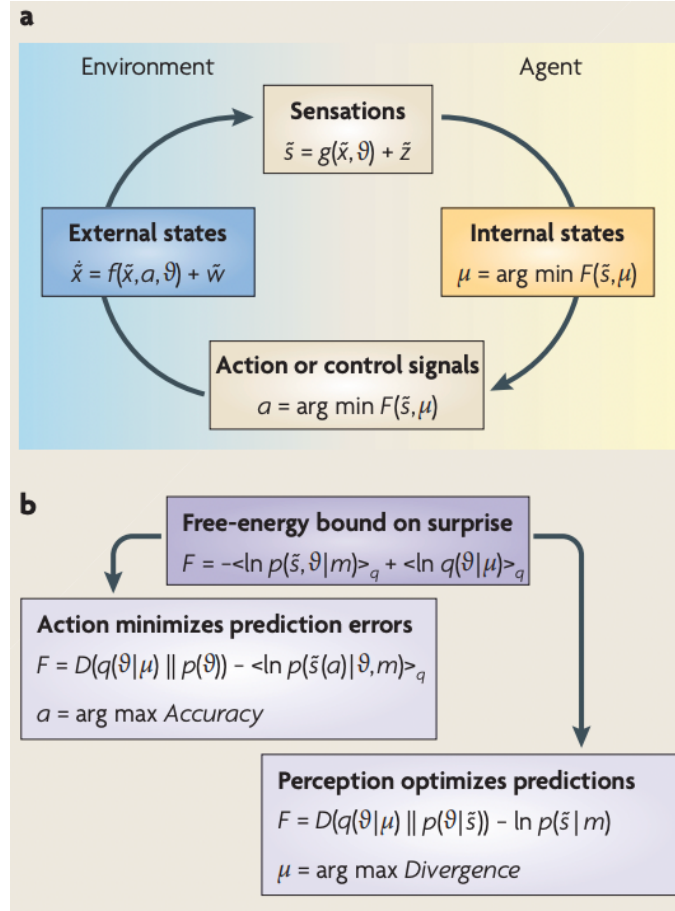
However, these predictions remain predictions and are therefore never certain. They generate more or less uncertainty, depending on available sensory inputs, environmental predictability, and internal model quality. It is precisely this uncertainty that orients our visual attention. When uncertainty is too high, we need to reduce this level of uncertainty by receiving additional sensory inputs, to perform the appropriate action. Conversely, when uncertainty is low, the system does not necessarily need additional sensory inputs, as it has a high level of confidence in its prediction. Visual attention is therefore oriented toward zones of interest that allow maximal reduction of the uncertainty generated by the predictive model (Ballard & Hayhoe, 2009; Hayhoe & Ballard, 2005).

2.1.2.1 The Free Energy Principle and Active Inference

The theoretical framework of active inference rests on the Free Energy Principle formulated by Friston (2010). According to this principle, the brain continuously minimizes a quantity called variational free energy, which constitutes an upper bound on surprise in the Bayesian sense of the term.

Formally, free energy can be decomposed as the sum of two terms. The first corresponds to surprise or inaccuracy. It measures how improbable observations are under the model. The second quantifies complexity. It measures the discrepancy between the approximate distribution and the true posterior. Minimizing free energy thus simultaneously improves prediction accuracy and refines internal beliefs.

Figure 4: Free Energy Principle (K. Friston, 2010)



In the context of attentional allocation, this formalization implies that eye saccades are epistemic actions serving to reduce uncertainty about hidden world states. Attention is preferentially allocated toward zones where observing additional information would most strongly reduce free energy.

More concretely, Itti & Baldi (2009) mathematized this phenomenon by introducing the notion of Bayesian surprise. It is defined as the Kullback-Leibler divergence between probability distributions before and after observation. This measure quantifies the system's surprise: the more an observation modifies the system's beliefs, the higher the surprise. Itti & Baldi (2009) demonstrated that this measure allowed predicting visual fixations more precisely than older models of visual salience, based solely on bottom-up stimulus properties like contrast, color, or orientation.

Epistemic uncertainty, for its part, can be formalized as the entropy of the posterior distribution. The higher this entropy, the more uncertain the system is about the world's state, and thus the higher the value of an epistemic action like a saccade toward an informative

zone. This mathematical formalization allows us to generate testable quantitative predictions concerning attentional allocation patterns as a function of task characteristics and system state.

2.1.2.2 Empirical Validation of Predictive Models

This theory has been tested through various convergent experimental protocols. Rothkopf et al. (2007) showed that during visual search tasks in a virtual environment, participants preferentially allocated their visual attention toward zones of interest that reduced uncertainty according to a computational model's predictions, rather than simply looking toward visually salient zones. Their results demonstrated that eye fixations were better predicted by an uncertainty-reduction-based model than by classical visual salience models.

Donnarumma et al. (2017) developed an active inference model that precisely replicates visual behavior patterns during tasks involving the prediction of others' actions. Their model explicitly formalizes the principle that saccades are experiments aimed at testing and refining the system's internal predictions about the current world state. Implemented within the Free Energy Principle framework, this model generates visual fixation patterns qualitatively and quantitatively similar to those observed in human participants.

More recently, Parr & Friston (2017) extended this framework by proposing that attention can be formalized as the optimization of precision, that is, the inverse of variance accorded to different sensory information sources. According to this view, attention corresponds to dynamic modulation of confidence accorded to different sensory channels, depending on their estimated reliability and their relevance for the ongoing task.

These various studies converge toward a common idea: visual attention, in a dynamic context, is an active process of information sampling guided by the system's predictive needs. This framework allows us to understand not only where participants direct their attention, but also why they direct their visual attention to specific areas of interest at specific moments during action unfolding.

2.1.3 Resolving the Gibson-Friston Theoretical Tension

Before continuing, it is essential to address an apparent theoretical tension between Gibson's (1979) ecological approach and Friston's (2010) computational approach that we have just presented. These two frameworks rest on fundamentally different epistemological premises.

Gibson supports a theory of direct perception according to which information necessary for action is directly available in the ambient optic structure, in the form of invariants and affordances. According to this framework, it is not necessary to postulate internal representations, inferences, or computational processes. Perception emerges directly from the dynamic coupling between agent and environment. Gibson explicitly rejects the computational metaphor of the brain and the notion of information processing.

Conversely, Friston proposes a fundamentally representational and computational theory in which the brain constructs internal generative models of the world, performs probabilistic inferences, and generates predictions that are confronted with sensory observations. This vision places internal representations and computational processes at the heart of cognition. This tension is not trivial and has generated substantial theoretical debates in the literature (Bruineberg et al., 2016; Chemero, 2013; Clark, 2015).

Nevertheless, several convergent arguments allow us to adopt an integrative theoretical position rather than exclusively choosing one framework or the other.

The ecological approach and the computational approach can be seen as operating at different levels of analysis in Marr's (2010) sense. Gibson describes the computational level, that is what problem is solved, and the implementational level, that is how the organism interfaces with its environment. Friston provides an algorithmic framework that makes explicit how the problem is solved, allowing mathematical formalization of underlying processes. These levels are complementary rather than contradictory.

Recent work has proposed syntheses between these approaches, notably through the concept of ecological Predictive Processing (Bruineberg et al., 2016; Hohwy, 2016). According to this perspective, internal generative models are not representations detached from the world, but structures that capture statistical regularities of the ecological

environment in which the organism is situated. These internal models are shaped by perceptual-motor experience and precisely encode the affordances and invariants that Gibson identifies. Thus, when Friston speaks of predictions, these can be reinterpreted as enacted anticipations based on environmental regularities discovered through action.

In the specific sporting context that interests us, this synthesis becomes particularly relevant and operative. Expert athletes have spent thousands of hours interacting with structured sporting environments. Through this extensive practice, they develop fine perceptual sensitivity to the invariants and affordances that Gibson describes, a ball's trajectory or an opponent's intentions revealed by their posture, while simultaneously constructing internal predictive models that allow them to anticipate future evolutions of these situations. These two perspectives describe the same adaptive phenomenon from different angles: Gibson emphasizes the informational content of the environment and the sensitivity developed to it, while Friston mathematically formalizes how the nervous system exploits this informational content to generate anticipations and guide action.

Our methodological positioning, which privileges ecologically valid tasks with real motor actions, practically resolves this tension. By studying attention in representative contexts preserving natural perception-action coupling, we avoid Gibson's criticisms addressed to artificial laboratory paradigms. Simultaneously, computational formalization allows us to generate testable quantitative predictions and rigorously analyze temporal patterns of attentional allocation. This constitutes an advance compared to qualitative descriptions often associated with the traditional ecological approach.

The active inference framework of Friston can be interpreted as fundamentally enactive (Kirchhoff & Kiverstein, 2018). The organism does not passively represent the world but acts to generate observations that confirm or not its predictions. This active dimension of inference converges with Gibson's insistence on the constitutive role of action in perception. Eye saccades, in this perspective, are both epistemic actions in Friston's terminology and active explorations of the ambient optic structure in Gibson's terminology.

This synthesis has direct implications for our work. We adopt Friston's mathematical formalization as an analytical tool allowing prediction and quantification of attentional

allocation patterns, while maintaining in parallel Gibson's ecological requirement concerning the representative validity of experimental tasks.

Concretely, this means that our computational models formalize how uncertainty guides attentional allocation in a Friston's perspective, but this uncertainty concerns ecologically relevant information preserved in representative tasks according to Gibson's constraint. Attention is studied in the context of effective motor actions modifying the environment, preserving perception-action coupling. Theoretical predictions concern the timing of attentional allocation in relation to the task's temporal structure, thus synthesizing contributions from both approaches.

2.1.4 Attentional Allocation in Dual-Task Situations

In natural complex situations, tasks are not unique and isolated but part of a continuum. In the football context that we will study in Chapter 2, athletes must manage several sub-tasks with potentially competing informational demands.

For example, when a player receives the ball from a teammate and has to make a pass to a second teammate, they have to not only maintain a precise representation of the incoming pass trajectory to ensure ball reception and control, but also visually explore their environment to spatially locate teammates as well as opponents and evaluate potential passing opportunities.

These two tasks require directing visual attention toward different zones of interest in the environment. They question the athlete about the compromise to adopt: how to allocate their visual attention between these different competing demands?

This question of the compromise between different attentional demands during dual-tasks has been studied in the literature. It has been theorized that each sub-task possesses its own predictive model, with its own respective predictions and uncertainties (Körding & Wolpert, 2004; Sullivan et al., 2012). The choice of the task toward which attention is oriented occurs through a continuous comparison mechanism. At each instant, attention is oriented primarily toward the predictive model that presents the most uncertainty. This mechanism allows reducing global uncertainty linked to different models by allocating resources toward the model that needs them most at each instant during action unfolding.

More formally, if we consider two competing tasks, for example controlling the incoming ball and scanning the environment for the outgoing pass, each possesses its generative model with its associated uncertainty. The system must resolve an optimization problem under constraint: maximize total uncertainty reduction while respecting sequential attentional allocation constraints, since we can indeed only fixate one spatial region at a time.

One possible formalization consists in allocating attention toward a given task at a given instant if the expected free energy reduction from observing this zone of interest, weighted by the probability of global success conditional on this task, exceeds that of all other competing tasks.

This mechanism generates testable and counter-intuitive predictions. For example, in a football situation, if the ball trajectory during pass reception is highly predictable, as during a slow and direct pass over a short distance, the predictive model of ball reception will generate low uncertainty, and so will require only minimal ball surveillance. Visual attention can then be allocated toward the task of preparing the future pass, even before the ball is received.

Conversely, if the ball trajectory is unpredictable, for example during a pass with bounces or a trajectory disturbed by wind, the predictive model linked to ball reception will maintain high uncertainty, and so will require visual attention oriented toward the ball until its reception. Attention can only be allocated toward preparing the future pass after resolution of this first uncertainty.

These predictions formalize intuitively what coaches empirically observe. We often hear coaches say that expert athletes seem to have more time to make their decisions. According to our theoretical framework, this impression does not result from superior information processing speed, but from a capacity to reallocate attention early toward future tasks thanks to more reliable predictive models for ongoing tasks.

2.1.5 Mechanisms of Perceptivo-Cognitive Expertise

The theoretical framework developed above generates clear and testable predictions concerning mechanisms by which expertise modifies attentional allocation. We propose that expertise rests on two complementary and interdependent mechanisms.

First, experts possess more precise and more reliable predictive models than novices. This qualitative improvement of internal predictive representations directly results from the accumulation of experience and deliberate training. Over thousands of hours of practice, experts' nervous systems progressively refine their internal models of sporting environment dynamics, including projectile trajectories, opponents' and teammates' displacement patterns, and the consequences of their own motor actions on the environment. This accumulation of experience allows the system to estimate with increasing precision the critical parameters that govern these dynamics.

In formal terms, experts have learned more precise a priori distributions, with lower variance, and are also better calibrated, with centering closer to reality, than novices. For a given situation, posterior uncertainty is lower in experts. This uncertainty reduction does not mean experts are omniscient, their predictions remain probabilistic and fallible. But the range of possible outcomes they envisage is better calibrated with reality. For example, facing an opponent's deceptive action, an expert will have learned through thousands of similar exposures which early kinematic cues reliably predict real action versus feint, like body orientation, gaze direction, or support pattern. Their predictive model therefore generates a posterior distribution concentrated on probable outcomes, whereas the novice, not having this structured knowledge, maintains a much flatter distribution reflecting high uncertainty.

Second, experts manifest superior capacity for anticipatory attention reallocation. This is a consequence of the first mechanism. Since their predictive models for ongoing tasks generate predictions with higher certainty, they can, earlier in action unfolding, consider that ongoing task uncertainty is sufficiently reduced and orient their visual attention toward information relevant for future tasks. This anticipatory reallocation constitutes, according to our theoretical framework, the central mechanism explaining why experts seem to act with more available time. It is not because they process information faster than novices, but because they begin processing information relevant for their future decisions earlier in the temporal sequence.

More formally, the system decides to reallocate attention from a first task to a second task when the first task's uncertainty passes below an acceptable threshold. Experts, having more precise models, reach this threshold faster than novices, triggering early reallocation.

This anticipatory reallocation mechanism generates a precise and testable behavioral prediction. In dual-task situation with competing informational demands, experts should manifest visual exploration patterns characterized by early gaze orientation toward cues relevant for future tasks and so adopting proactive behavior. Conversely, novices should maintain their attention on information linked to the first task until its effective completion and then they switch to searching for useful information for the second task, a behavior that would be characterized as sequential or reactive.

Concretely, in our football paradigm involving pass reception followed by an outgoing pass, we predict that experts will reallocate their attention from the incoming ball toward the peripheral environment significantly earlier than novices. This reallocation could intervene even before ball contact if the incoming trajectory is predictable, allowing them to locate teammates and opponents.

Moreover, experts should present an exploration pattern characterized by early and brief environmental scans, while novices should present a sequential pattern with prolonged ball surveillance followed by late scans. These hypotheses will be directly tested in the first experimental study of Chapter 2.

2.1.6 Effect of Mental Fatigue on Attentional Allocation

Beyond the expertise question, our theoretical framework also allows formulating specific predictions concerning mental fatigue's effect on attentional allocation. Mental fatigue is defined as a psychobiological state resulting from prolonged or intense cognitive effort, characterized by reduced available cognitive resources (Boksem & Tops, 2008; Hockey, 2011). According to our theoretical framework, mental fatigue should differentially affect components of the attentional allocation system, primarily degrading processes involved in flexible and anticipatory attention reallocation, while relatively sparing automated and reactive processes.

This hypothesis rests on a well-established neuropsychological distinction between two cognitive processing modes (Kahneman, 2011; Schneider & Shiffrin, 1977). Controlled executive processes depend on frontal attentional resources, notably dorsolateral prefrontal cortex and anterior cingulate cortex. They involve top-down control, flexibility, and inhibition capacity. These processes are vulnerable to mental fatigue because they depend on availability

of limited attentional resources that progressively deplete. Conversely, automated processes are largely independent of executive resources. In fact, they rely on stabilized procedural representations and require little conscious control. These processes are more robust to cognitive exhaustion, operating via subcortical and posterior cortical neural circuits less dependent on frontal resources.

In the context of attentional allocation, anticipatory reallocation toward future tasks before ongoing task completion precisely constitutes the type of flexible and controlled process that should be vulnerable to fatigue. This reallocation requires meta-cognitive evaluation of residual uncertainty level, it necessitates a decision to interrupt ongoing allocation despite task non-completion, and flexible switching toward a new information source. These three components are classically associated with frontal executive functions sensitive to mental fatigue.

Concretely, we formulate two competing hypotheses concerning mental fatigue's effect in experts.

According to a first hypothesis centered on reallocation timing degradation, under mental fatigue, experts could preserve the general structure of their allocation patterns. They would continue exploring the same zones of interest, but this exploration's temporality could shift toward later moments, approaching patterns observed in novices' behaviors. Fatigue would affect meta-cognitive capacity to evaluate early that uncertainty is sufficiently reduced and so delay the decision to reallocate attention. This hypothesis also predicts increased inter-trial variability in reallocation timing under fatigue, reflecting degraded consistency of executive control.

According to a second hypothesis centered on processing efficiency degradation, fatigue might not affect the strategic timing of exploration but only information processing speed once attention is oriented toward a zone of interest. Under fatigue, experts would present visual fixations as well as scans of longer duration. This reflects a reduced information processing rate, even if their temporal sequence remains preserved. This distinction between timing degradation (when to explore) and efficiency degradation (duration to extract information) has important theoretical implications.

If the first hypothesis concerning timing is confirmed, this would suggest that anticipatory reallocation rests on controlled executive processes vulnerable to exhaustion. Expertise, while conferring more precise predictive models, does not protect against degradation of the meta-cognitive control allowing optimal exploitation of these models under reduced resource constraint. This would imply that perceptual-cognitive training should explicitly target robustness of attentional timing facing fatigue.

If the second hypothesis concerning efficiency is confirmed, this would suggest that experts have automated not only their predictive models but also their visual exploration strategies. The temporal sequence of allocation thereby becomes relatively robust to reduced available cognitive resources. Fatigue would primarily affect sensory and perceptual processing speed, namely lower-level processes, but it would preserve high-level temporal structure. This would imply that expertise confers a form of protection against cognitive fatigue effects on strategic aspects of attentional allocation.

A third possibility is that a complex interaction emerges, with differential effects according to action phases or sub-task types. For example, anticipatory reallocation could be degraded for the most proactive early scans, while ball surveillance in the reception phase could simply be slowed.

These considerations allow us to formulate several formal and testable hypotheses that will guide our experimental work. Under mental fatigue, reallocation timing from the ball toward the peripheral environment should be significantly delayed in experts, reducing the temporal gap with novices. Under mental fatigue, the average duration of visual fixations and total duration of scanning phases should be significantly increased in experts. This reflects information processing slowdown. Under mental fatigue, inter-trial variability in reallocation timing should significantly increase in experts, reflecting increased inconsistency of executive control. Finally, mental fatigue effects on attentional allocation patterns should be more pronounced in experts than in novices, since experts exploit sophisticated anticipatory strategies dependent on executive resources, whereas novices use simpler sequential strategies less vulnerable to frontal resource exhaustion.

The second experimental study of Chapter 2 was specifically designed to test these hypotheses. We will compare visual behavior adopted by expert footballers during a football

dual-task under mental fatigue, induced through a demanding cognitive task, versus without fatigue in a control condition.

2.1.7 Justification of Sport-Context and Football Choice

To close this first part, we wish to justify the choice of the sporting domain and specifically football as study context. This choice rests on several convergent theoretical and methodological considerations.

Sport, and more particularly team sports, represent a 360° environment containing various competing sources of information. As previously mentioned, a footballer must jointly control and manipulate the ball, visually explore the environment to identify available teammates for a passing opportunity, and monitor opponents and their anticipated intentions. They also have to manage external contextual factors such as match score, accumulated physical fatigue, or environmental pressure around the field. This informational richness, as well as the necessity to arbitrate between these different competing demands in real time under pressure, makes team sports an ideal context for studying visual exploration strategies during dual-tasks or multiple tasks.

Sport also imposes strict and unique temporal constraints. Unlike laboratory tasks where pace can often be controlled by the participant, sporting tasks unfold according to independent dynamics imposed by the environment, like projectile speed (ball), other actors' displacements (teammates and opponents), as well as continuous game evolution. These temporal constraints imply that the system must allocate its attention optimally for performance purposes, under penalty of immediate functional failure. This temporal pressure precisely constitutes the context in which the attentional allocation mechanisms we study have evolved and naturally manifest.

Moreover, the sporting context allows identifying different expertise levels in a clear and ecologically validated manner. High-level competitive athletes, whether at national or international level, have accumulated thousands of hours of deliberate practice in their domain (Ericsson et al., 1993), and have generally exceeded ten thousand hours according to the classical estimate. They have been selected through years of competition in rigorous hierarchical systems. This natural selection guarantees that differences observed between experts and novices truly reflect differences developed through extensive practice, rather than

uncontrolled pre-existing differences. Since sporting performance is objectively measurable through victories, defeats, and individual statistics, validity of classification into expertise levels is directly verifiable.

The sporting context has also benefited from major technological advances. These advances allow both recording the entire situation to measure performance-related variables, but also more finely measuring visual behavior adopted by the participant during the situation, by the development of mobile eye-trackers. Mobile eye-tracking technology evolution now allows the participant to move freely in playing space while performing actions proper to the situation, with acceptable quality and acquisition frequency (approximately 100 Hz to 120 Hz for our generation of mobile eye-trackers with spatial precision of 0.5° to 1°). This technology has revolutionized research possibilities. Thanks to these technological innovations, we can refine research questions and measure visual exploration strategies under ecological conditions without substantially altering participant behavior, which was not previously possible with fixed systems requiring head immobilization.

Beyond general arguments favoring the sporting context, several specific reasons justify football's choice as application domain. Football naturally presents the dual-task situation that we wish to study. Ball control constitutes a foveal and proximal task. Environmental scanning constitutes a peripheral and distant task. This configuration is ecologically valid, and representative of situations encountered in competitive matches, contrasting with artificial setup imposed in the laboratory. Pass reception followed by an outgoing pass constitutes a fundamental action sequence in football.

Football has been extensively studied in the perceptual-cognitive expertise domain. Our meta-analysis, which will be presented in Part 2, includes twenty-four football studies out of ninety articles. This provides a solid empirical basis for comparisons and integration into existing knowledge corpus. Validated experimental paradigms already exist, allowing reliance on proven methodologies while enriching them.

The results generated will also have direct applied relevance for training perceptual-cognitive capacities in footballers, which is a major area of interest for professional clubs and national federations. This applied relevance facilitates collaboration with clubs and

recruitment of high-level expert participants, increasing potential work impact beyond the academic sphere.

Technically, football is well-suited with the use of mobile eye-tracker. Displacements are fluid, without violent shocks like in rugby. Studied actions can be decomposed into experimentally controlled sequences, like reception followed by a pass to another teammate. The environment can be standardized, for example on synthetic field or a gymnasium with controlled lighting, optimizing record quality while preserving ecological validity.

For these various convergent reasons, football constitutes an optimal study context for measuring fundamental principles of visual attention in natural and representative context. We benefit from precision in measuring performance and visual attention that is difficult to attain in other contexts, while maintaining experimental control over the situation.

Football can be seen as a set of natural dual-task situations where attentional allocation must be optimized under strict temporal constraints to achieve multiple competing objectives. Mechanisms identified in this context have the potential to be generalized beyond football itself, extending toward other domains involving the prediction of others' actions, and sensorimotor coordination in real time.

Now that we have established the formalized theoretical framework guiding our work, resolved apparent conceptual tensions, and justified our fundamental methodological choices, Part 2 will present a quantitative synthesis of existing empirical literature on perceptual-cognitive expertise in sport. This meta-analysis will allow precisely identifying empirical gaps that our experimental work will address in following chapters.

2.2 Literature Review: Quantitative Synthesis via Meta-Analysis

2.2.1 Objectives and Relevance of the Meta-Analysis

This second part presents results of our meta-analysis conducted to quantify the state of empirical literature on perceptual-cognitive expertise in a sport context. This meta-analysis pursues three complementary and interdependent objectives.

First, it updates main results concerning expertise effects on performance variables and visual behavior in a sport context, since the foundational and most cited meta-analysis on this subject published by Mann and colleagues in 2007). This update is particularly relevant as nearly twenty years have elapsed since the publication, a period during which the field has experienced substantial technological advances, especially the emergence of mobile eye-trackers allowing measurements of gaze behavior in ecological situations.

Second, through complete and systematic classification of articles according to five key methodological moderators, this meta-analysis identifies which moderating variables explain the substantial heterogeneity observed between studies, revealing under which specific conditions expertise effects are most pronounced. This moderator approach allows going deeper than averaged global conclusions to identify theoretically informative conditional patterns. For example, does expert advantage differ according to sport type, type of stimuli presentation, or mode of response imposed on participants?

Third, and this is perhaps the most important objective for the present doctoral work, this meta-analysis allows us to precisely identify the gaps that remain in current empirical literature, establishing our specific research questions in the following chapters. Indeed, an exhaustive quantitative synthesis reveals not only what we know with certainty, but also, and just as critically, what we still don't know. These empirical gaps constitute priority investigation spaces for advancing theoretical understanding of the domain.

2.2.2 Methodology

From a methodological perspective, we conducted a comprehensive bibliographic search in accordance with the PRISMA 2020 guidelines (Page et al., 2021), which represent the international standard for transparent and reproducible reporting of systematic reviews and

meta-analyses. This search was carried out on two major online databases covering human movement sciences and cognitive sciences: Scopus and PubMed. We included articles published between January 2005 and March 2025, a timeframe that covers all studies published after Mann and colleagues' meta-analysis, ensuring a complete update without overlapping with the original corpus.

Search equations were constructed to maximize sensitivity while maintaining acceptable specificity, and using the same structure as used in the previous meta-analyses. They included three main components combined via Boolean operators. The first component included terms related to perceptual-cognitive skills of interest, such as anticipation, decision-making, pattern recognition, visual search, perceptual-cognitive skill, including orthographic variants. The second component included terms related to expertise or skill level. The third component specified sporting context via the term sport. The exact detail of search equations for each database, including specific syntaxes and applied filters, is found in Table 1.

Table 1: Search equations for Scopus and PubMed databases

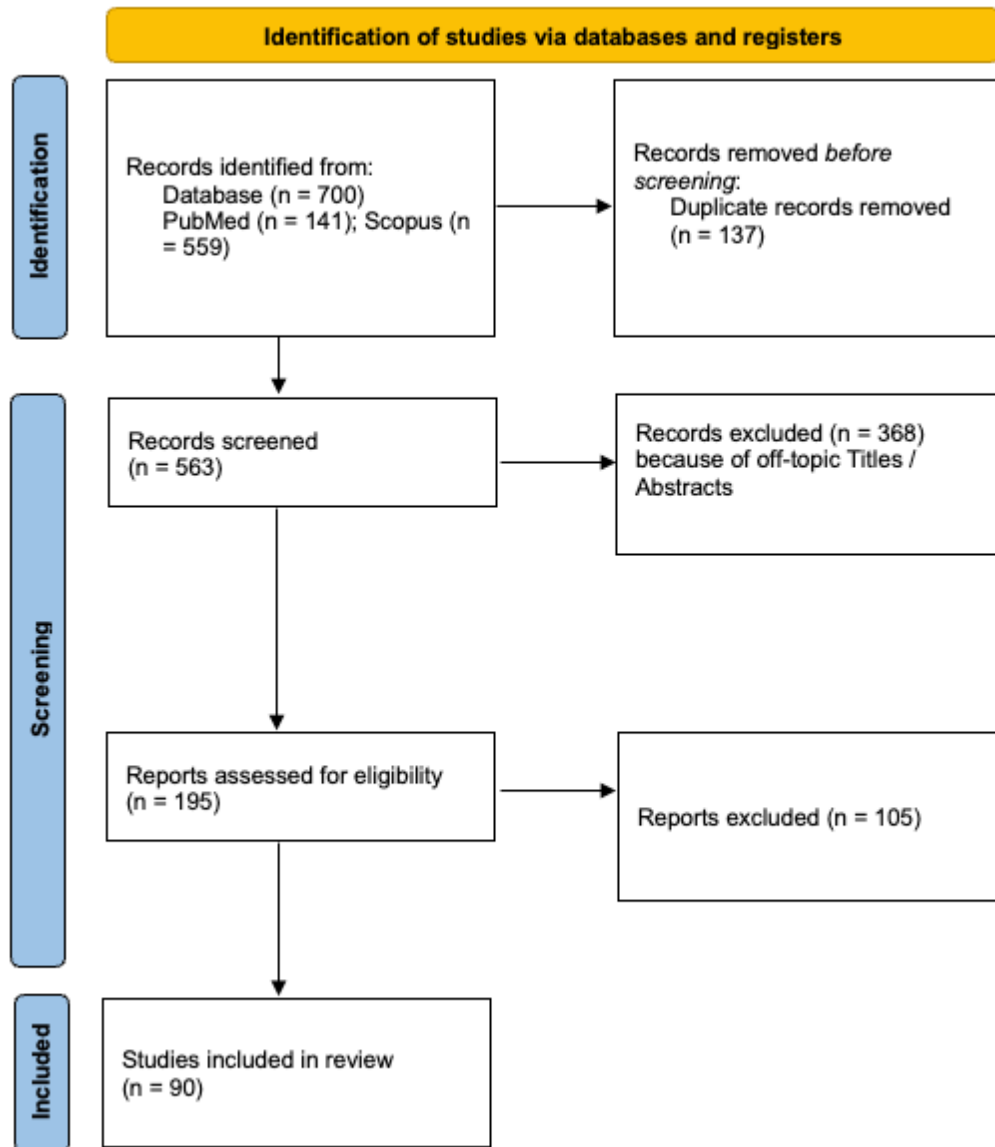
Database	Search Query	Date	Results
Scopus	((((((((((anticipation [Title / Abstract]) OR ("cue use" [Title / Abstract])) OR ("decision making" [Title / Abstract])) OR ("eye movement" [Title / Abstract])) OR ("eye tracking" [Title / Abstract])) OR ("information processing" [Title / Abstract])) OR ("occlusion" [Title / Abstract])) OR ("quiet eye" [Title / Abstract])) OR ("visual attention" [Title / Abstract])) OR ("visual search" [Title / Abstract])) AND (sport [Title / Abstract])) AND (expertise [Title / Abstract]))	24/03/2025	N = 559
PubMed	TITLE-ABS-KEY (anticipation OR "cue use" OR "decision making" OR "eye movement" OR "eye tracking" OR "information processing" OR occlusion OR "quiet eye" OR "visual attention" OR "visual search") AND TITLE-ABS-KEY (sport) AND TITLE-ABS-KEY (expertise)	24/03/2025	N = 141

To be included in our meta-analysis, studies had to meet three strict eligibility criteria. First, they had to compare at least two groups of participants with different expertise levels in a specific sport context, allowing the calculation of a standardized effect size between groups. Second, they had to include at least one performance dependent variable, such as performance accuracy or response time, or a variable linked to gaze behavior, like number of visual fixations, their average duration, or quiet eye duration. Third, they had to contain sufficient statistical data, typically means and standard deviations by group or test statistics enabling precise calculation of a standardized effect size using Hedges' g .

Studies using paradigms that were non-representative of real sport context were excluded. For example, tasks involving basic perceptual discrimination unrelated to specific demands of the studied sport, or protocols measuring general cognitive capacities, like working memory, without a domain-specific perceptual-motor component, did not meet our inclusion criteria.

After different successive screening stages, including duplicate elimination, title and abstract screening, and full-text review of potential eligible studies, 90 unique studies were included in this meta-analysis. These studies generated 175 independent effect sizes extracted from comparisons between athletes presenting high skill level and less skilled or novice athletes.

Figure 5: PRISMA flowchart showing study selection process



Effect sizes were calculated using Hedges' g , a standardized measure of difference between groups correcting small sample bias inherent to Cohen's d . A positive effect size indicated superior values for more skilled athletes, while a negative effect size indicated superior values for less skilled athletes. For variables where a lower score represents better performance, like response time, signs were reversed to ensure coherent interpretation, so that positive values always indicate an expert advantage.

Effect sizes were synthesized via three-level random-effects models implemented in the metafor package in R (Viechtbauer, 2010). These multilevel models account for variability

between studies, variability within studies when multiple independent comparisons are extracted from the same publication, and sampling error. This approach provides a more accurate representation of the hierarchical structure of meta-analytic data compared to traditional two-level models. Heterogeneity was quantified via the I^2 index, representing the proportion of total variability attributable to real differences between studies rather than sampling error. I^2 values around 25% are considered low, 50% as moderate, and 75% as high according to Higgins & Thompson (2002).

Moderation analyses were systematically conducted to identify methodological variables explaining this heterogeneity. Five moderators were analyzed for each dependent variable. Sport type distinguished strategic sports like football, basketball or handball, interceptive sports like tennis or baseball, and a residual category grouping other sports like shooting sports or climbing. Type of paradigm distinguished anticipation tasks, decision-making, eye movement recording, temporal occlusion, spatial occlusion, recognition, recall, and general task performance. Type of stimulus presentation distinguished static slides, dynamic films or videos, virtual environments, and real-world situations on field. Response mode distinguished verbal responses, non-sport-specific movements like pressing a button, and sport-specific movements like performing a strike or pass. Finally, type of expertise classification distinguished studies using achieved competition level, quantitative years of experience, tests or classifications via questionnaires, or mixed criteria combining several indicators.

Publication bias was assessed using funnel plot asymmetry tests, including Egger's regression, and by visually inspecting funnel plots to detect possible asymmetries suggesting selective publication favoring significant results. These analyses will be reported when relevant for results interpretation.

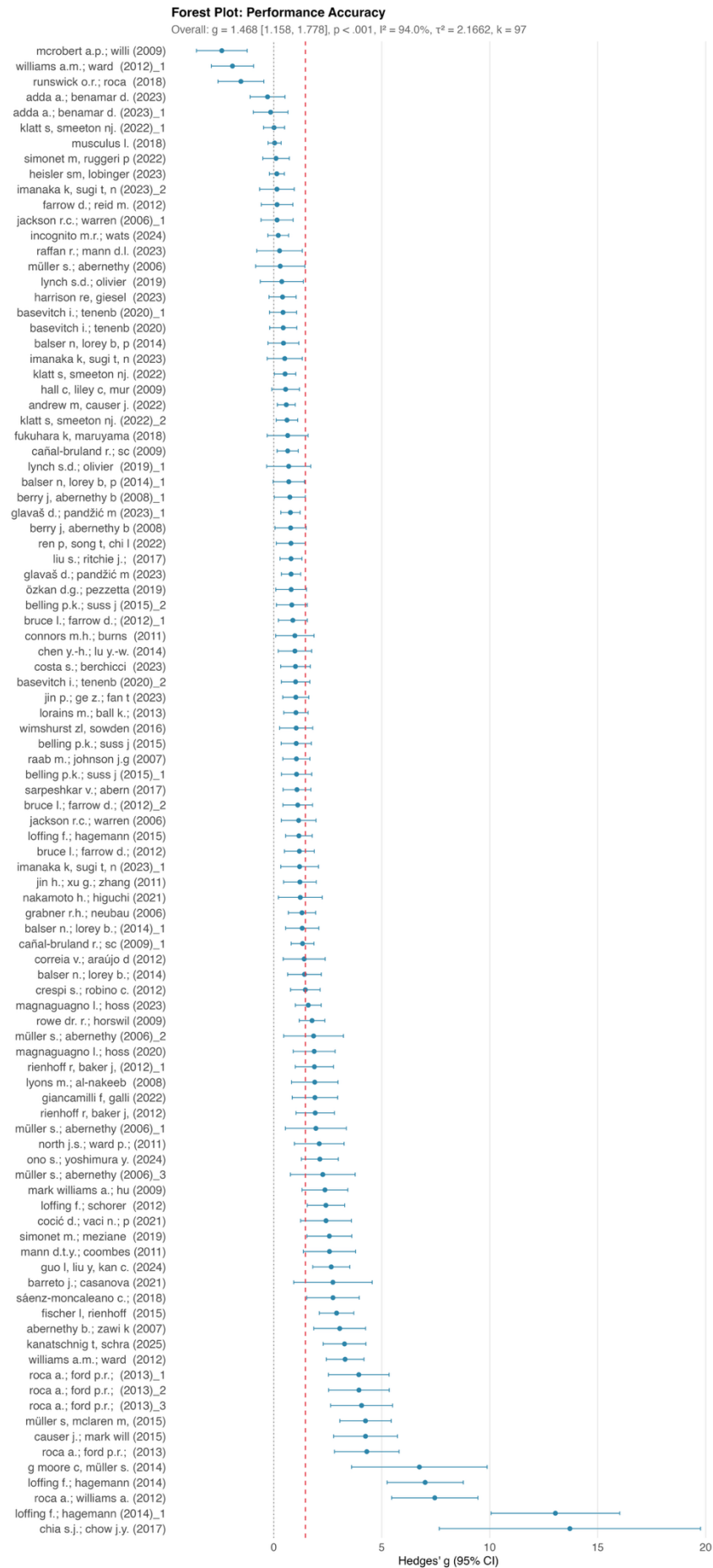
2.2.3 Results

2.2.3.1 Performance Accuracy

Performance accuracy, defined as percentage of correct decisions, exact predictions, or appropriate responses in sport-specific tasks, has historically been the most frequently measured dependent variable in perceptual-cognitive expertise studies. This variable directly captures athletes' ability to extract relevant information from their environment and produce appropriate judgments or decisions, which represents the functional core of expertise in open and dynamic sports.

Analysis of 97 effect sizes reveals a very large and robust expert advantage ($g = 1.47$, 95% CI [1.16, 1.78], $p < .001$). This very large effect size means that, on average, expert athletes perform approximately 1.5 standard deviations above novices on prediction or decision-making tasks. This overall convergence confirms and extends the findings of Mann et al.'s (2007), demonstrating the robustness of expert advantage across two decades of research conducted in various sport contexts and with varied methodologies (see Figure 6).

Figure 6: Forest plot showing effect sizes (Hedges' g) for performance accuracy across all 97 comparisons with 95% confidence intervals



However, this overall convergence hides substantial heterogeneity between studies ($Q(96) = 742.19$, $p < .001$, $I^2 = 94.0\%$, $\tau^2 = 2.17$). The I^2 index of 94% indicates that almost all observed variability reflects real differences between studies rather than random sampling error. The 95% prediction interval, extending from negative values to extremely positive values, suggests that a new study could observe either a null effect, or even a slight advantage for novices under certain specific conditions, or a very large effect superior to two standard deviations in favor of experts. This considerable heterogeneity motivates systematic analysis of moderators likely to explain these variations.

Moderator analysis reveals complex and theoretically informative patterns. Sport type does not exert significant global effect ($Q_M = 1.63$, $p = .443$), with similar effect sizes between strategic sports ($g = 1.61$, $k = 57$), interceptive sports ($g = 1.15$, $k = 30$), and others ($g = 1.49$, $k = 10$). Although team sports tend descriptively to show slightly larger effects, possibly due to more complex tactical cognitive demands involving reading others' intentions and team coordination, this difference does not reach statistical significance threshold. This robustness of expert advantage across all sport types suggests existence of fundamental perceptual-cognitive mechanisms that generalize beyond specific disciplines.

Paradigm type also shows no significant global effect ($Q_M = 12.06$, $p = .099$), but notable tendencies emerge. Eye movement recording paradigms ($g = 2.15$, $k = 7$) as well as temporal occlusion ($g = 1.80$, $k = 22$) produce the largest effects, suggesting that these methodological approaches preserve kinematic and temporal richness allowing experts to fully exploit their sophisticated predictive models.

Regarding the type of presentation, despite non-significant global effect ($Q_M = 6.45$, $p = .092$), a clear ecological gradient emerges. Tasks performed in real-world settings produce the largest effects ($g = 1.92$, $k = 18$), followed by dynamic videos ($g = 1.54$, $k = 65$), virtual environments ($g = 1.10$, $k = 4$), and finally static images ($g = 0.59$, $k = 10$).

The response mode used constitutes a moderator approaching significance for the performance accuracy variable ($Q_M = 5.87$, $p = .053$). Verbal responses produce the largest effects ($g = 2.46$, $k = 13$), sport-specific movement produce large effects ($g = 1.52$, $k = 27$), and non-sport-specific movements produce more modest though substantial effects ($g = 1.23$, $k = 56$).

Finally, expertise classification type presents global effects that reach the significance threshold ($Q_M = 9.17$, $p = .027$). Classification via achieved competition level produces the largest effects ($g = 1.99$, $k = 51$), followed by mixed criteria ($g = 1.16$, $k = 26$), and quantitative experience in years ($g = 0.68$, $k = 15$).

Table 2: Moderation analysis results for performance accuracy showing effect sizes (g), confidence intervals, number of comparisons (k), heterogeneity statistics (Q_M , I^2), and p -values for all five moderators

Moderator	k	g	95% CI	QM	I ² (%)	p
Overall	97	1.47	[1.16, 1.78]	742.19	94.0	<.001***
Sport Type						
Others	10	1.49	[0.96, 2.02]	1.63	-	.443
Interceptive	30	1.15	[0.70, 1.59]		-	
Strategics	57	1.61	[1.14, 2.08]		-	
Paradigm Type						
Anticipation	26	1.22	[0.69, 1.75]	12.06	-	.099
Decision Making	24	1.21	[0.70, 1.73]		-	
Eye movement	7	2.15	[1.76, 2.54]		-	
Recall	4	0.21	[-1.15, 1.56]		-	
Recognition	5	0.74	[-0.17, 1.64]		-	
Spatial Occlusion	4	4.02	[-1.68, 9.71]		-	
Task Performance	5	3.31	[-0.07, 6.69]		-	
Temporal Occlusion	22	1.80	[1.09, 2.51]		-	
Stimulus Type						
Static slides	10	0.59	[0.27, 0.92]	6.45	-	.092
Virtual Environment	4	1.10	[0.51, 1.70]		-	
Video/Dynamic	65	1.54	[1.08, 1.99]		-	
Real world	18	1.92	[1.55, 2.30]		-	
Expertise Type						
Experience	15	0.68	[0.31, 1.05]	9.17	-	.027*
Mix	26	1.16	[0.72, 1.60]		-	
Level of Competition	51	1.99	[1.43, 2.55]		-	
Test/Classification/Quest.	5	0.71	[0.35, 1.08]		-	
Response Mode						
Non-Specific movement	56	1.23	[0.83, 1.64]	5.87	-	.053
Specific movement	27	1.52	[1.10, 1.95]		-	
Verbal	13	2.46	[1.32, 3.61]		-	

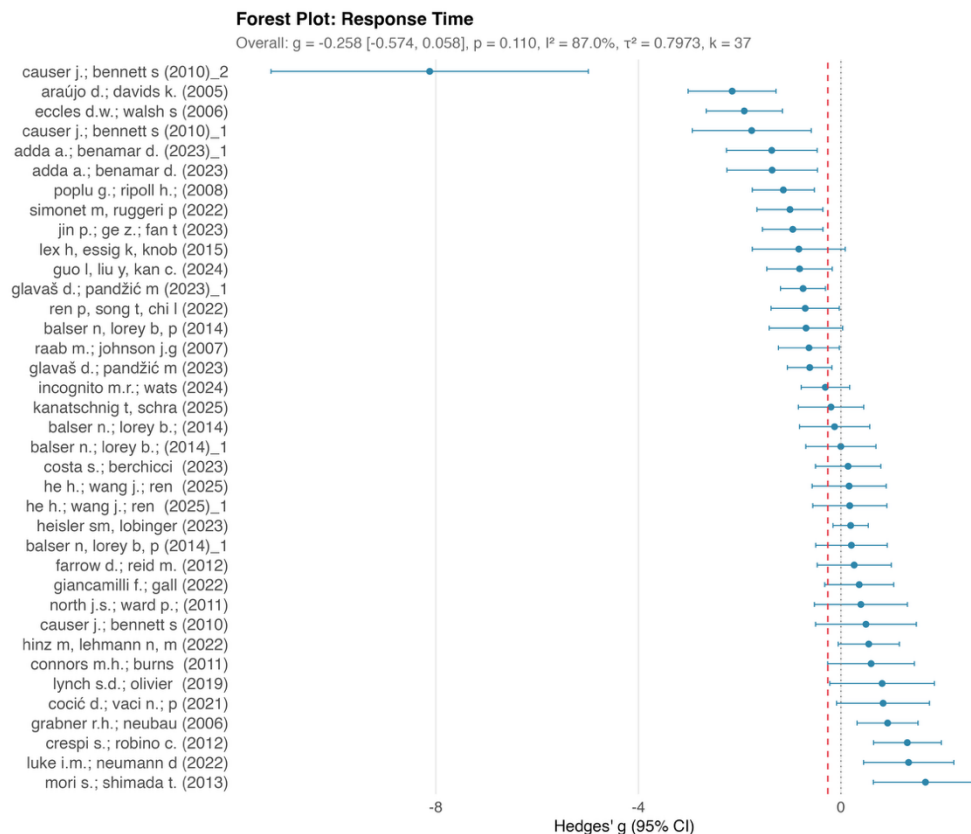
Note. k = number of effect sizes; g = Hedges' g; 95% CI = 95% confidence interval; Q_M = Q-statistic for moderator effect; I^2 = heterogeneity.

* $p < .05$. ** $p < .01$. *** $p < .001$.

2.2.3.2 Response Time

For response time variable, one might intuitively expect to observe results largely favoring expert athletes, reflecting superior information processing speed. However, analysis of 37 effect sizes indicates a substantially more complex and nuanced pattern. The best athletes do not systematically respond faster than novices. There certainly exists a tendency favoring experts, but the effect is weak and is not significant ($g = -0.26$, 95% CI $[-0.57, 0.06]$, $p = .110$). Moreover, heterogeneity between studies is considerable ($Q(36) = 216.98$, $p < .001$, $I^2 = 87.0\%$, $\tau^2 = 0.80$), and the prediction interval extends very broadly on each side of zero (95% CI: -2.01 to 1.49), demonstrating great result variability and important uncertainty regarding predictions for future studies.

Figure 7: Forest plot showing effect sizes (Hedges' g) for response time across all 37 comparisons with 95% confidence intervals



This absence of significant global effect contrasts strongly with massive results observed for performance accuracy and suggests that speed does not constitute a universal marker of perceptual-cognitive expertise. This dissociation between accuracy and response time is theoretically informative. It suggests that experts are not systematically faster, but rather that they adaptively calibrate their temporal allocation according to specific task demands and

context. In situations where speed is functionally critical for success, experts can indeed respond faster. In situations where decisional quality predominates and where no temporal pressure exists, experts may conversely take more time to extract richer information, producing better quality decisions without necessarily producing them faster.

Moderator analysis precisely supports this interpretation of contextual specificity of speed advantage. Sport type presents no significant global effect ($Q_M = 3.72$, $p = .156$) but reveals some specificities. Interceptive sports show a significant and substantial effect ($g = -0.64$, $p = .005$, $k = 11$), while strategic sports ($g = -0.16$, $p = .360$, $k = 19$) and others ($g = -0.50$, $p = .652$, $k = 7$) show no significant effect. This specificity is perfectly coherent with differentiated functional demands of these sporting categories. Indeed, in interceptive sports like tennis, baseball, or badminton, temporal windows available for processing information and initiating a response are drastically constrained by projectile's high speed and short distances, so decisional speed then becomes functionally critical and discriminating between expertise levels. Conversely, in strategic sports where tactical and decisional quality predominates, experts and novices can adopt relatively similar temporal strategies, experts potentially investing more time to extract richer tactical information rather than systematically accelerating their responses.

Paradigm type presents significant effects ($Q_M = 18.16$, $p = .011$). Task performance paradigms ($g = -2.01$, $p < .001$, $k = 2$), decision-making ($g = -0.48$, $p = .017$, $k = 11$), and recognition ($g = -0.82$, $p = .002$, $k = 2$) show significant effects favoring experts' superior response time. Conversely, anticipation paradigms show strictly no effect ($g = 0.08$, $p = .705$, $k = 12$). This pattern reveals that experts' speed advantage only emerges when speed is either explicitly valued in instructions, or functionally necessary to succeed at the task.

Stimulus presentation type also presents significant results ($Q_M = 7.85$, $p = .049$). Virtual environments show a large and significant effect ($g = 1.11$, $k = 2$, $p = .001$), contrasting with absence of effect for videos ($g = -0.09$, $p = .586$, $k = 21$) and static slides ($g = -0.63$, $p = .063$, $k = 7$).

Response mode presents no significant effects ($Q_M = 1.34$, $p = .719$), strongly contrasting with its role as the most powerful moderator for performance accuracy. Finally, expertise categorization also shows no significant effect ($Q_M = 0.93$, $p = .628$).

Table 3: Moderation analysis results for response time showing effect sizes (g), confidence intervals, number of comparisons (k), heterogeneity statistics (Q_M , I^2), and p-values for all five moderators

Moderator	k	g	95% CI	Q_M	I^2 (%)	p
Overall	37	-0.26	[-0.57, 0.06]	216.98	87.0	.110
Sport Type						
Others	7	-0.50	[-2.65, 1.66]		-	
Interceptive	11	-0.64	[-1.09, -0.20]	3.72	-	.156
Strategies	19	-0.16	[-0.51, 0.18]		-	
Paradigm Type						
Anticipation	12	0.08	[-0.35, 0.52]		-	
Decision Making	11	-0.48	[-0.87, -0.08]		-	
Eye movement	5	-1.31	[-4.38, 1.76]		-	
Recognition	2	-0.82	[-1.35, -0.29]	18.16	-	.011*
Spatial Occlusion	2	-0.14	[-0.56, 0.29]		-	
Task Performance	2	-2.01	[-2.58, -1.44]		-	
Temporal Occlusion	2	0.82	[0.14, 1.51]		-	
Stimulus Type						
Static slides	7	-0.63	[-1.28, 0.03]		-	
Virtual Environment	2	1.11	[0.44, 1.79]	7.85	-	.049*
Video/Dynamic	21	-0.09	[-0.42, 0.24]		-	
Real world	7	-1.32	[-3.17, 0.53]		-	
Expertise Type						
Experience	9	-0.48	[-0.96, 0.01]		-	
Mix	15	-0.28	[-0.67, 0.11]	0.93	-	.628
Level of Competition	13	-0.26	[-1.22, 0.71]		-	
Response Mode						
Non-Specific movement	26	-0.24	[-0.56, 0.08]		-	
Specific movement	9	-0.81	[-2.22, 0.61]	1.16	-	.561
Verbal	2	0.33	[-1.57, 2.24]		-	

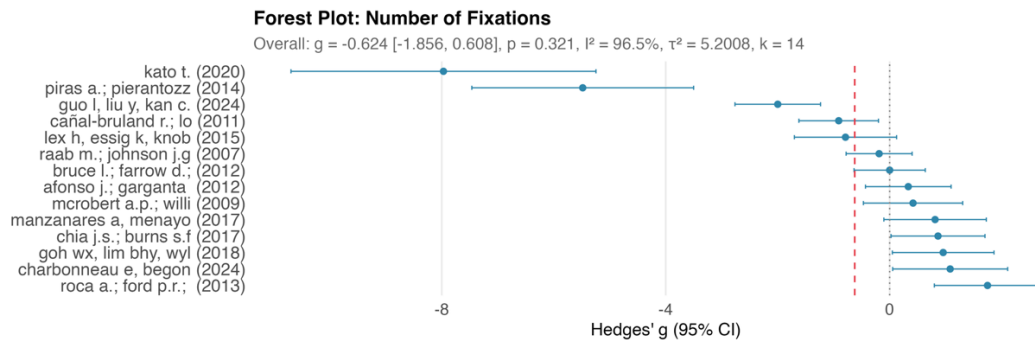
Note. k = number of effect sizes; g = Hedges' g; 95% CI = 95% confidence interval; Q_M = Q-statistic for moderator effect; I^2 = heterogeneity.

*p < .05. **p < .01. ***p < .001.

2.2.3.3 Number of Visual Fixations

Regarding the number of visual fixations variable, 14 effect sizes were analyzed. Results suggest that the most skilled athletes tend to perform fewer visual fixations than less skilled athletes, a descriptive pattern coherent with hypothesis of more efficient visual exploration in experts. However, the statistical significance threshold was not reached ($g = -0.62$, 95% CI $[-1.86, 0.61]$, $p = .321$). Moreover, observed heterogeneity is extreme ($Q(13) = 127.75$, $p < .001$, $I^2 = 96.5\%$, $\tau^2 = 5.20$), with a 95% prediction interval extending from -5.09 to $+3.85$. This large interval indicates that in future studies, experts could produce between five standard deviations fewer visual fixations than novices, but also up to four standard deviations more visual fixations, demonstrating quasi-total unpredictability regarding effect direction and amplitude in a given context.

Figure 8: Forest plot showing effect sizes (Hedges' g) for number of visual fixations across all 14 comparisons with 95% confidence intervals



This extreme heterogeneity suggests that number of visual fixations constitutes a variable highly sensitive to methodological and contextual variations not systematically characterized in literature. Analysis of the five moderators did not reveal any significant effect allowing explanation of this massive variability: sport type ($Q_M = 1.49$, $p = .474$), paradigm type ($Q_M = 1.60$, $p = .808$), presentation type ($Q_M = 1.89$, $p = .596$), response mode ($Q_M = 0.83$, $p = .661$), expertise classification type ($Q_M = 3.81$, $p = .283$). This total absence of significant moderation despite 96% heterogeneity suggests that critical factors determining fixation number in a given study are not captured by our coding moderators. These factors could include other characteristics of the tasks, like stimulus presentation duration or number of elements to monitor, or methodological definitions of visual fixations varying substantially between eye-tracking systems and visual fixation thresholds used.

Table 4: Moderation analysis results for number of visual fixations showing effect sizes (g), confidence intervals, number of comparisons (k), heterogeneity statistics (Q_M , I^2), and p-values for all five moderators

Moderator	k	g	95% CI	Q_M	I^2 (%)	p
Overall	14	-0.62	[-1.86, 0.61]	127.75	96.5	.321
Sport Type						
Other	5	-1.98	[-5.66, 1.70]	1.49	-	.474
Interceptive	3	-0.25	[-2.00, 1.50]		-	
Strategies	6	0.01	[-0.71, 0.73]		-	
Paradigm Type						
Decision Making	3	0.47	[-0.69, 1.62]	1.60	-	.808
Eye movement	6	-1.55	[-4.61, 1.51]		-	
Recognition	3	-1.25	[-2.01, -0.49]		-	
Stimulus Type						
Static slides	2	-0.86	[-1.43, -0.30]	1.89	-	.596
Video/Dynamic	4	0.44	[-0.38, 1.25]		-	
Real world	7	-1.59	[-4.15, 0.96]		-	
Expertise Type						
Experience	3	-2.09	[-5.67, 1.49]	3.81	-	.283
Mix	3	-2.49	[-7.66, 2.69]		-	
Level of Competition	7	0.37	[-0.28, 1.02]		-	
Response Mode						
Non-Specific movement	2	-0.86	[-1.42, -0.31]	0.83	-	.661
Specific movement	9	-1.06	[-3.06, 0.94]		-	
Verbal	3	0.47	[-0.69, 1.62]		-	

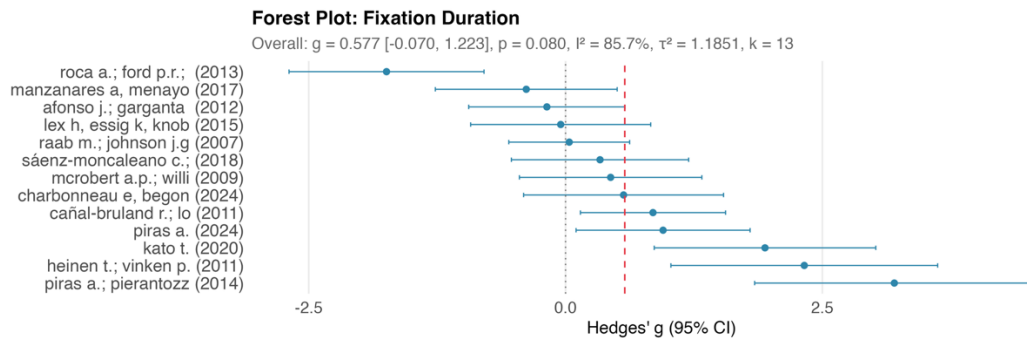
Note. k = number of effect sizes; g = Hedges' g; 95% CI = 95% confidence interval; Q_M = Q-statistic for moderator effect; I^2 = heterogeneity.

* $p < .05$. ** $p < .01$. *** $p < .001$.

2.2.3.4 Visual Fixations Duration

For the average visual fixation duration variable, we find qualitatively similar results to those for the number of fixations. Experts tend to perform longer visual fixations than novices, a descriptive pattern coherent with hypothesis of deeper informational extraction from selected regions. However, as with the number of fixations, the statistical significance threshold was not reached ($g = 0.58$, 95% CI [-0.07, 1.22], $p = .080$). Heterogeneity remains high ($Q(12) = 63.19$, $p < 10^{-8}$, $I^2 = 85.7\%$, $\tau^2 = 1.19$), and the prediction interval broadly contains zero value, indicating that it is not possible to reliably predict either direction or amplitude of effects in a future study.

Figure 9: Forest plot showing effect sizes (Hedges' g) for visual fixation duration across all 13 comparisons with 95% confidence intervals



Moderator analysis reveals that sport type shows a tendency, but effects are not significant globally ($Q_M = 4.66$, $p = .097$), with precision sports grouped in the other sports category presenting the largest effect ($g = 1.47$, $p = .023$, $k = 5$). This tendency is intuitively coherent as precision sports like shooting sports, golf, or archery privilege informational extraction quality over speed, potentially favoring longer fixations in experts who systematically extract more information from each fixation. Paradigm type ($Q_M = 5.12$, $p = .275$), presentation type ($Q_M = 5.50$, $p = .138$), and response mode ($Q_M = 4.29$, $p = .232$) did not reveal any significant effect.

On the other hand, expertise categorization presents significant effects ($Q_M = 11.80$, $p = .008$). Categorization via quantitative experience in years produces a very large effect ($g = 2.74$, $p < .001$, $k = 2$), in comparison with competition level which produces no effect ($g = 0.15$, $p = .614$, $k = 8$). However, we may express some doubts about the generalization of these results due to the small number of studies in each “category”.

Table 5: Moderation analysis results for visual fixation duration showing effect sizes (g), confidence intervals, number of comparisons (k), heterogeneity statistics (Q_M , I^2), and p-values for all five moderators

Moderator	k	g	95% CI	QM	I^2 (%)	p
Overall	13	0.58	[-0.07, 1.22]	63.19	85.7	.080
Sport Type						
Others	5	1.47	[0.21, 2.73]	4.66	-	.097
Interceptive	2	0.39	[-0.23, 1.00]		-	
Strategies	6	0.00	[-0.74, 0.74]		-	
Paradigm Type						
Decision Making	2	-0.81	[-2.55, 0.93]	5.12	-	.275
Eye movement	6	1.28	[0.24, 2.32]		-	
Recognition	2	0.44	[-0.44, 1.32]		-	
Task Performance	2	0.29	[-1.01, 1.59]		-	
Stimulus Type						
Static slides	2	0.44	[-0.44, 1.32]	5.50	-	.138
Video/Dynamic	3	-0.40	[-1.67, 0.87]		-	
Real world	7	1.22	[0.35, 2.08]		-	
Expertise Type						
Experience	2	2.74	[1.80, 3.68]	11.80	-	.008**
Mix	2	0.92	[-1.03, 2.87]		-	
Level of	8	0.15	[-0.43, 0.72]		-	
Competition					-	
Response Mode						
Non-Specific movement	2	0.44	[-0.44, 1.32]	4.27	-	.118
Specific movement	9	0.94	[0.19, 1.68]		-	
Verbal	2	-0.81	[-2.55, 0.93]		-	

Note. k = number of effect sizes; g = Hedges' g; 95% CI = 95% confidence interval; Q_M = Q-statistic for moderator effect; I^2 = heterogeneity.

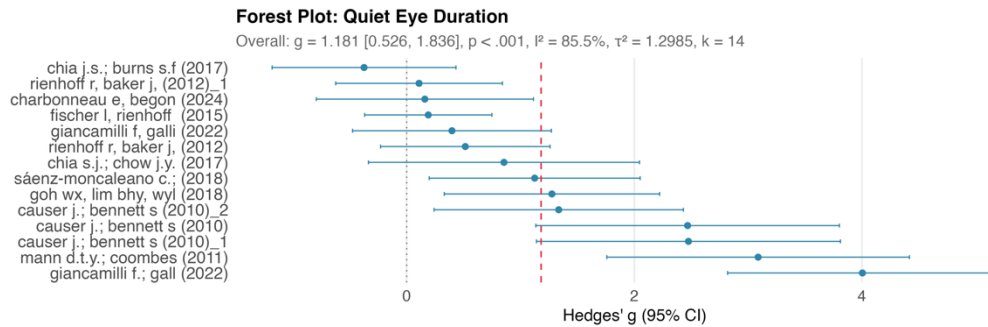
*p < .05. **p < .01. ***p < .001.

2.2.3.5 Quiet eye Duration

14 effect sizes were analyzed for quiet eye duration variable, defined as the duration of the final visual fixation directed toward a critical target before motor action initiation. Analysis reveals that experts perform significantly longer quiet eyes than novices, with a large effect size ($g = 1.18$, 95% CI [0.53, 1.84], $p < .001$). This variable radically distinguishes itself from the two previous oculometric metrics by producing a robust and statistically significant global effect. However, we find high heterogeneity between studies ($Q(13) = 73.15$, $p < .001$, $I^2 =$

85.5%, $\tau^2 = 1.30$), although slightly lower than that the heterogeneity observed for number of fixations and duration.

Figure 10: Forest plot showing effect sizes (Hedges' g) for quiet eye duration across all 14 comparisons with 95% confidence intervals



Nevertheless, most studies report longer quiet eye duration in experts compared to novices. Only 2 studies out of 14 analyzed revealed longer duration of quiet eye in favor of novices, and these reversals were not statistically significant. The prediction interval (95% CI: -1.05 to 3.42), while remaining large and including zero value, remains centered on substantial positive values, indicating that future studies will probably replicate this advantage directing toward the most skilled athletes. This directional consistency distinguishes quiet eye from other oculometric metrics and suggests it captures a fundamental and generalizable mechanism of perceptual-motor expertise.

Moderator analysis reveals no significant effect, whether for sport type ($Q_M = 0.98$, $p = .612$), paradigm type ($Q_M = 0.72$, $p = .396$), or expertise classification type ($Q_M = 0.71$, $p = .701$). This absence of significant moderation mainly reflects limited number of studies available for each sub-category, drastically limiting statistical power of moderation tests. Nevertheless, descriptive patterns suggest tendencies coherent with theoretical expectations. In fact, we observe larger effects in precision sports grouped in other category ($g = 1.26$, $k = 9$) and in strategic sports ($g = 1.49$, $k = 3$), where quiet eye plays a particularly critical functional role in stabilizing preparation and action execution, compared to interceptive sports ($g = 0.36$, $k = 2$) where extreme temporal constraints may limit possibility of maintaining prolonged quiet eye.

Table 6: Moderation analysis results for quiet eye duration showing effect sizes (g), confidence intervals, number of comparisons (k), heterogeneity statistics (Q_M , I^2), and p-values for all five moderators

Moderator	k	g	95% CI	Q_M	I^2 (%)	p
Overall	14	1.18	[0.53, 1.84]	73.15	85.5	<.001***
Sport Type						
Others	9	1.26	[0.58, 1.95]	0.98	-	.612
Interceptive	2	0.36	[-1.11, 1.83]		-	
Strategies	3	1.49	[-0.90, 3.88]		-	
Paradigm Type						
Eye movement	12	1.31	[0.56, 2.06]	0.72	-	.396
Task Performance	2	0.31	[-0.20, 0.82]		-	
Expertise Type						
Mix	5	0.84	[-0.64, 2.32]	0.71	-	.701
Level of	8	1.40	[0.68, 2.13]		-	
Competition					-	

Note. k = number of effect sizes; g = Hedges' g; 95% CI = 95% confidence interval; Q_M = Q-statistic for moderator effect; I^2 = heterogeneity.

*p < .05. **p < .01. ***p < .001.

2.2.4 Results Synthesis

Detailed variable-by-variable analysis reveals several transversal theoretically informative patterns that transcend individual metric specificities. First, an ecological representativeness gradient emerges in general. Real field situations consistently produce the largest effects, followed by dynamic videos, then virtual environments, and finally static images producing the weakest effects. This gradient is perfectly coherent with representative validity principles formulated by Brunswik and reaffirms the critical importance of preserving informational structure and natural ecological constraints in expertise evaluation protocols. Experts developed their competences in rich, dynamic, and temporally constrained environments. Protocols that deviate from these ecological characteristics systematically underestimate the real magnitude of expert advantage.

Second, a striking dissociation emerges between performance accuracy and response time. Accuracy shows large, robust, and generalizable expert advantage ($g = 1.47$), constituting by far the most reliable marker of perceptual-cognitive expertise. Conversely, response time only shows a weak and non-significant overall effect ($g = -0.26$), with really high heterogeneity

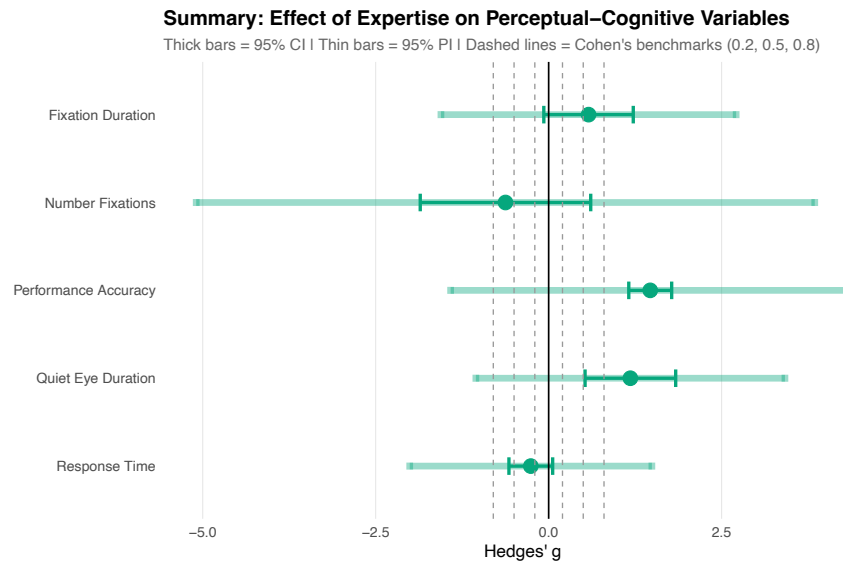
and effects only emerging in specific contexts where speed is functionally critical. This dissociation suggests that expertise manifests not primarily through general information processing acceleration, but rather through qualitative improvement of this processing, producing more accurate decisions without necessarily producing them faster. Experts seemingly adaptively calibrate their temporal allocation according to contextual demands, privileging decisional quality when time permits and only accelerating when necessary. This meta-cognitive flexibility itself constitutes a sophisticated manifestation of expertise.

Third, among gaze behavior metrics, quiet eye radically distinguishes itself by its robustness ($g = 1.18$, $p < .001$), contrasting with fragility of the number of fixations and the average duration of fixations whose global effects remain non-significant. This dissociation suggests that quiet eye captures a fundamental visuo-motor integration process generalizable across contexts, whereas fixation number and duration reflect more contextually specific and methodologically sensitive adaptations. Quiet eye, as final temporal window of informational consolidation immediately preceding action, would constitute the most reliable oculometric signature of expertise.

Fourth, response mode's role differs drastically according to the considered variable. For performance accuracy, response mode constitutes the most powerful moderator ($Q_M = 5.87$, $p = .053$), with effects varying from $g = 1.23$ for non-specific movements to $g = 2.46$ for verbal responses. On the other hand, for response time, response mode did not show moderation ($Q_M = 1.34$, $p = .719$). This dissociation suggests that cognitive mechanisms underlying accuracy and speed are partially distinct and differentially affected by response production constraints.

Fifth, and this is perhaps the most concerning result for global interpretation, residual heterogeneity remains massive even after accounting for five systematically coded moderators. I^2 indices after moderation typically remain between 80% and 95% for all variables, indicating that explicitly coded moderators explain only a little fraction of the total variance observed. This massive residual heterogeneity implies that critical factors determining effects amplitude in a given study are not systematically captured by our coding categories.

Figure 11: Comparison Forest plot showing pooled effect sizes with 95% confidence intervals for all five dependent variables



2.2.5 Comparison with Mann et al. 2007 Foundational Meta-Analysis

The present meta-analysis constitutes the first systematic and exhaustive update of Mann et al.'s (2007) seminal work, which remains, nearly twenty years later, the most cited and influential reference on perceptual-cognitive expertise in sport. Mann and colleagues originally synthesized 42 studies published between 1967 and 2004, generating 388 effect sizes from 1288 participants. Our synthesis substantially extends this corpus by analyzing 90 studies published between 2005 and 2025, that is, the entirety of post-Mann scientific production over a twenty-year period, representing approximately 1750 additional participants.

The results converge strongly on several critical dimensions, confirming the robustness of Mann et al.'s fundamental conclusions across time and the accumulation of independent research. Regarding performance accuracy, Mann et al. reported an average point-biserial correlation of $r_{pb} = .31$, corresponding to a medium effect according to Cohen's conventions. Our synthesis reveals a very large effect ($g = 1.47$), though this apparent increase in amplitude primarily reflects the conversion between different metrics rather than a substantive change. For quiet eye, Mann et al. reported an average correlation of $r_{pb} = .62$ based on only 5 studies. Our synthesis, with 14 studies, fully confirms this conclusion with an effect size of $g = 1.18$.

Moderation by stimulus presentation type also replicates Mann's findings with high fidelity. They observed a clear gradient where field situations produced the largest effects, followed by videos, then static images. Our synthesis reproduces more or less this gradient with very coherent quantitative values. However, certain notable divergences emerge that merit thorough discussion. For response time, the previous meta-analysis reported a significant correlation of $r_{pb} = .35$, suggesting that experts respond faster. In contrast, our synthesis with a substantially larger sample reveals a more complex pattern: global effect is weak and non-significant ($g = -0.26$, $p = .110$), with massive heterogeneity ($I^2 = 87.0\%$).

2.2.6 Discussion and gap identification

2.2.6.1 Main Conclusions

Meta-analysis of 90 studies and 175 independent comparisons published between 2005 and 2025 updates, refines, and substantially extends Mann et al.'s (2007) foundational meta-analysis. Several key conclusions emerge with a high degree of certainty. First, the expert advantage for performance accuracy is large, robust, and generalizable ($g = 1.47$, 95% CI [1.16, 1.78], $p < .001$), persisting across all sport types, paradigms, and methodologies. Second, quiet eye duration distinguishes itself as the only robust and generalizable oculometric marker ($g = 1.18$, 95% CI [0.53, 1.84], $p < .001$). Then, response time does not constitute a universal expertise marker but specifically emerges in contexts where speed is functionally critical. We can also note that a systematic ecological representativeness gradient emerges across variables, and that response mode constitutes accuracy's most powerful moderator. Finally, expertise operationalization by competition level produces substantially larger effects than quantitative experience for accuracy.

2.2.6.2 Current Synthesis Limitations

Despite the strength of these findings, this review faces a fundamental challenge that underpins the entire literature: the remarkable heterogeneity of research paradigms makes generalization particularly difficult. Even within the same sport, studies vary considerably in terms of experimental design, stimulus characteristics, response requirements, and skill operationalization. For example, one study may examine anticipation in tennis using video clips occluded with verbal predictions, while another studies the same skill using displays of light points with motor responses. This methodological fragmentation makes it problematic to compare effect sizes across studies, as the underlying concepts being measured may differ considerably despite similar terminological labels.

This paradigmatic diversity is likely the primary source of the extreme residual heterogeneity observed throughout our analyses. Even after accounting for five systematically coded moderators, the unexplained variance remains considerable, suggesting that finer methodological distinctions, often unreported or inconsistently documented in primary studies, account for much of the variability in effect sizes. The field has yet to converge on standardized protocols that would enable more meaningful and systematic cross-study comparisons.

Beyond this core limitation, several additional constraints temper the conclusions that can be drawn. Significant small-study effects for several variables raise concerns about potential publication bias, while the overwhelming dominance of cross-sectional designs precludes any causal inference regarding the developmental trajectories underlying expert-novice differences. Furthermore, the binary categorization of participants into expert versus novice groups obscures the continuous and multidimensional nature of real-world expertise, and the predominant reliance on global aggregated metrics collapses temporally extended dynamic processes into static summary statistics.

2.2.6.3 Three Major Gaps Motivating Present Doctoral Work

Beyond these general limitations, systematic analysis of 90 studies reveals three major specific gaps that remain largely unexplored in the current empirical literature. These gaps, absent or substantially under-explored in the existing corpus, directly motivate the objectives, methodology, and research questions of this present doctoral work.

The first gap concerns quasi-total absence of fine temporal dynamics characterization of attentional allocation in ecological dual-task situations. The vast majority of the 90 synthesized studies rely on global and aggregated gaze behavior metrics. These metrics reduce a dynamic process unfolding over several seconds to a handful of summary statistics. This temporal dimension remains largely unexplored empirically, despite being central to the predictions of the active inference computational models that we have formalized. Among the 90 synthesized studies, none systematically analyzes the fine temporal dynamics of visual exploration in relation to motor execution phases in ecological dual-task paradigms characterized by competing informational demands.

The second gap concerns total absence of studies experimentally examining mental fatigue effect on visual exploration strategies in ecological sporting context. Among the 90 studies included in our meta-analysis, none experimentally examines how mental fatigue affects experts' perceptual-cognitive strategies. This absence is particularly surprising given that mental fatigue constitutes a frequently encountered state in real competitive contexts. Understanding whether and how mental fatigue affects experts' sophisticated visual exploration strategies holds major theoretical interest for elucidating which cognitive resources are specifically involved in efficient attentional allocation.

The third gap concerns the absence of formal computational models of attentional allocation in sporting dual-tasks allowing quantitative prediction of observed patterns. Among the literature, none develops and tests formal computational models that mathematically specify principles governing optimal attention allocation under limited resource constraints and competing informational demands. Literature remains largely descriptive, documenting that experts differ from novices on various behavioral and gaze behavior metrics, but without explicitly formalizing how and why these differences emerge via precise computational principles.

These three identified gaps, namely absence of fine temporal dynamics characterization in ecological dual-task, absence of studies examining mental fatigue effect, and absence of formal computational modeling, directly motivate the structure, objectives, and methodology of present doctoral work, which will be detailed in Part 3. Specifically, our work aims first to finely characterize temporal dynamics of attentional allocation during ecological dual-task in football. Second, it aims to experimentally examine the effect of mental fatigue induction, via a demanding cognitive task, on these attentional allocation strategies. Third, our work aims to develop a formal computational framework based on active inference principles, enabling the mathematical formalization of how uncertainty guides attentional allocation and quantitatively accounting for differences observed between experts and novices, as well as mental fatigue effects.

This triple ambition, simultaneously empirical-descriptive, experimental-causal, and theoretical-computational, structures all empirical and theoretical work presented in following chapters. In Part 3, we will precisely detail conceptual positioning, methodological choices, and formal hypotheses derived from this triple objective.

2.3 Research Positioning and Detailed Objectives

Previous parts allowed introducing the theoretical framework in which this doctoral work is situated. They also identified, through an exhaustive meta-analysis of 90 studies, substantial empirical and conceptual gaps that remain in current literature.

This third part presents in detail how this doctoral work precisely addresses these gaps. We will justify methodological choices made and formulate specific hypotheses tested during experimental studies in following chapters. More specifically, this part articulates our approach positioning that combines three complementary and interdependent dimensions.

The first dimension is empirical-descriptive, aiming to finely characterize temporal patterns of attentional allocation. The second dimension is experimental-causal, allowing to test mental fatigue effects via controlled manipulation. The third dimension is theoretical-computational, formalizing mathematically the underlying mechanisms identified via empirical data.

2.3.1 Synthesis of Identified Gaps and Prioritization

Meta-analysis presented in Part 2 revealed three major gaps structuring current literature on perceptual-cognitive expertise in sport. These three gaps are conceptually distinct but closely interconnected and motivate the present doctoral work.

The first gap is the most critical from both theoretical and empirical viewpoints. It concerns quasi-total absence of fine temporal dynamics characterization of visual exploration strategies in ecological dual-task situations. Most studies synthesized in our meta-analysis use global and aggregated oculometric metrics, as the number of visual fixations or their average duration. These metrics do not reflect the dynamic process unfolding over several seconds but just resume it to a few summary statistics.

Total number of visual fixations during a complete trial, average fixation duration calculated on all performed fixations, or quiet eye duration measured as single temporal window are certainly informative at a macroscopic level, but they mask precisely the dimension that our theoretical framework presented in Part 1 identifies as potentially central to expertise: precise timing of attentional allocation.

This temporal dimension remains largely unexplored empirically, although it is central in predictions of active inference computational models that we formalized. Knowing that experts perform on average fewer visual fixations than novices does not inform us about the critical moment when they reallocate their attention. In fact, we want to understand when precisely they orient their attention from information relevant for ongoing task toward information relevant for future tasks. This timing precisely constitutes the theoretical mechanism proposed to explain why experts seem to have more time available for their decisions.

The second gap concerns total absence of studies experimentally examining mental fatigue effect on perceptual-cognitive strategies in ecological sport context, and this absence is even more surprising as mental fatigue constitutes a psychobiological state frequently encountered in real competitive contexts. Understanding whether and how mental fatigue affects experts' sophisticated attentional allocation strategies presents major theoretical interest, enabling to elucidate the nature of cognitive resources involved.

If anticipatory reallocation rests on controlled executive processes, it should be vulnerable to mental fatigue. Conversely, if strategies have been largely automated through extensive practice, they could remain relatively robust to cognitive exhaustion. This question was theoretically formulated in Part 1, but it remains totally unexplored empirically.

The third identified gap concerns absence of formal computational models allowing quantitative prediction of observed visual exploration patterns. Literature remains largely descriptive, as it advances that experts differ from novices without explicitly formalizing how and why these differences emerge via precise computational principles. Computational theoretical frameworks presented in Part 1, notably active inference and Free Energy Principle, offer powerful mathematical tools to formalize these questions. But these tools have not been instantiated, parameterized, and quantitatively tested in sporting domain.

These three gaps form a coherent set motivating an integrative approach. They are not independent but mutually complement each other. The first gap identifies what must be precisely measured: fine temporal dynamics. The second identifies how to test theoretical hypotheses concerning nature of involved processes: via mental fatigue manipulation. The

third identifies the need for mathematical formalization allowing progress from phenomenological description toward mechanistic understanding.

2.3.2 Positioning and General Methodological Approach

Present doctoral work adopts a triple approach synergistically combining fine empirical description, controlled experimental manipulation, and formal computational modeling. This integrative approach constitutes a substantial methodological advance compared to existing literature. Most studies adopt unidimensional approaches focused either on description, or on experimentation, or on modeling. They rarely systematically combine these three dimensions.

The empirical-descriptive dimension aims to characterize with fine temporal resolution attentional allocation patterns adopted by expert and novice footballers. We designed an ecological dual-task involving pass reception followed by an outgoing pass depending on the movement of a teammate. This work requires using mobile eye-tracking technologies allowing in situ behavioral recording. We thus preserve natural perception-action coupling and authentic spatiotemporal task constraints. Unlike previous studies content with global aggregated metrics, our approach temporally decomposes the attentional allocation process. We analyze the timing of visual scans in relation to successive motor action phases. This allows precisely identifying when attention is oriented toward which critical areas of interest.

The experimental-causal dimension aims to test theoretical hypotheses concerning cognitive mechanisms underlying efficient attentional allocation, by controlling mental fatigue induction. If anticipatory reallocation rests on controlled executive processes dependent on limited frontal resources, mental fatigue induction via a demanding cognitive task should specifically degrade these processes, resulting into delayed visual exploration timing in experts under fatigue. Conversely, if strategies have been largely automated, fatigue should primarily affect informational processing speed, lengthening the visual fixations and the scans, without altering timing of visual exploration structure. This experimental approach allows separating between competing hypotheses concerning nature of involved processes.

The theoretical-computational dimension aims to develop a formal model based on active inference principles. This model must quantitatively account for empirically observed patterns. In fact, it mathematically formalizes how uncertainty associated with different internal predictive models guides attentional allocation. The system follows a free energy

reduction optimization principle, and the model generates quantitative predictions concerning attention reallocation timing as a function of experimentally manipulable task characteristics, like incoming ball trajectory predictability. This computational approach allows progress from phenomenological description toward formal and testable mechanistic understanding.

These three dimensions are complementary rather than independent. A detailed empirical analysis identifies the behavioral patterns to explain. Next, experimental manipulation tests proposed mechanisms. Finally, computational modeling formalizes these mechanisms in mathematically precise manner. It generates verifiable quantitative predictions that enable iterative refinement of the model. This integrative approach is precisely what is missing in the current literature and therefore represents the main methodological contribution of this work.

The choice of team sports, and football in particular, as the field of application was justified in detail in Part 1. It is based on several converging arguments. Football naturally presents the dual-task situation we wish to study. In fact, it involves competing informational demands from incoming ball control and exploring peripheral environment to prepare for the outgoing pass. This configuration is ecologically valid, and representative of situations encountered in competitive matches. Moreover, football makes it easy to identify and recruit participants with widely varying levels of expertise, we can recruit players from recreational level to professional level. Finally, technological improvements in mobile eye-tracking now permit in situ measurements on real field with sufficient spatial and temporal precision to finely measure temporal dynamics of attentional allocation.

2.3.3 Research Questions and Formal Hypotheses

Our approach generates several complementary and hierarchized research questions, which correspond to our three dimensions that we want to study: empirical, experimental, and computational dimensions. These questions are formalized into verifiable hypotheses that will structure analyses presented in following chapters.

2.3.3.1 Axis 1: Temporal Dynamics Characterization of Attentional Allocation

The first research question structures the first experimental study presented in Chapter 2. It concerns the precise assessment of differences in the temporal dynamics of visual exploration between expert and novice footballers during an ecological dual-task, representative of

situations that they might encounter during matches. This question directly addresses the first gap identified in the meta-analysis, as we not only analyze aggregated measures of gaze behavior, but go further by analyzing the dynamics of gaze behavior in order to understand when attention is directed to which critical areas of interest. Furthermore, this analysis is carried out in relation to motor action phases.

Our theoretical framework presented in Part 1 generates specific hypotheses concerning this temporal dynamic. Experts have more accurate predictive models for anticipating the trajectory of the ball they receive. They should therefore reach a sufficiently low level of uncertainty more quickly to consider that continuous monitoring of the ball is no longer necessary. This rapid reduction in uncertainty should allow them to quickly redirect their attention to other areas of the peripheral environment in order to see the movements of their target teammates, effectively giving them more time to process tactical information relevant to passing decisions. Conversely, novices have less accurate predictive models. They must maintain their attention on the ball until a later stage of its trajectory, or even until it is fully received. Only then can they shift their attention to the peripheral environment. This difference in the timing of the shift in attention is thought to be the central mechanism explaining why experts seem to have more time to make their decisions and are therefore faster in their decision-making.

More formally, we formulate the following hypotheses concerning expertise:

- **Hypothesis 1a:** Experts will shift their attention from the incoming ball toward peripheral environment, and more specifically to the target teammate, significantly earlier than novices in trial temporal sequence. This reallocation could potentially occur even before ball contact if incoming trajectory is sufficiently predictable.
- **Hypothesis 1b:** Experts should also present a pattern characterized by early and prolonged scans during ball reception phase, reflecting a proactive behavior.
- **Hypothesis 1c:** Conversely, novices should exhibit sequential behavior, initially monitoring the ball closely until it is fully received, followed by delayed and potentially shorter exploratory phases, as they need to maintain continuous visual control over the ball. This reflects sequential behavior where the second task is only undertaken after the first has been completed.

These hypotheses will be tested in Chapter 2's first experimental study, in which we will compare visual exploration strategies of young expert footballers, playing at a national level and recreational novices during dual-task. This task involves pass reception, and so ball manipulation, followed by a pass toward moving teammate.

Beyond traditional global measures such as the number and duration of visual fixations, which we will continue to measure in order to ensure comparability with existing literature, we will specifically analyze the fine temporal dynamics of attention allocation. We will use several innovative indicators. First, we will measure the moment when participants scan the environment in relation to the reception of the ball. This will allow us to identify the precise moment in the trajectory when participants judge that they can reorient their attention. We will also quantify the average duration of scans of the peripheral environment during the different temporal phases of the trial. This will allow us to identify whether the differences between groups mainly concern the pre-reception or post-reception phase of the ball. We will analyze, frame by frame, the probability that participants look at cues related to the ball versus the running direction of the target teammate. This will allow for a temporal characterization of attentional priorities throughout the trial.

2.3.3.2 Axis 2: Mental Fatigue Effect on Attentional Allocation Strategies

The second research question structures the second experimental study also presented in Chapter 2. It concerns the effect of experimentally induced mental fatigue, through a cognitively demanding task, on experts' visual exploration strategies. This question directly addresses the second gap identified in meta-analysis. In fact, it allows us to test theoretical hypotheses concerning the nature of cognitive resources involved in anticipatory reallocation of attention.

As formalized in detail in Part 1, two competing hypotheses can be formulated concerning the effect of mental fatigue.

According to an initial hypothesis focusing on the deterioration in the timing of attention reallocation, mental fatigue should mainly affect controlled executive processes. These processes are involved in the metacognitive assessment of residual uncertainty and in the flexible decision to redirect visual exploration despite the failure to complete the task at hand. Under the effect of fatigue, experts would maintain the general structure of their exploration

patterns. They would visit the same areas of interest, but the timing of this exploration would shift to later or more random moments, approaching the patterns observed in novices. This deterioration in timing would reflect a reduced ability to quickly assess that uncertainty has been sufficiently reduced to allow attention to be switched. In addition, inter-trial variability in the timing of reallocation should increase in the presence of fatigue. This reflects increased inconsistency in executive control.

According to a second hypothesis focused on the deterioration of processing efficiency, mental fatigue would not affect the strategic timing of exploration, but only the speed of information processing once attention is directed towards an area of interest. When fatigued, experts would exhibit longer visual fixations and longer phases of environmental scanning. This reflects a reduction in the rate of information processing. However, their temporal sequence would remain unaffected. This dissociation suggests that experts have automated not only their predictive models, but also their visual exploration strategies. The temporal structure of allocation thus becomes relatively robust in the face of reduced cognitive resources. Fatigue would mainly affect low-level perceptual processes rather than high-level strategic aspects.

These two hypotheses predict distinct and empirically verifiable behavioral patterns. More formally, we formulate the following hypotheses concerning mental fatigue:

- **Hypothesis 2a:** Under induced mental fatigue, experts should take considerably longer to shift their visual exploration from the ball to the surrounding environment. This would reduce the time difference with novices if the hypothesis of timing degradation is valid.
- **Hypothesis 2b:** In the case of mental fatigue, the average duration of visual fixations and scans should be significantly increased among experts. This reflects a slowing down of information processing.
- **Hypothesis 2c:** In the presence of mental fatigue, inter-trial variability of visual exploration timing towards the peripheral environment should increase significantly in experts. This reflects increased inconsistency in executive control if the hypothesis of timing degradation is correct.

These hypotheses will be tested in the second experimental study in Chapter 2. We use a crossed experimental design where expert footballers perform same dual-task under two counterbalanced conditions. In the mental fatigue condition, participants first perform a demanding cognitive task, the Time Load Dual Back, for approximately sixteen minutes. This task aims to induce a state of frontal cognitive resource exhaustion. In the control condition, participants watch an emotionally neutral documentary of equivalent duration. Fatigue induction is assessed using subjective measures on a visual analogue scale before and after each task but is also verified by an objective analysis of performance during the cognitive task itself. Comparative analysis of visual behavior between the two conditions allows us to directly test whether mental fatigue affects visual exploration strategies or primarily the efficiency of information processing.

2.3.3.2 Axis 3: Computational Modelling of Visual Exploration

The third research question structures Chapter 3. Here, we go beyond simply describing what athletes do and attempt to understand why they do it from a computational perspective. The aim is to adapt an existing computational model and test whether it can reproduce, through simulation, the visual exploration patterns observed in our experiments. This question directly addresses the third gap identified in the literature, as we progress from phenomenological description to a formal mechanistic understanding.

The model we use is based on the active inference framework introduced in Part 1. Specifically, we adapted the classic T-Maze paradigm, well established in the active inference literature, to the specificities of our dual task. This adaptation formalizes the hypothesis that the distribution of attention between competing tasks is governed by a principle of free energy optimization.

The model proposes that the system simultaneously maintains two internal predictive models: one concerning the task of receiving the ball, the other concerning the identification of the target partner's running direction. Each model generates predictions about future states relevant to its task and quantifies the uncertainty associated with these predictions. Attention is dynamically directed towards the model with the highest uncertainty at each moment, as this is where additional sensory information would be most useful for reducing uncertainty.

To test the validity of this formalization, we performed simulations using Matlab. By systematically manipulating the different matrices within the model (observation likelihoods, state transition probabilities, outcome preferences), we simulated agent behavior under various conditions. The central question was whether the visual exploration patterns generated by the simulated agent would correspond to those measured in real participants.

This simulation approach has two objectives: to validate that the optimization of free energy principle provides a sufficient explanatory mechanism and to identify the critical parameters that explain inter-individual and contextual differences. Two main hypotheses guided our simulations:

- **Hypothesis 3a** concerns the effect of expertise. When the model is set up with high a priori accuracy on the ball's trajectory, corresponding to an expert profile based on extensive experience, the simulated agent should spontaneously produce an early shift of attention, reflecting the patterns observed in real experts. Conversely, when this accuracy is reduced to reflect a novice profile, the agent should maintain its attention on the ball for longer periods. If the model manages to reproduce these differences only by manipulating a priori accuracy, this would validate the hypothesis that expertise fundamentally translates into more accurate internal predictive models.
- **Hypothesis 3b** concerns the influence of task-related rewards. When the reward associated with successfully receiving the ball is increased compared to the second task, the agent should prioritize the task of receiving the ball and maintain their attention on the ball for longer periods, thereby delaying reallocation to peripheral exploration. Conversely, when the reward structure favours the correct identification of the partner's running direction, the agent should shift its attention earlier. This would demonstrate that the model captures how task-related motivational factors and rewards modulate the temporal dynamics of attention allocation, beyond purely perceptual considerations.

Naturally, the model may fail to reproduce observed patterns. If this occurs despite systematic adjustments of the parameters, it would suggest that additional mechanisms, not considered by the active inference framework alone, must be considered. Such a result would in itself constitute valuable theoretical information.

This computational approach represents a significant theoretical contribution. By mathematically formalizing the role of uncertainty in attentional allocation, it goes beyond simple descriptions and provides a rigorous basis for testing theoretical hypotheses using data from experimentation. Moreover, it offers a unified framework for interpreting our experimental results: differences between experts and novices, for example, can be interpreted not as notions of “better attention” but as concrete variations in the precision of internal predictive models. This perspective also has practical implications, as it highlights specific aspects of the cognitive system on which training interventions could focus in order to optimize performance.

2.3.4 Transversal Methodological Choices and Justification

Beyond specific research questions for each study, several transversal methodological choices structure all empirical work. These choices merit explicit justification. They aim to simultaneously maximize protocols' ecological validity, allowing generalization of conclusions to real performance situations, and measurement precision, allowing rigorous testing of formalized hypotheses.

The football dual-task paradigm we developed constitutes the methodological core of our two experimental studies. This paradigm involves three participants: the central participant whose behavior is recorded, a passer positioned six meters facing the participant, and a teammate positioned twelve meters behind the participant. The task begins with a pass from participant toward passer, who immediately returns ball without controlling it. At moment of passer's ball contact, teammate performs intensive five-meter run in one of three possible directions: left, right, or toward middle. Participant must receive ball then perform pass to teammate if the run was to the left or to the right, or toward passer if the teammate ran toward middle. This configuration naturally creates a dual-task situation with competing informational demands. Participant must maintain informational coupling with incoming ball to ensure its reception while visually exploring surroundings. They have to identify teammate's running direction and prepare the second pass.

This paradigm presents several substantial advantages compared to previous research. By involving real motor actions with the ball manipulation rather than arbitrary responses like button presses, it preserves the natural perception-action coupling that is so central to sports

performance. Moreover, the temporal constraints are authentic, in fact the teammate's direction is unpredictably revealed at the moment of the passer's ball contact, creating realistic temporal pressure that participants cannot anticipate. The structure of the task also lends itself well to analysis, as it can be divided into two distinct tasks that allow us to track the dynamics of attention distribution. We designed it to find a balance between accessibility and difficulty, meaning that it is simple enough for novices to perform without specific constraints, but complex enough to reveal significant differences between novices and experts. Finally, the situation is ecologically representative because it reflects real match situations where players must continually arbitrate between ball control and tactical exploration of their surroundings.

The use of mobile eye-trackers in situ represents the second key methodological choice. We use Tobii Pro Glasses 3 system, a mobile binocular device that samples gaze behavior at 100 Hz with spatial precision of approximately 0.5° of visual angle. This system allows participants to move freely around the field and perform the natural motor actions required by task while continuously recording their gaze behavior. This approach differs radically with traditional studies using fixed eye-trackers requiring the head to be immobilized. Although these fixed systems certainly offer higher spatial precision, they completely destroy the coupling between perception and action and prevent study of tasks involving body movements. Mobile eye-tracking also allows the recording of head and body movements coordinated with eye movements. We thus capture visual exploratory activity in its complete ecological complexity.

The measures analyzed combine both classical and innovative indicators, classical indicators ensuring comparability with existing literature. We continue measuring the number of visual fixations and their average duration, classical variables allowing comparison with meta-analysis results. However, we add several fine temporal metrics absent from existing literature, in order to address the identified gaps. In fact, we quantify the number of scans and their average duration. A scan is defined as any head movement orienting face opposite ball with apparent intention to search for peripheral environment information. We measure these exploration phases timing in relation to ball reception, allowing us to precisely identify when participants judge they can switch their attention to the teammate. We analyze the probability that participants are looking at different critical areas of interest at any given moment, allowing for a frame-by-frame characterization of the evolution of attentional priorities. These

precise temporal measurements are precisely what is lacking in the existing literature and allow us to test hypotheses derived from the theoretical framework.

The choice of study populations aims to maximize the contrast between levels of expertise while ensuring the ecological validity of the classification. For the first study comparing experts and novices, the experts are national-level soccer players. They play either in the top French junior league or at least in the fifth senior division for senior players, corresponding to the national level. In addition, they all have more than ten years of practical experience. The novices, on the other hand, are amateur players with less than three years of experience who play exclusively in recreational leagues. This maximum contrast ensures sufficient statistical power to detect differences in behavior, even if they are moderate in magnitude.

For second study manipulating mental fatigue, we exclusively focus on experts. We want to test whether their sophisticated strategies are vulnerable to cognitive exhaustion. Cross-over design with condition order counterbalancing allows controlling order and accumulated fatigue effects between sessions. Mental fatigue is induced by the Time Load Dual Back task. This is a demanding task for working memory, as participants observe a sequence of visual stimuli presented, alternating between numbers and letters, and must indicate whether the current stimulus corresponds to the previous stimulus for letters, and indicate whether it was an even or odd number. The difficulty of the task was personalized by conducting a pre-test to calculate the high cognitive load threshold. It has been demonstrated in the literature that sixteen minutes of this sustained cognitive effort effectively induces a state of mental fatigue characterized by a reduction in the availability of executive resources (Borrágán et al., 2017).

Fatigue is assessed using several methods. Subjectively, participants complete visual analog scales before and after fatigue induction, evaluating their perceived mental fatigue. Objectively, we analyze performance evolution during cognitive task itself, particularly changes in performance accuracy over the duration of the task. These convergent indicators ensure that the behavioral changes observed in the subsequent dual task are indeed the result of induced mental fatigue rather than simple temporal evolution or practice effects.

2.3.5 Expected Contributions

This doctoral work's expected contributions are multiple. They operate at different levels.

At the empirical level, we provide the first detailed temporal analysis of gaze dynamics during an ecological dual task in sport. We go beyond the aggregate measures that dominate the existing literature. This characterization reveals that the differences between experts and novices reside primarily in the timing of attention switching rather than in its total amount. Expertise concerns the timing rather than the quantity of visual scanning. This temporal perspective opens new avenues for understanding the adaptive mechanisms by which experts optimize their limited attentional resources in complex and dynamic situations.

At the experimental level, we provide the first evidence regarding the effect of mental fatigue on visual exploration strategies in an ecological context. We reveal whether the visual exploration strategies used by experts are resistant to mental fatigue or, conversely, vulnerable due to their dependence on limited executive resources. This dissociation between the preservation of visual search strategies and the deterioration of information processing efficiency fuels theoretical debates concerning automation versus executive control in expertise. It also has direct practical implications for the management of cognitive load during training and competition.

On a theoretical level, we propose a formal computational model of attention allocation in dual-task sports. We move from a phenomenological description to a formal and verifiable mechanistic understanding. The model mathematically specifies how uncertainty guides attention, generates quantitative predictions, and provides a unified framework for interpreting differences in skill level. This computational formalization represents a significant advance in this field, enabling rigorous hypothesis testing.

More broadly, this work contributes to a fundamental understanding of human cognition in complex and dynamic situations. Although sport is our specific field of application, it serves as an experimental model for many other areas involving expert performance, like driving, piloting, professional performance, and everyday life. The mechanisms by which humans optimize their limited attentional resources when faced with competing demands for information under time constraints are a fundamental question that transcends sport itself. Our integrative approach, combining the study of behavioral dynamics, controlled experimental design to study the effects of mental fatigue induction on visual exploratory activity, and formal computational modeling, offers a methodological template that can potentially be transposed to these other domains.

In the following chapter 2, we will present in detail the results of two experimental studies. We will test our hypotheses concerning the effects of expertise on visual exploration strategies in an ecological and representative dual task, as well as those concerning the effects of mental fatigue induction on visual exploration strategies in experts. The methodologies, results, and their theoretical implications will be presented systematically and in detail for each experiment. These empirical results will then serve as the basis for developing and testing the computational model presented in Chapter 3.

3. Chapter 2: Empirical Studies on Visual Exploration Strategies in Representative Dual-Task in Football: Effects of Expertise and Mental Fatigue

After presenting the theoretical framework and meta-analytic synthesis in Chapter 1, we identified some major gaps in the current literature on perceptual-cognitive expertise in sport. The first gap concerns the almost total absence of studies examining the temporal dynamics of visual behavior in ecological dual-task situations. The second gap concerns the absence of experimental studies examining the effects of mental fatigue on visual exploration strategies in representative sports contexts.

In this chapter, we will directly address these first two gaps through two complementary experimental studies using an ecological dual-task paradigm in football. Both studies use mobile eye-tracking technology to record visual exploratory activity in real time, while preserving the natural perception-action coupling, particularly through ball manipulation, that characterizes expert performance in ecological contexts.

The first study provides a temporal characterization of the visual exploration strategies adopted by expert and novice footballers during a dual task in football, consisting of receiving a pass and then passing to a moving teammate. Unlike previous research, which relied on aggregate global measures, including the number of visual fixations and their durations, and therefore did not take temporal dynamics into account, our approach decomposes the process of attention allocation between successive phases of the task. This study allows us to test the central theoretical hypothesis formulated in Part 1: do expertise differences reside mainly in the specific timing of environmental exploration rather than in its frequency or the areas of interest gazed at? More specifically, we examine whether experts exhibit anticipatory behavior, reallocating their attention to peripheral information before completing the current task, in particular by having better internal models for predicting the trajectory of the ball, while novices adopt reactive sequential behavior.

The second study examines whether and how experimentally induced mental fatigue affects these visual exploration strategies in expert players. Using a controlled crossover design, we manipulate participants' cognitive state through a demanding working memory task before they perform the same dual-task paradigm. This experimental approach allows us to decide between competing hypotheses concerning the nature of the cognitive processes

underlying the allocation of visual attention. Indeed, if these strategies depend on controlled executive processes that are vulnerable to frontal resource exhaustion, mental fatigue should specifically interfere with the temporal structure of visual exploration, thereby delaying or randomizing the timing of switching attention to the second task. Conversely, if these strategies have become largely automated through intensive practice, fatigue should mainly affect the efficiency of low-level information processing, extending the duration of visual fixations and scans, while preserving the structure of visual exploration.

The results of these two studies constitute a scientific article currently under review in an international peer-reviewed journal. This article is presented in its entirety in the following chapter, retaining its original structure.

Where and When to Look: How Expertise and Mental Fatigue Shape Visual Exploration in a Football Task

Aurélien Dehorne^{*1,2,3}, Guillaume Hacques^{*3,4}, Téo Lepine³, Riccardo Palumbo^{1,2}, Giovanni Pezzulo⁵ and Pierpaolo Iodice^{3,4}

¹ Center for Advanced Studies and Technology, University G. d'Annunzio of Chieti – Pescara

² Department of Neuroscience, Imaging and Clinical Sciences, University G. d'Annunzio of Chieti–Pescara

³ CETAPS, UR 3832, Faculty of Sport Sciences, University of Rouen Normandy

⁴ Le Mans Université, Movement – Interactions – Performance, MIP, UR 4334

⁵ Institute of Cognitives Sciences and Technologies, National Research Council, Rome, Italy

*These two authors contributed equally to this work

Correspondence concerning this article should be addressed to Guillaume Hacques, Le Mans Université, Movement – Interactions – Performance, MIP, UR 4334, Avenue Olivier Messiaen, 72085 Le Mans Cedex 09, France. Email: guillaume.hacques@univ-lemans.fr

ORCID:

Aurélien Dehorne <https://orcid.org/0009-0002-5248-9429>

Guillaume Hacques <https://orcid.org/0000-0002-9760-6556>

Téo Lépine

Riccardo Palumbo <https://orcid.org/0000-0003-4230-5817>

Giovanni Pezzulo <http://orcid.org/0000-0001-6813-8282>

Pierpaolo Iodice <https://orcid.org/0000-0001-7167-8917>

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Data Availability: Data are available online (<https://osf.io/fkrds/>)

Abstract

Skillful performance requires picking up information at the right time to both accurately perform ongoing action and search for subsequent ones. The current experiment aimed to compare the visual exploratory activity (VEA) of skilled ($n = 23$) and novice ($n = 21$) players in a football-based dual task scenario that required to manage competing visual demands for ball manipulation and environmental scanning. Skilled players performed the task faster than novices and showed a more proactive VEA: they spent more time looking at cues related to future passing opportunities while novices looked more at cues related to ball reception. In addition, skilled players made longer scanning movements before receiving the ball, but they did not perform significantly more head movements than novices. Under mental fatigue, skilled participants preserved their VEA patterns but required longer visual fixations, suggesting a reduced rate of information processing. These findings suggest that expertise in VEA is characterized by the efficient allocation of visual attention rather than its sheer quantity.

Keywords: Eye-tracking, Gaze behavior, Affordances, Scanning, Expertise

Word Count: 12447 words

Public Significance Statement: This experiment focused on the timing of visual exploratory activity for skilled performance in sports. By comparing the gaze behavior of skilled and novice football players in a decision-making task, results revealed that skilled players might be quicker to perform the task because they initiate searching for their next actions earlier, not because they make more exploratory head movements. These results support that skill acquisition in sports involves recognizing the optimal moments to shift visual attention from ongoing action to future opportunities, enabling effective chaining of actions. Applying these results to training imply focusing on when athletes can search for new opportunities rather than just increasing the quantity of their exploratory actions.

Where and When to Look: How Expertise and Mental Fatigue Shape Visual Exploration in a Football Task

We live in a world full of action opportunities, requiring continuous arbitration between alternative courses of action (Cisek & Kalaska, 2010; Pezzulo & Cisek, 2016). When performing dual tasks, such as receiving an object from one person and passing it to another or driving on a crowded highway while searching for an exit, we must also arbitrate between their competing visual demands, such as looking at the first versus the second person, or at other cars versus traffic signs. Beyond these everyday activities, most skilled behaviors, such as sports, also involve competing visual demands. For example, in soccer and basketball, when receiving the ball from a teammate and launching it to another; or in car and motorcycle racing, when driving while also remaining aware of the position and intentions of other drivers. This prompts the question of what guides visual exploration in such challenging conditions (Hayhoe & Ballard, 2005).

Decades of research have shown that skilled motor performance relies on internal forward models that support the prediction of action consequences and the planning of accurate movements (Friston et al., 2010; Kawato, 1999; Parr et al., 2022; Wolpert et al., 1995). Crucially, the predictions generated by these models become increasingly uncertain over time, requiring calibration through external observations. Various theoretical models propose that it is this uncertainty that drives gaze toward informative locations-gathering observations to reduce the model's uncertainty (Friston et al., 2012; Itti & Baldi, 2009). Conversely, when models generate highly confident predictions, no information seeking behavior is required, since information that can be predicted with high confidence does not need to be attended to.

Extending this line of thought, it has been proposed that when two internal models are active simultaneously, for example, one predicting the movements of the person handing over an object and the other predicting the movements of the person to whom the object must be passed, the model with greater uncertainty demands more information and thus directs attention to its own most informative location (Donnarumma et al., 2017; Rothkopf & Ballard, 2010). For instance, when the movement of the first person is predictable, gaze can shift early to the second person. In contrast, when the first person's movement is difficult to predict, it must be monitored continuously.

Previous empirical studies have examined the relationship between predictability and gaze dynamics, revealing both anticipatory and information-gain-driven patterns of eye movements. In one experiment, participants observed an actor reaching for one of two objects (a large and a small one), either with or without hand preshaping (Ambrosini et al., 2015). The study revealed that when participants had no clue about the actor's intention, whether to grasp the small or the large object, they simply followed the actor's moving arm with their eyes, as it was the only informative element in the visual scene, until it reached one of the objects. Conversely, when they could infer the actor's intention from the hand preshape, they made anticipatory saccades to the to-be-grasped object, since the moving hand no longer offered additional information once the goal had been inferred. A computational model of the task successfully replicated these findings, based on the assumption that information gain guides eye movements (Donnarumma et al., 2017). Other studies have shown that eye movements during reading and language processing typically land on informative locations while skipping predictable text (Donnarumma et al., 2023; Levy, 2008). In addition, Sullivan et al. (2012) and Johnson et al. (2014) demonstrated that in dual-task paradigms, where multiple tasks are ongoing simultaneously, the allocation of visual attention is dynamically modulated by the growth of uncertainty across tasks. Specifically, the predictive accuracy of the internal model for one task determines the temporal threshold for attentional disengagement, allowing a shift of resources to another task module. This continuous process enables the minimization of uncertainty across task modules, thereby fulfilling the overarching demands of the dual task. Another study using virtual reality settings to investigate how participants search for task-relevant objects revealed that gaze behavior is systematically shaped by both the structure of the environment and the observer's task goals, supporting the view that visual exploration is actively controlled to reduce uncertainty in a goal-directed manner (Rothkopf et al., 2007). Yet another line of research addressed skilled performance in dynamic tasks and showed that participants often exhibit "just-in-time" gaze behavior, fixating on task-relevant elements only at the moment when information is needed to guide ongoing or upcoming actions. For instance, Ballard et al. (1997) demonstrated that, in a block-copying task, participants looked at each block only immediately before they needed to act upon it, rather than memorizing all block positions in advance. Similarly, in more recent work, Keshava et al. (2024) observed that skilled athletes tracking a moving ball timed their gaze to extract critical information just prior to making an interceptive movement, rather than continuously monitoring the ball throughout its flight. Taken together, these studies emphasize the

efficiency and adaptiveness of visual attention, showing that gaze is deployed strategically-driven by task demands and the need to minimize uncertainty at key decision points.

Visual search strategies have been studied extensively in sports, too, as they are important for skilled athletes' effective and accurate decisions in performance context (D. Y. Mann et al., 2007). The sports domain is particularly interesting to study the relations between predictability, uncertainty and visual strategies, since athletes are assumed to have superior internal models that generate accurate predictions (Harris et al., 2022). In keeping, skilled athletes are able to pick-up more reliable cues from their surroundings to predict unfolding events, such as when anticipating the side of the kick in a penalty task (Savelsbergh et al., 2002), when predicting the ball trajectory in baseball (M. F. Land & McLeod, 2000; D. L. Mann et al., 2013), the success of basketball shots (Aglioti et al., 2008) and the direction of the ball in penalty kicks in soccer (Tomeo et al., 2013). Given these premises, it is expected that athletes' skill level influences the way they visually explore the environment. However, visual search strategies of skilled athletes have long been investigated in laboratory settings, generally involving watching videos of specific sporting situations (Kredel et al., 2017). Such methods, although enabling high experimental control, distort information-movement coupling usually experienced by athletes in performance context (Fajen et al., 2009) and may affect their visual search strategies (Dicks et al., 2010).

A more recent research trend investigates visual search strategies by analysing football players' whole-body behavior during real games, to identify visual exploratory activity (VEA, also called scanning) (Jordet, 2005; Jordet et al., 2013, 2020). Originally grounded in James Gibson 's theory of affordances (J. J. Gibson, 1966), VEA reflects players' activity to search for and specify affordances in their surroundings – or action opportunities, such as, in soccer, passing opportunities to teammates, carrying the ball to a free space of the field, or protecting the ball from the threat of an opponent (Jordet, 2005; van Andel et al., 2019). The highly dynamic nature of the game of football (and of other team sports) requires players to not limit their search for affordances to the amplitude of the available visual field in front of them, but to also look at what is happening in their back (therefore covering all around them at 360°) – therefore requiring coordination of the eye, head and body movements to pick up information in the environment (Franchak, 2019; E. J. Gibson, 1988, J. J. Gibson, 1966). In keeping, VEA is not limited to eye movements and has been defined as:

A body and/or head movement in which the player's face is actively and temporarily directed away from the ball, seemingly with the intention of looking for teammates, opponents or other environmental objects or events, relevant to perform a subsequent action with the ball (Jordet et al., 2013, p.2).

Besides, VEA is conceived as a means to engage in the preparation and prospective control of future actions, that is “the means by which actors adapt behavior in advance to the constraints and behavioral opportunities in the environment” (Fajen et al., 2009, p.88).

The original method to investigate VEA consist in annotating players' head movements during the 10-s before ball reception and the actions performed with the ball (Aksum, Pokolm, et al., 2021; Jordet et al., 2013, 2020; McGuckian et al., 2018; Pokolm et al., 2022). Results have shown that head movement frequency was affected by various game constraints such as the player's role, the pressure of the defending opponent, or the location of the player on the pitch (Jordet et al., 2020). VEA was also associated with on-ball performance with higher frequency of high movements being associated with higher pass completion percentage (Jordet et al., 2013). In addition, head movement frequency was higher when action direction was in direction of the opposite goal than sideward of toward player's own goal (Jordet et al., 2013, 2020) and when the action type was passing than dribbling or finishing (Jordet et al., 2020). In summary, performing a high frequency of head movement was deemed to be the mark of the most skilled players; therefore, various methodologies aimed at increasing players' VEA, for example through imagery (Jordet, 2005; Pocock et al., 2019).

Beyond the frequency of head movements, various studies investigated the timing of VEA relative to ball reception (McGuckian et al., 2018, 2019; van Andel et al., 2019). In a laboratory task, head movement frequency before gaining possession of the ball was negatively correlated with the response time of the participants, whereas head movement frequency when in ball possession was positively correlated with the response time (McGuckian et al., 2019). A study from van Andel et al. (2019) proposed that VEA is used for different purposes according to when it occurs relative to action onset. More specifically, they proposed that early VEA would aim at searching for the different available opportunities (Exploration for Orientation) whereas late VEA would aim at specifying the selected affordance (“Exploration for Specification”). These two functions were hypothesized to be associated with different VEA patterns, notably regarding the acceleration profile of the head

movements as exploring for orientation would aim for discovering the surrounding environment while exploration for specification would aim to fixate a specific location.

A recent eye-tracking study performed by (Aksum, Brotangen, et al., 2021) suggested that performing VEA between touches of the ball by teammates or when the ball trajectory could be anticipated would be an optimal strategy. However, this strategy demands athletes to capture clues to anticipate coming events, based on information pickup before initiating VEA. To adjust the balance between the two goals when players are about to receive the ball, it could be suggested that players would optimize their VEA to minimize its cost in terms of effort, that is minimizing the time looking away from the ball to control its reception in case of passing and to track the direction of the game, but looking away for a sufficiently long period of time to assess three types of information: namely, the location of free space to move, the availability of a teammate, or the absence of a relevant opportunity. As emphasized by the coaches interviewed in Eldridge et al. (2023), perceiving such information enables skilled players to make better decisions and manage the rhythm of the game.

Together, this body of work supports the perspective that visual exploration patterns are not merely reactive responses to salient stimuli, but proactive strategies governed by internal models and shaped by the informational requirements of complex, often overlapping tasks. Despite these advancements, some open questions remain. First, it is unclear whether skill level (as a proxy for superior internal models and predictive capabilities) influences the choice of anticipatory versus reactive VEAs in realistic settings, in which multiple tasks pose competing informational demands. Second, it is unclear whether taxing participants' cognitive processing, for example, by inducing mental fatigue (Hockey, 2011; Kool & Botvinick, 2014), influences their VEAs or only lower levels of perceptual processing.

In this study, we performed two experiments that address the above questions. In the first experiment, skilled and novice soccer players were engaged in a sequential task in which they had to receive the ball from one teammate ("passing player") and then pass it to another teammate in movement ("running player"). This dual task poses competing informational demands, as it requires maintaining information coupling with the ball for controlling its reception, while also visually exploring the movements of the second teammate to prepare passing the ball. Therefore, it presents an interesting trade-off, since scanning the movements of the running player while receiving the ball affords a better preparation of the passing action

but at the cost of losing information about the incoming ball. We reasoned that since skilled players have better predictive models compared to novice players, which plausibly afford a better prediction of the ball and of the other players, the two groups should show distinct (more anticipatory versus more reactive) VEAs. Specifically, while receiving the ball, skilled players should look early on at the target necessary to specify the future action (i.e., the running player), whereas novices should look longer at the targets necessary to specify the current receiving action (i.e., the passing player and the ball). Conversely, novices should initially focus on the ball that they need to receive and look for passing opportunities only after receiving it.

In the second experiment, skilled players performed the same task under two experimental conditions, with or without mental fatigue. This design allows us to assess whether mental fatigue impairs strategic aspects of participants' visual processing (e.g., when they collect information about the running player) or only low-level aspects of information processing (e.g., the time required to process useful information). We reasoned that if mental fatigue reduces participants' anticipatory capabilities, they should show distinct VEAs in the two conditions - and perhaps approach the VEAs of novices when they are mentally fatigued. Conversely, if mental fatigue only affects low level aspects of participants' information processing, their visual exploration patterns should be similar in the two conditions.

Experiment 1

Method

Transparency and Openness

These studies adhere to the transparency standards outlined in the Journal Article Reporting Standards (JARS; Appelbaum et al., 2018). We report all data exclusions, manipulations, and measures. Studies were not pre-registered. Sample size for Experiment 1 was determined based on an a priori power analysis using G*Power version 3.1.9.6 (Faul et al., 2007). Data were analyzed using R version 4.3.2 (R Core Team, 2023), with the following statistical packages: dplyr version 1.1.4 (Wickham, François, et al., 2023c) for data manipulation, stringr version 1.5.1 (Wickham, 2023b) for string processing, tidyverse version 2.0.0 (Wickham et al., 2019) for integrated data science tools, effectsize version 1.0.0 (Ben-Shachar et al., 2020) for partial eta squared calculation, forcats version 1.0.0 (Wickham, 2023a) for factor-level handling, and ggplot2 version 3.5.0 (Wickham, 2016) for data visualization. Statistical analyses were conducted either using JASP version 0.18.3 (JASP Team, 2024), or R version 4.3.2 (R Core Team, 2023).

Data are available on the project's Open Science Framework (OSF) repository (<https://osf.io/fkrds/>).

Participants

The participants were 44 male football players divided into two groups based on their skill level. The skilled group ($n = 23$) was composed of players aged 17-22 years ($M_{\text{Skilled-Age}} = 17.87$ years, $SD = 1.58$), with more than 10 years of football experience ($M_{\text{Skilled-YearsOfExperience}} = 11.04$ years, $SD = 2.98$). All skilled players either competed in the best French youth league or played at a minimum in the 5th French division for senior players. They were volunteers from the elite group of a professional club academy and from the university football team of the University of Rouen Normandy. The novice group ($n = 21$) included players aged 17-30 years ($M_{\text{Novices-Age}} = 21.95$ years, $SD = 3.58$), with less than 3 years of football experience ($M_{\text{Novices-YearsOfExperience}} = 1.00$ year, $SD = 1.38$) and played exclusively in recreational leagues. Novices were volunteer students from the University of Rouen Normandy. Data for Experiment 1 were collected in 2023.

An a priori power analysis was conducted using G*Power 3.1 (Faul et al., 2007) to determine the required sample size. The analysis indicated that a minimum of 31 participants would be required to detect an effect size of $f^2 = 0.35$ ($\alpha = 0.05$, $1 - \beta = 0.80$) in our linear mixed model design with skill level (2 levels) $\times$ run direction (3 levels) as fixed effects. We recruited 44 participants to ensure robust statistical power.

Participants (and parents / guardians where applicable) provided written informed consent to take part in the experiment and were free to withdraw at any time. This research was approved by the CERSTAPS Research Ethics Committee (Opinion number: IRB00012476-2023-13-01-217).

Protocol

Participants were invited to the gymnasium where the experiment took place. Upon arrival, they completed a questionnaire providing information about their football profile and vision quality. Instructions and informed consent forms were provided to the participants in advance of the data collection.

The football task involved 3 participants: the “participant”, whose behavior and eye movements were recorded and two teammates, which played the roles of “passing player” and “running player”, which were not equipped with mobile eye-tracking systems.

The participant was equipped with the Tobii Pro Glasses 3 mobile eye-tracking system (Tobii AB, 2020) and the calibration procedure was performed, by following Tobii’s recommendations.

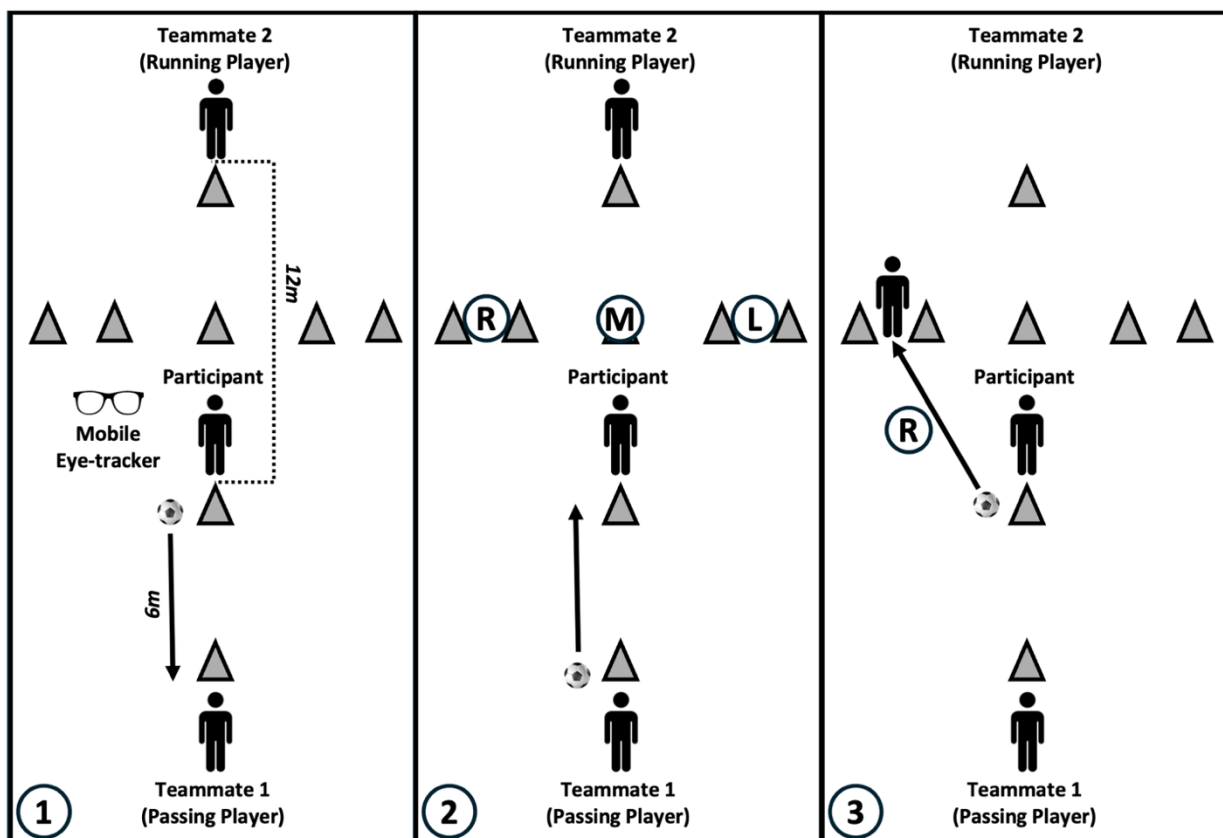
The task was explained and demonstrated to the three participants by the experimenters. The participant was instructed to perform the task as quickly and accurately as possible. Then, the participant performed a block of 25 trials. The first 4 were used as warm-up trials and were not analyzed. The recording quality of the eye-tracker and the point of gaze were checked every 5 trials by asking the participant to look at specific targets in the gymnasium. If a trial was judged by the experimenters as poorly executed (for example, if the initial pass required a side movement of the participant), it was noted for removal from the analysis and repeated at the end of the block.

Some individuals who played the role of “participants” also subsequently volunteered to play the role of “teammates” (but we did not allow individuals to be teammates before they were participants, in order to ensure that they had no prior exposure to the task when they were “participants”).

Dual Task Design

We developed a dual task that emulated a typical match-play scenario in football and required participants to engage in VEA. The task involved three participants: the participant in the middle, who wore the mobile eye-tracking device and whose behavior was investigated; the passing player, who was positioned in front of the participant at 6 meters; and the running player, who was positioned behind the participant at 12 meters (see Figure 12).

Figure 12: Illustration of the Dual Task used in both Experiments 1 and 2



Note. Panel (1) shows the initial setup and the start of the dual task. The participant, who wears the eyetracking device, passes the football to the passing player, at 6 meters in front of him. Panel (2) shows that, at the reception of the football, the passing player returns the pass (without stopping the ball) to the participant. Simultaneously, during the foot-ball contact of the return

pass, the running player, who is positioned 12m in the back of the participant, makes a 5m intense run in one of three possible directions (R: Right, M: Middle, L: Left). Panel (3) shows a simulation of a response of the task for a right (R) run condition. After the reception of the pass from the passing player, the participant controls the ball if necessary, and passes, as quickly and accurately as possible, to the receiving player between the cones.

First, the participant had to pass the ball to the passing player. The passing player then had to make a return pass to the participant without stopping the ball. The passing player's contact with the ball was the signal for the running player to make an intense short run in one of three possible directions, which influenced the participant's task. If the run was made to the left or right between the cones, the participant had to pass the ball between the two cones in the direction of the running player. If the run was made towards the middle, the participant had to pass back to the passing player. The direction of the runs was randomized, with an equal number of trials ($n = 7$) for each of the three directions.

Data Collection

Gaze Behavior. Participants' gaze behavior was recorded with the Tobii Pro Glasses 3 eye-tracker (Tobii AB, 2020). This device is a mobile binocular eye-tracker that tracks visual behavior at a sampling rate of 100 Hz using multiple infrared illuminators (8 per eye) and cameras (2 per eye). It also captures the external scene at 25 Hz using a high-definition camera (1920 x 1080 pixels). Eye-tracking calibration and data acquisition were conducted using the Tobii Glasses 3 software (Tobii AB, 2019).

Before each participant's trial block, the eye-tracker was calibrated with the participant standing at arm's length from the calibration target. The accuracy of the gaze tracking was then verified by asking the participant to fixate again on the target as it was moved within the scene camera's field of view. If the calibration failed or the point of gaze did not overlap with the target, the procedure was repeated until that the gaze location was considered sufficiently accurate.

The eye-tracking recordings were subsequently processed using Tobii Pro Lab software (Tobii AB, 2021), applying the "raw" data filter, to perform frame-by-frame mapping of the gaze data.

Performance. To assess task success and measure performance times, we used the recordings captured by the Tobii Pro Glasses 3 system. Task response start and end points were annotated using Dartfish video analysis software (Dartfish, 2024). We defined the task response start point as the first frame showing the participant's foot contacting the ball following the reception of the return pass from the passing player. The task response endpoint was marked by the first frame after the participant's final ball contact during the pass to the running player, constituting the task response.

Data Analysis

Gaze Behavior. The visual exploratory activity of the participants was analyzed by measuring the number of performed exploratory phases (scans), their duration, and the gaze dynamics. In our study, an exploratory phase (scan) was characterized by any head/body movement performed at any point during the trial to collect information about the running player's running direction. These exploratory phases were identified using external scene video recordings from the eye-tracker. The start of an exploratory phase was identified when participants initiated head movement, characterized by motion blur in the eye tracker recording due to head displacement. Conversely, the end of the exploratory phase was identified when participants completed their head movement, marked by the return of a clear image in the eye-tracker recording.

Gaze behavior was quantified using two primary metrics: the number of visual fixations per second and the mean fixation duration (ms). Following the recommendations for dynamic visual tasks (Holmqvist et al., 2011), a visual fixation was defined as a period with a minimum duration of 50ms (i.e. 5 consecutive frames), during which the participant's gaze was directed toward one of three areas of interest: (i) the ball, (ii) the passing player, or (iii) the running player.

Gaze behavior related to task-relevant AOIs was quantified using dwell time. Six AOIs were defined: (i) the ball, (ii) the pass area, (iii) the passing player, (iv) the running player, (v) the target area, and (vi) other irrelevant areas of the scene.

Using these gaze annotations, we analyzed the visual attention patterns of each participant across all trials. We calculated the average frame-by-frame probability that participants gazed toward cues related to the ball, which included the following AOIs: (i) the ball, (ii) the pass area, and (iii) the passing player. We also measured the probability that participants gazed

toward cues related to the run direction, which included: (iv) the running player and (v) the target area. For the run direction category, we additionally included the entirety, from the start until the end, of the scans performed as cues related to the run direction, as these scans reflected participants' intentions to seek information about the running player's movement.

To assess the reliability of the coding method, we randomly selected trials from five participants for re-analysis three months after the first coding. Cohen's Kappa showed almost perfect agreement ($\kappa = 0.928$) between the two coding sessions (McHugh, 2012).

Performance. Task performance was assessed by measuring the accuracy and the time to perform the task. A trial was considered successful if the participant made a pass in the direction required by the running player's run. The time to perform the task was defined as the duration between the reception of the pass from the passing player and the participant's final ball contact (i.e., the last pass of the trial).

Statistical Analysis

The effects of participants' skill level and of the direction of the run on task success were assessed using two separate Chi-square tests of independence.

Additionally, we employed linear mixed models (LMMs) to examine the influence of skill level and run direction on task performance and gaze behavior. Specifically, the participants skill level and the direction of the run were included as fixed effects variables and the participants' ID as random intercepts in the models. Post-hoc analyses were conducted using Bonferroni-adjusted p-values.

A multivariate analysis of variance (MANOVA) was performed to analyze the dwell time spent in each area of interest, with skill level as the independent variable.

Effect sizes were reported as Cramer's V for Chi-square tests of independence, partial eta-squared (η^2) for LMMs, and Wilk's Λ for the MANOVA.

Cohen's d value was calculated for each eye-tracking data point on a period of 2 seconds before and after the reception of the ball to compare the gaze dynamics of skilled players and novices. The threshold value of 0.5 over a period of more than 5 data points (i.e., 50ms) was

chosen as a reflection of a medium effect size (Cohen, 2013) to identify the key time periods where the gaze location differed between the two groups of participants.

Data treatments were performed using RStudio software (R Core Team, 2023) and statistical analyses were conducted using JASP software (JASP Team, 2024).

Results

Football Task Performance

Decision Accuracy. The Chi-square test of independence revealed no significant association between skill level and accuracy, $\chi^2(1, 920) = 2.41$, $p = .121$, Cramer's $V = 0.051$. Very few trials were incorrectly performed, with only 2 errors out of 481 trials (0.42%) for skilled players, and 6 errors out of 439 trials (1.37%) for novices.

A significant association was found between run direction and accuracy, $\chi^2(2, 920) = 7.06$, $p = .029$, Cramer's $V = 0.088$, indicating a very small effect size. However, as mentioned above, the number of incorrect trials remained minimal, with only 2 errors out of 313 trials (0.64%) when the direction of the run was on the right, and 6 errors out of 306 trials (1.96%) when the direction of the run was in the middle. No errors were observed when the direction of the run was on the left.

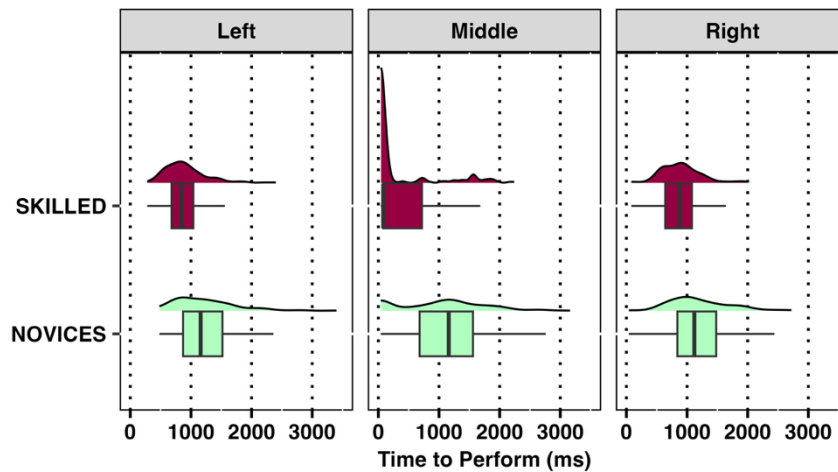
Time to Perform the task. Linear Mixed Model (LMM) revealed an effect of skill level on the time to perform the task, $F(1, 42.03) = 16.15$, $p < .001$, $\eta^2 = 0.28$. The skilled group performed the task significantly faster than the novice group ($MS_{\text{skilled}} = 760\text{-ms}$, 95% CI [611, 910]; $M_{\text{Novices}} = 1192\text{-ms}$, 95% CI [1035, 1349], $p_{\text{S-N}} < .001$) (see Figure 13).

The direction of the run also significantly affected the time to perform the task, $F(2, 864.40) = 43.91$, $p < .001$, $\eta^2 = 0.09$. Participants performed the task faster when the direction of the run was to the middle, compared with the right ($MM_{\text{middle}} = 803\text{-ms}$, 95% CI [689, 917]; $MR_{\text{right}} = 1053\text{-ms}$, 95% CI [939, 1167], $p_{\text{Mid-R}} < .001$), and the left conditions ($ML_{\text{left}} = 1072\text{-ms}$, 95% CI [958, 1186], $p_{\text{Mid-L}} < .001$). We found no significant difference on the time to perform the task between the right and the left conditions ($p_{\text{R-L}} = 1$).

The interaction between the skill level and the running player's running direction significantly affected the time to perform the task, $F(2, 864.40) = 22.06$, $p < .001$, $\eta^2 = 0.05$.

For skilled players, the performance was faster when the run was to the middle, compared to the left (MSMid = 466-ms, 95% CI [228, 704] ; MSL = 909-ms, 95% CI [784, 1035], pSMid-SL < .001), and to the right (MSR = 905-ms, 95% CI [775, 1034], pSMid-SR < .001), but no difference where observed between the run to the left and to the right (pSRSL = 1). For novices, no significant difference in time to perform the task was observed between the three directions of the run (MNMid = 1142-ms, 95% CI [976, 1307]; MNR = 1202-ms, 95% CI [1037, 1366]; MNL = 1233-ms, 95% CI [1068, 1397], pNMid-NR = 1, pNMid-NL = .304, pNL-NR = 1).

Figure 13: Time to Perform the Dual Task in Experiment 1

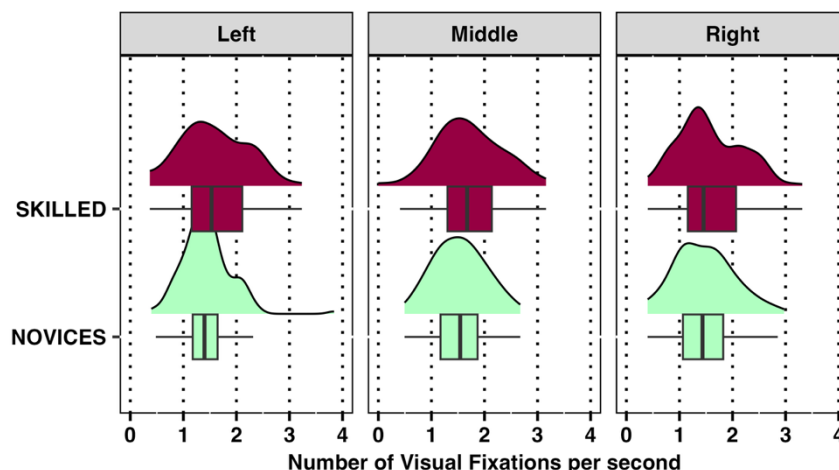


Note. Time (in milliseconds) to perform the task, from the reception of the ball until the last foot-ball contact, across run directions conditions (Left, Middle, Right). The purple (dark grey) boxplot represents the skilled players, and the green boxplot (light grey) represents novices.

Eye-Tracking variables

Number of visual fixations per second. LMM didn't reveal a significant effect of the skill level on the number of fixations per second per trial, $F(1, 41.88) = 2.71$, $p = .107$, $\eta^2 = 0.06$, or an effect of the interaction between the skill level and the direction of the run, $F(2, 872.19) = 0.6584$, $p = .518$, $\eta^2 < 0.01$. However, an effect of the run direction was observed, $F(2, 872.19) = 4.5433$, $p = .011$, $\eta^2 = 0.01$. The frequency of visual fixations was slightly higher in the middle condition, compared with the left condition (MMiddle = 1.62 fixations/sec, 95% CI [1.52, 1.72] ; MLeft = 1.51 fixations/sec, 95% CI [1.41, 1.61], pMid-L = .018), and the right condition (MRight = 1.52 fixations/sec, 95% CI [1.43, 1.62], pMid-R = .043). We found no significant difference on the amount of visual fixations per second between the left and the right conditions (pR-L = 1) (see Figure 14).

Figure 14: Number of Visual Fixations per second in Experiment 1

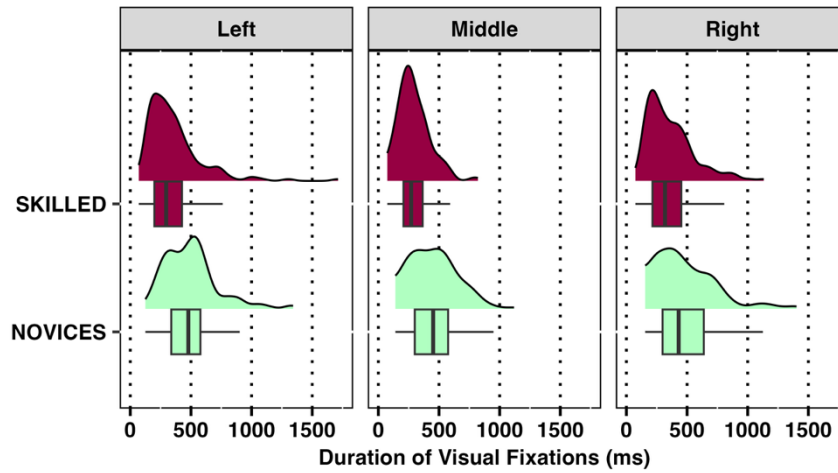


Note. Number of visual fixations per second performed by participants across run directions conditions (Left, Middle, Right). The purple (dark grey) boxplot represents the skilled players, and the green boxplot (light grey) represents novices.

Mean Duration of visual fixations. The mean duration of visual fixations was affected by the skill level, $F(1, 42.02) = 14.54$, $p < .001$, $\eta^2 = 0.26$ (Figure 15). Skilled players performed, on average, visual fixations of shorter durations compared to the novices ($M_{\text{Skilled}} = 338$ ms, 95% CI [285, 390] ; $M_{\text{Novices}} = 481$ ms, 95% CI [426, 535], $p_{S-N} < .001$). LMM also revealed an effect of run direction on the mean duration of visual fixations, $F(2, 870.21) = 8.88$, $p < .001$, $\eta^2 = 0.02$. Participants performed longer visual fixations in the middle condition, compared with the left condition ($M_{\text{Middle}} = 375$ ms, 95% CI [335, 416] ; $M_{\text{Left}} = 426$ ms, 95% CI [385, 467], $p_{\text{Mid-L}} < .001$) and the right condition ($M_{\text{Right}} = 426$ ms, 95% CI [385, 467], $p_{\text{Mid-R}} < .001$). However, we found no significant difference on the mean duration of visual fixations between the left and the right conditions ($p_{R-L} = 1$).

LMM didn't reveal a significant effect of the interaction between the skill level and run direction on this variable, $F(2, 870.21) = 1.20$, $p = .301$, $\eta^2 < 0.01$.

Figure 15: Duration of Visual Fixations in Experiment 1



Note. Duration (in milliseconds) of visual fixations performed by participants across run directions conditions (Left, Middle, Right). The purple (dark grey) boxplot represents the skilled players, and the green boxplot (light grey) represents novices.

Scan Characteristics

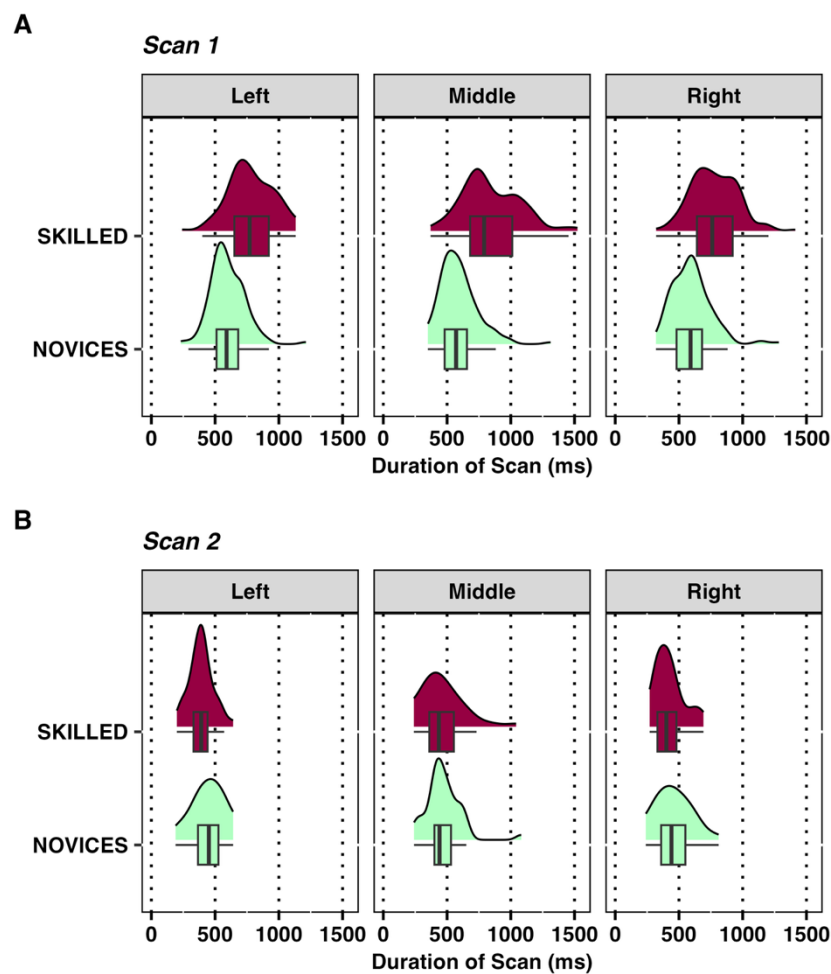
Number of Scans. LMM didn't reveal a significant effect of the skill level on the number of scans per trial, $F(1, 41.92) = 0.85$, $p = .361$, $\eta^2 = 0.02$, or an effect of the direction of the run, $F(2, 872.14) = 0.11$, $p = .892$, $\eta^2 < 0.01$, or an effect of the interaction between the skill level and the direction of the run on this variable, $F(2, 872.14) = 0.19$, $p = .825$, $\eta^2 < 0.01$. Participants performed no scan in 0.3% of the trials, only 1 scan in 72.6% of the trials, 2 scans in 23.0% of the trials and more than 2 scans in 4.0% of the trials.

Duration of Scans. Figure 16A shows the duration of the first scan, regardless of the number of scans the participant performed during the trial. LMM revealed an effect of the skill level on the duration of the first scan, $F(1, 41.98) = 28.97$, $p < .001$, $\eta^2 = 0.41$. The duration of the first scan was longer for skilled than for novice players ($M_{\text{Skilled}} = 799\text{-ms}$, 95% CI [748, 852]; $M_{\text{Novices}} = 596\text{-ms}$, 95% CI [540, 651], $p_{\text{S-N}} < .001$) (see Figure 16).

The direction of the run significantly affected the duration of the first scan, $F(2, 869.11) = 5.80$, $p = .003$, $\eta^2 = 0.01$. The duration of the first scan was longer when the direction of the run was to the middle, compared to the right ($M_{\text{Middle}} = 717\text{-ms}$, 95% CI [677, 757] ; $M_{\text{Right}} = 688\text{-ms}$, 95% CI [649, 728], $p_{\text{Mid-R}} = .011$) and the left ($M_{\text{Left}} = 687\text{-ms}$, 95% CI [647, 727], $p_{\text{Mid-L}} = .009$). However, there was no significant difference in the duration of the first scan between right and left runs ($p_{\text{R-L}} = 1$).

The interaction between skill level and direction of the run was significant, $F(2, 869.11) = 9.65$, $p < .001$, $\eta^2 = 0.02$. Focusing on skilled players, when the direction of the run is to the middle (MSMid = 844ms, 95% CI [789, 899]), these skilled players perform a longer first scan than when the run is to the right (MSR = 778-ms, 95% CI [724, 833], $p_{\text{SMid-SR}} < .001$), and when the run is to the left (MSL = 776-ms, 95% CI [721, 830], $p_{\text{SMid-SL}} < .001$). However, no significant difference was shown in the duration of the first scan in the skilled players when the run was made to the left compared to the right ($p_{\text{SL-SR}} = 1$).

Figure 16: Duration of Scans in Experiment 1



Note. Duration (in milliseconds) of first (A) and second (B) scans, across run directions (Left, Middle, Right). The purple (dark grey) boxplot represents the skilled players, and the green boxplot (light grey) represents novices.

For novices, there was no significant difference in the duration of the first scan between the direction of the run (MNMid = 590-ms, 95% CI [533, 647]; MNR = 598-ms, 95% CI [541, 656]; MNL = 599-ms, 95% CI [541, 656]; pNMid-NR = 1, pNMid-NL = 1, pNR-NL = 1).

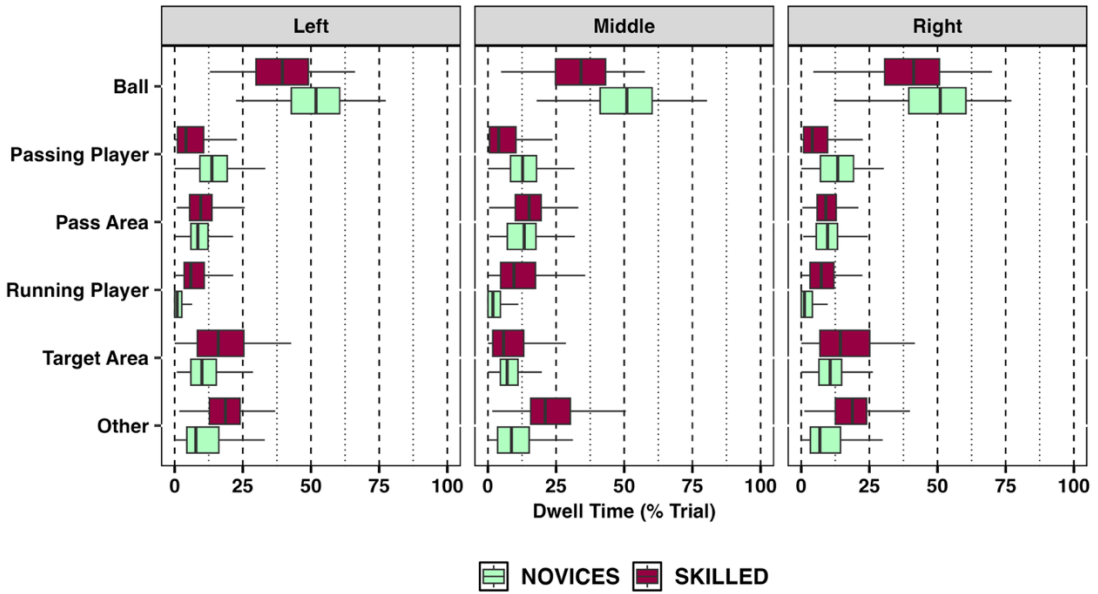
Figure 16B shows the duration of the second scan (when present). LMM revealed no effect of the players skill level on the duration of the second scan, $F(1, 31.83) = 1.39$, $p = .247$, $\eta^2 = 0.04$, and no significant effect of the interaction between the skill level and the direction of the run, $F(2, 231.26) = 1.44$, $p = .239$, $\eta^2 = 0.01$.

However, LMM revealed a significant effect of the direction of the run on the duration of the second scan, $F(2, 231.26) = 3.37$, $p = .036$, $\eta^2 = 0.03$. The duration of the second scan was longer when the direction of the run was to the middle (MMiddle = 459-ms, 95% CI [424, 493]), compared with when it was to the left (MLeft = 410-ms, 95% CI [377, 444], pMid-L = .031), but not compared to the right (MRight = 437-ms, 95% CI [403, 471], pMid-R = .755). There was also no significant difference between the left and the right conditions (pR-L = .475) (see Figure 16B).

Gaze Dynamics

AOI Dwell Time. The multivariate ANOVA revealed a significant effect of the skill level, Approximative Wilk's $\Lambda = 0.55$, $F(1,918) = 124.34$, $p < .001$ on the gaze dwell time in the areas of interest. Figure 17 shows the percentages of time spent per trial on each area of interest for each condition. Post hoc tests revealed that, regardless the direction of the run, the skilled players spent, on average, a higher proportion of their time, compared to novices looking at the running player (MSkilled = 9.23 %, 95% CI [8.55, 9.91]; MNovices = 2.3 %, 95% CI [2.04, 2.56], $p < .001$) and at the target area (MSkilled = 13.79 %, 95% CI [12.84, 14.74]; MNovices = 10.48 %, 95% CI [9.81, 11.16], $p < .001$), and also to other areas (MSkilled = 19.97 %, 95% CI [19.06, 20.87]; MNovices = 10.72 %, 95% CI [9.83, 11.61], $p < .001$). In contrast, the novices spent more time looking at the ball (MNovices = 50.56 %, 95% CI [49.27, 51.84]; MSkilled = 37.56 %, 95% CI [36.38, 38.75], $p < .001$) and the passing player (MNovices = 14.01 %, 95% CI [13.23, 14.79]; MSkilled = 6.59 %, 95% CI [5.94, 7.25], $p < .001$), compared to the skilled players. Post hoc tests didn't reveal any significant difference in the proportion of time spent looking at the pass area between novices and skilled players (MNovices = 11.14 %, 95% CI [10.49, 11.79]; MSkilled = 11.72 %, 95% CI [11.15, 12.28], $p = .186$).

Figure 17: Dwell Time in Experiment 1



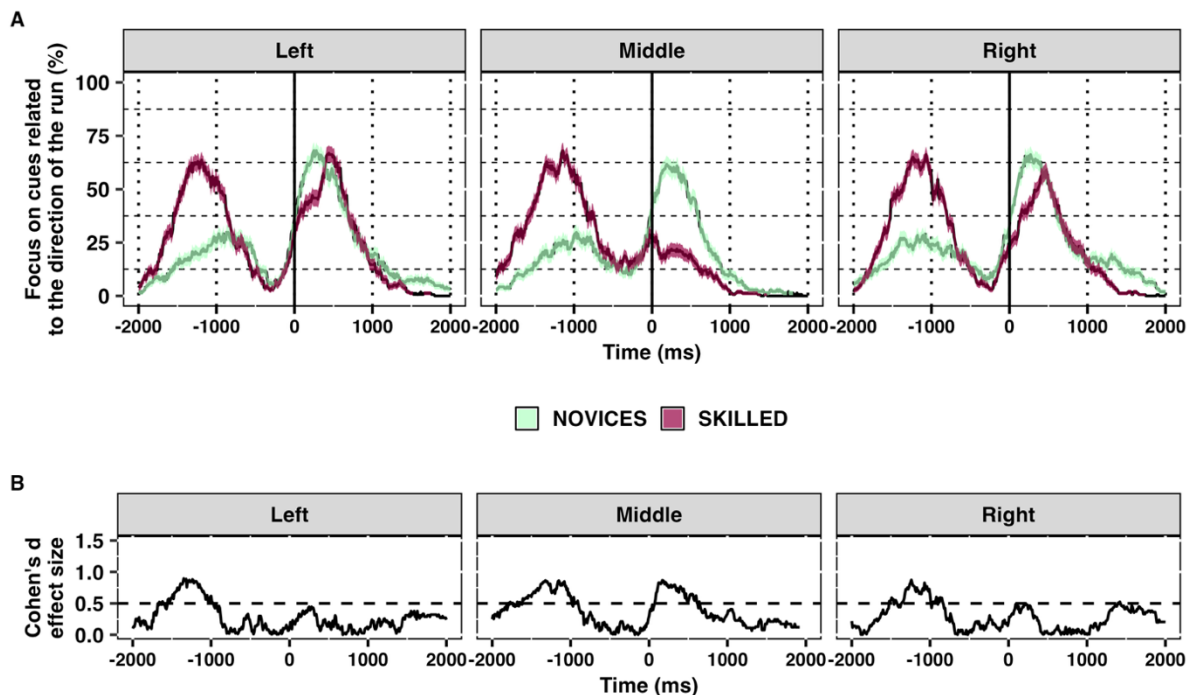
Note. Mean dwell time (% of trial duration) spent on each area of interest (ball, passing player, pass area, running player, target area, other), across run directions conditions (Left, Middle, Right). The purple (dark grey) boxplots represent the skilled players, and the green boxplots (light grey) represent novices.

Gaze Dynamics. We next considered the differences in gaze dynamics (considering the entirety of the scans performed) on cues related to the direction of the run (i.e., running player and target area) between the two groups (see Figure 18). Cohen's d was above the value 0.5 from -1550-ms to -980-ms and from -1370-ms to -830-ms when the running players' movement direction was to the left or the right respectively. When the direction of the run was to the middle, the gaze dynamics of the two groups differed from -1610-ms to -900-ms and from 70-ms to 610-ms. Thus, skilled participants look at cues related to the direction of the run earlier than the novices in the three conditions and for a longer period of the trial when the direction of the run is toward the middle. In the later stage of the trial, after they receive the ball, both skilled and novice participants orient themselves towards the running player (when the direction is left or right). However, while their behavior looks the same, it is important to consider that for skilled participants (who have already gathered knowledge about the running player's direction), the orienting movement serves mainly to prepare to pass the ball. Conversely, for novice participants (who do not yet know the running player's direction) the orienting movement serves also to gather knowledge about the running player's direction. This difference can be appreciated by considering that when the direction of the running player is

the middle, the novice participants show the orienting movement towards the running player, but the skilled participants do not. This is because the latter (but not the former) know already that they have to pass the ball to the passing player and hence orienting again towards the running players is useless.

Instinctively, when looking at this figure, we might associate the different peaks with scans, but this is not always the case. Indeed, it is important to recall that this figure represents only the probability of participants looking at cues related to the direction of the run (such as the target area, the running player, as well as the entirety of the scans performed as explained previously), which means that if a participant performs a scan, it will appear as a peak on this figure, but also if they only look at the target area (for example, when receiving the ball and orienting their body and the ball) without performing a scan, it will still appear as a peak in the figure. To sum up, a player could display a gaze dynamic with two peaks in the figure while having performed only one scan, and this is why during the majority of trials, only one scan was performed (see Results - Scan characteristics - Number of scans) but we can observe two peaks on the figure, and particularly for skilled players in the left and right conditions.

Figure 18: Gaze Dynamics on Cues Related to the Direction of the Run in Experiment 1

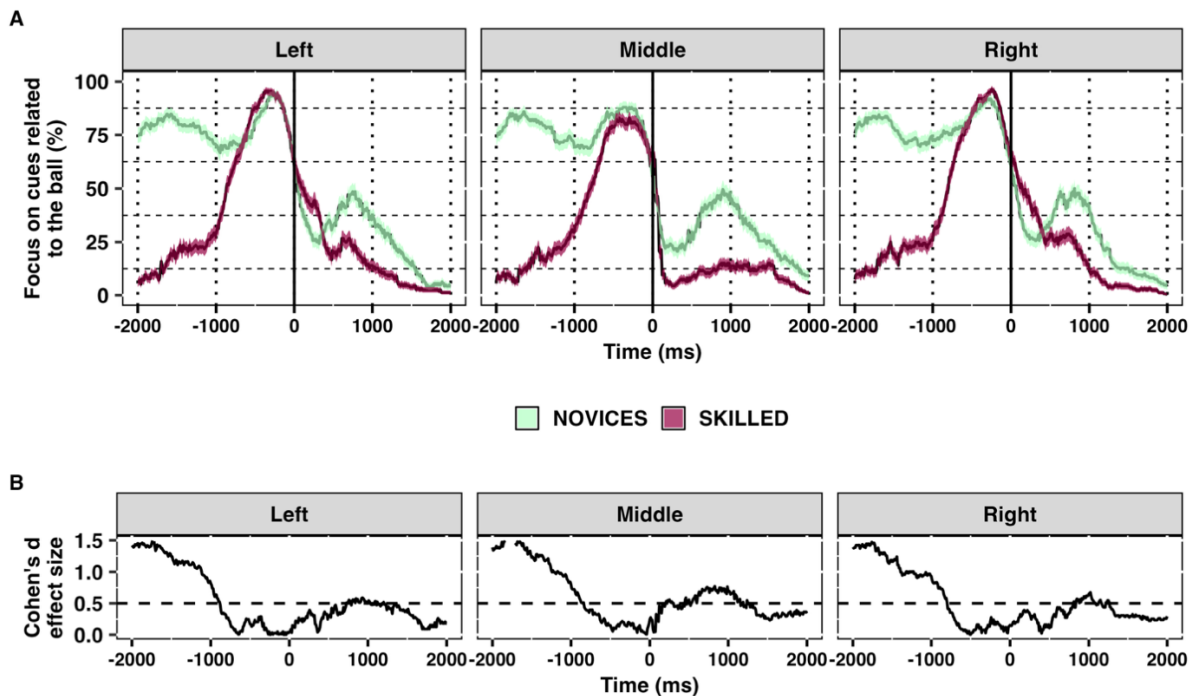


Note. Panel (A) shows, for skilled players (purple (dark grey)) and novices (green (light grey)), the focus on cues related to the direction of the run (in %) on a period (in milliseconds) from

2000-ms before to 2000ms after ball reception ($t = 0$ -ms). Panel (B) shows Cohen's d effect sizes comparing skilled players and novices' gaze patterns over the same period. Dashed lines indicate medium effect size threshold ($d = 0.5$).

We also considered the differences in gaze dynamics on cues related to the ball (ball, pass area, and passing player) between the two groups (see Figure 19). Cohen's d was above the value 0.5 from -2000ms to -890ms and from 730-ms to 980-ms when the running players' movement direction was to the left. When the direction of the run was to the right, the gaze dynamics of the two groups differed from -2000ms to -780-ms, from 840-ms to 1060-ms, and from 1220-ms to 1260-ms. Finally, when the direction of the run was to the middle, the gaze dynamics differed from -2000-ms to -840-ms, from 200-ms to 300-ms, and 410-ms to 1150-ms of the trial. Thus, novices focus more on the ball than skilled participants early in the trial and they appear to look more at the ball after ball reception. The values of the effect sizes indicate that the latter difference is more marked in the middle condition.

Figure 19: Gaze Dynamics on Cues Related to the Ball in Experiment 1



Note. Panel (A) shows, for skilled players (purple (dark grey)) and novices (green (light grey)), the focus on cues related to the ball (in %) on a period (in milliseconds) from 2000 ms before to 2000 ms after ball reception ($t = 0$ ms). Panel (B) shows Cohen's d effect sizes comparing

skilled players and novices' gaze patterns over the same period. Dashed lines indicate medium effect size threshold ($d = 0.5$).

Summary of the Main Results of Experiment 1

Taken together, the results of Experiment 1 show that as expected, skilled participants performed the task faster than novice participants. Despite both groups showing a similar number of scans, skilled participants showed longer durations of their first scan and looked longer at cues regarding the running player and target area, as opposed to participants that looked longer at the ball and the passing player.

Interestingly, our results reveal that skilled and novice participants used distinct VEAs. Skilled participants first made an anticipatory scan at cues related to the running players' movement direction before ball reception, then to the incoming ball. Then, when the running player's direction was to the left or right, skilled participants looked back at the running player just before ball reception, in order to correctly pass the ball to him. They did not look back at the running player when the direction of the run was to the middle, because they had to pass the ball to the passing player instead. Furthermore, skilled participants rarely looked back at the ball after its reception.

Conversely, novice participants used a different and more reactive VEA: they focused on the ball almost until its reception and then, when they were about to receive the ball, they looked at the movements of the running player. Finally, they looked back at the ball shortly after its reception, across all conditions.

In sum, this experiment shows that skilled and novice players adopted distinct VEAs, more anticipatory versus more reactive, during the dual task. A possible explanation is that skilled participants can focus rapidly on the second task, because their internal model of ball passing permits predicting the ball trajectory with low uncertainty, whereas novice participants have to look at the incoming ball longer in order to reduce their uncertainty - and can only focus on the second task afterwards.

Experiment 2

Experiment 1 revealed two distinct (anticipatory versus more reactive) VEAs in skilled and novice players engaged in the dual task football paradigm and suggests that the difference might be due to the different accuracy of internal models and predictive strategies across the two participant groups. In Experiment 2, we examine whether and how taxing skilled participants' cognitive processing with mental fatigue affects their VEAs in the dual task. We reasoned that if mental fatigue decreases the accuracy of internal models and predictive strategies used by skilled participants, they should adopt the reactive VEAs that are similar to those used by novices. Rather, if mental fatigue only disrupts low level perceptual processing, skilled participants should use the same anticipatory strategies identified in Experiment 1 - and the mental fatigue effects should only become apparent in factors related to lower-level visual processing.

To disambiguate between these two hypotheses, two groups of skilled players performed the same dual task paradigm in football presented in Experiment 1, but in two crossover conditions: either after performing a high-load cognitive task, the Time Load Dual Back, to induce mental fatigue (fatigue condition), or after watching an emotionally neutral documentary as a control condition (control condition).

Method

Participants

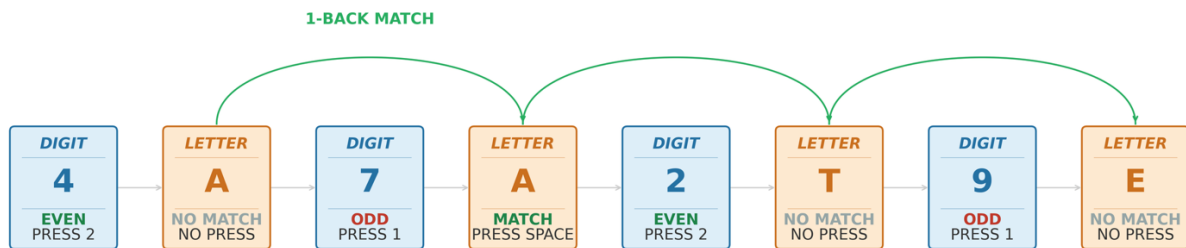
Thirteen skilled male soccer players ($\text{Mage} = 19.5 \pm 2.1$ years) were recruited for this crossover study. Most of the players were recruited from a French professional club academy and played in the top French Under-19 Youth league, while others were from the university football team of University of Rouen Normandy. All players had been playing football for at least 10 years. Participants signed informed consent to take part in the experiment and were free to withdraw at any time. Three more players withdrew between the different days of data collection due to injuries. Data for Experiment 2 were collected in 2024.

Mental Fatigue Induction

To induce a sensation of mental fatigue, we used a cognitive task called Time Load Dual Back (TLoadDBack) developed by (Borragán et al., 2017). This task combines a classic working memory updating task of the N-Back type (Kirchner, 1958) with an inference task (parity decision task). Its effectiveness in inducing a high cognitive load has been demonstrated in several studies.

Eight letters (A, C, T, L, N, E, U, P) and eight digits (1, 2, 3, 4, 6, 7, 8, 9) were presented alternately at the center of a 21.5-inch screen (HP ProOne 600 G6 22 All-in-One PC, HP Inc.; refresh rate: 60 Hz), in Arial font, size 120. Participants were instructed to press the “Space” key with their left hand if the letter presented on the screen was identical to the previous one, and to indicate whether the digits were odd or even by pressing the “1” key (Odd) or the “2” key (Even) on the numeric keypad with their right hand. These keys were covered with distinct colored stickers (White for the “Space” key, Blue for the “1” key, and Green for the “2” key) to avoid any potential conflict between the keyboard key and parity judgments.

Figure 20: Illustration of the Time Load Dual Back task



The stimuli were presented in a pseudo-random order, continuously, in blocks of 30 letters and 30 digits. The stimulus presentation duration was individualized for each participant based on a pre-test (Borragán et al., 2017).

The pre-test, conducted prior to the main experiment, required participants to perform at their maximum cognitive load level. The goal was to measure the shortest stimulus presentation duration while maintaining an accuracy level above 85% for an entire block. The pre-test included an introduction to help participants understand the task, followed by the pre-test itself. The first block started with a stimulus presentation duration of 1200 milliseconds,

with an increment of 100 ms between each block, until the accuracy of a block fell below 85%. Participants took a short break between each block.

The experimental task (TLoadDBack) lasted approximately 16 minutes. In contrast, during the control condition, participants watched an emotionally neutral documentary of equivalent duration.

Subjective Ratings

Subjective ratings of mental fatigue were assessed using a screen-based Visual Analogue Scale (VAS), following established methodologies. Participants were asked the following question: “How are you feeling right now? Please click on the scale to indicate your feeling of fatigue”. The scale was anchored at one end on the left with “Not mentally tired at all” and on the other end on the right with “Extremely tired mentally”.

The sensation of mental fatigue was measured before and after the pre-test to familiarize participants with the scale, and before and after each condition.

Protocol

Instructions and informed consent forms were provided to the participants in advance of the data collection.

Participants were first invited to the laboratory and asked to complete two questionnaires: the Fatigue Severity Scale (Krupp et al., 1989), the St. Mary’s Hospital Sleep Questionnaire (Ellis et al., 1981). After completing the questionnaires, participants indicated their sensation of mental fatigue on the screen-based VAS.

Participants were then randomly assigned to either perform the Time Load Dual Back task or watch an emotionally neutral documentary for 16 minutes. After this, they again reported their mental fatigue on the VAS.

Subsequently, participants were taken to the adjacent gymnasium where the football task was conducted. They were equipped with the Tobii Pro Glasses 3 eye-tracker (Tobii AB,

2020) and the calibration procedure was performed, following Tobii's recommendations. Eye-tracking and video recordings from the gymnasium were then started.

The same football dual task paradigm used in Experiment 1 was explained orally by the experimenters with the same instructions, and accompanied by a demonstration.

The accuracy of the eye-tracker was verified every 5 trials by having participants look at fixed targets in the gymnasium. If the video quality or the point of gaze were not concordant, the calibration was conducted again, and the 5 trials between checks were repeated at the end of the block.

Due to the complexity of scheduling constraints among this category of athletes, participants were invited to return within a period of two to four weeks following their initial session to complete the same procedure, but under the alternative condition to which they had not been assigned during the first data collection day.

Dual Task Design

The football dual task paradigm employed in Experiment 2 was identical to that used in Experiment 1 (see Figure 12), simulating a characteristic match-play scenario in football that necessitates participants to engage in VEA.

Data Collection

Gaze Behavior. Gaze behaviour of participants was recorded using the same mobile binocular eye-tracker device Tobii Pro Glasses 3 (Tobii AB, 2020) as in Experiment 1. Calibration procedure and acquisition were managed with Tobii Glasses 3 software (Tobii AB, 2019).

The calibration procedure was the same as that used in Experiment 1, following Tobii's recommendations.

Eye-tracking recordings were then processed using Tobii Pro Lab software (Tobii AB, 2021), applying the 'raw' data filter to perform frame-by-frame mapping of the gaze data.

Performance. We used the recording system in the gym where the dual task in football was performed to measure the duration and success of task performance. This recording system included three high-definition cameras (1280 x 720 pixels) with a sampling rate of 25 Hz, which allowed the task to be recorded from multiple angles: one camera provided a top-down view, and two cameras provided side views. Task response start and end frames were accurately annotated using Dartfish video analysis software (version 10, Dartfish, 2024).

We defined, as for Experiment 1, the start frame of the task response as the moment when the participant's foot made contact with the ball after receiving the return pass from the passing player. The end of the task response was defined as the first frame when the participant's foot clearly no longer touched the ball while making a pass to the running player in the left and right conditions, or to the passing player in the middle condition.

Data Analysis

To assess the homogeneity of participants' initial levels of fatigue sensation between the different experimental conditions, we used the Fatigue Severity Scale (FSS; Krupp et al., 1989), a validated instrument measuring the impact of fatigue on daily activities over the previous week.

The evolution of the sensation of mental fatigue was evaluated using both subjective and objective measures. Subjective assessment was based on a visual analog scale (VAS) administered before and after each experimental condition, i.e. before and after the Time Load Dual Back (TLDB) task, as well as before and after viewing the emotionally neutral documentary (control condition). This methodology enabled us to verify the similarity of initial mental fatigue states on participants' arrival before each experimental condition, and investigate the evolution of this mental fatigue sensation induced by each condition. Objective evaluation was based on analysis of performance on the TLDB task, measured by the percentage of correct responses per block of stimuli (30 digits and 30 letters).

As in Experiment 1, we use eye tracking to analyze the average number of visual fixations per second and the mean duration of visual fixations. As in Experiment 1, visual fixations were defined as periods of at least 50 ms during which participants' gaze was directed toward one of three AOIs: the ball, the passing player, or the running player.

Participants' performance (accuracy, time to perform the task), visual exploratory activity (number of scans, the duration of scans), and gaze behavior related to areas of interest (dwell time) were assessed using the same methods as definitions as in Experiment 1.

Statistical Analysis

Paired-sample t-tests were first conducted to test whether participants arrived at the same state of fatigue between the two conditions. They were therefore conducted on the number of hours slept and the sleep quality and satisfaction scores for the previous night, measured using items from the St. Mary questionnaire (Ellis et al., 1981), as well as on the impact of fatigue on daily activities during the last week, measured using the Fatigue Severity Scale (Krupp et al., 1989).

These paired samples t-tests were also conducted to control the different manipulations on the participants' feeling of mental fatigue. We conducted a paired samples t-test to compare mental fatigue sensations before each experimental condition (before the cognitive task and before the emotionally neutral documentary). We also performed a paired samples t-test after each experimental condition, as well as on the differences pre-post each experimental condition to verify a greater induction of mental fatigue sensation during the cognitive task, and therefore a higher mental fatigue sensation after this condition.

We employed a linear mixed model (LMM) to measure the evolution of performance per block of stimuli (30 digits and 30 letters) throughout the cognitive task. The position of the block relative to the total duration of the task was included as a fixed factor and participant ID as a random intercept in this model.

To assess the effects of mental fatigue and run direction on performance in the football task, we performed Fisher's exact tests, due to the very low number of missed trials, for task accuracy, and we also performed a LMM for time to perform the task. For this model, the fixed factors included were condition and run direction, and participants' ID was included as a random intercept. Post-hoc analyses were performed using Bonferroni-adjusted p-values.

Other LMMs were also performed to assess the effect of mental fatigue and run direction on variables related to gaze behaviour, i.e. the number of visual fixations per second, the

average duration of visual fixations, and the duration of scans. In these models, the fixed factors included were condition and run direction, while participants' ID was included as a random intercept. Post-hoc analyses were performed using Bonferroni-adjusted p-values.

To measure the effects of mental fatigue and run direction on the number of scans performed per trial, we performed a generalized linear mixed model (GLMM) with a Poisson distribution and a logarithmic link. As with LMMs, we included condition and run direction as fixed factors, and participants' IDs as random intercept.

To analyse the time spent in each AOI (Dwell Time), we performed a multivariate analysis of variance (MANOVA), including condition and run direction as independent variables.

To compare the visual patterns between the two conditions, we measured Cohen's d value for each eye-tracking frame, over a period extending from 2000 ms before and after the reception of the ball during the passing player's return pass. To identify the crucial phases during which the visual patterns differed between the two conditions, we chose to select a period of more than 5 frames (i.e. 50 ms) during which Cohen's d was equal to or higher than 0.5, corresponding to a medium effect size (Cohen, 2013).

Effect sizes were reported as Cohen's d for paired samples t-tests, Pearson's r for Wilcoxon signed-rank tests, partial eta-squared (η^2) for LMMs, and Wilk's Λ for the MANOVA.

Data processing and the various statistical analyses were carried out using RStudio software (R Core Team, 2023).

Results

Sleep Quality & State of Fatigue

Sleep Quality was measured using sleep duration, in hours, sleep quality scores (from 1 (Very Bad) to 6 (Very Well)), and sleep satisfaction scores (from 1 (Very Unsatisfied) to 5 (Completely Satisfied)) items from the St. Mary's Hospital Sleep Questionnaire (Ellis et al., 1981), which measures the overall sleep quality during the last 24 hours. Paired Samples T-Test revealed no significant differences between the different condition' previous nights of the experimentation on sleep duration, $t(12) = -0.584$, $p = .570$, Cohen's $d = 0.16$

(SleepDurationControl = 7.96 hours $\pm$ 1.69; SleepDurationMentalFatigue = 8.27 hours $\pm$ 1.36). As both sleep quality and sleep satisfaction were measured using ordinal data and the assumption of normality was violated, non-parametric Wilcoxon signed-rank tests were performed to compare measurements between previous night of fatigue condition and control condition. A Wilcoxon signedrank test with continuity correction revealed no significant differences between different condition' previous nights for sleep quality (SleepQualityControl = 4.62 $\pm$ 0.77; SleepQualityMentalFatigue = 4.69 $\pm$ 0.75, $V = 4$, $p = .850$, $r = 0.05$), and for sleep satisfaction (SleepSatisfactionControl = 3.23 $\pm$ 1.17; SleepSatisfactionMentalFatigue = 3.92 $\pm$ 0.28, $V = 1.5$, $p = .071$, $r = 0.50$).

State of fatigue was measured using the Fatigue Severity Scale from Krupp et al. (1989), which measures the impact of fatigue on participants' life during the last week. Overall, the mean score on this questionnaire was 33.73 $\pm$ 9.15 and a paired samples t-test was computed to assess for participants who had more than 1 week of interval between different conditions data collection ($n = 9$), that they have the same impact of fatigue on their daily life. No significant difference was revealed by the statistical test (FSSMentalFatigue = 32.67 $\pm$ 8.97; FSSControl = 33.33 $\pm$ 7.30, $t(8) = 0.42$, $p = .686$, Cohen's $d = 0.14$).

Mental Fatigue Assessment

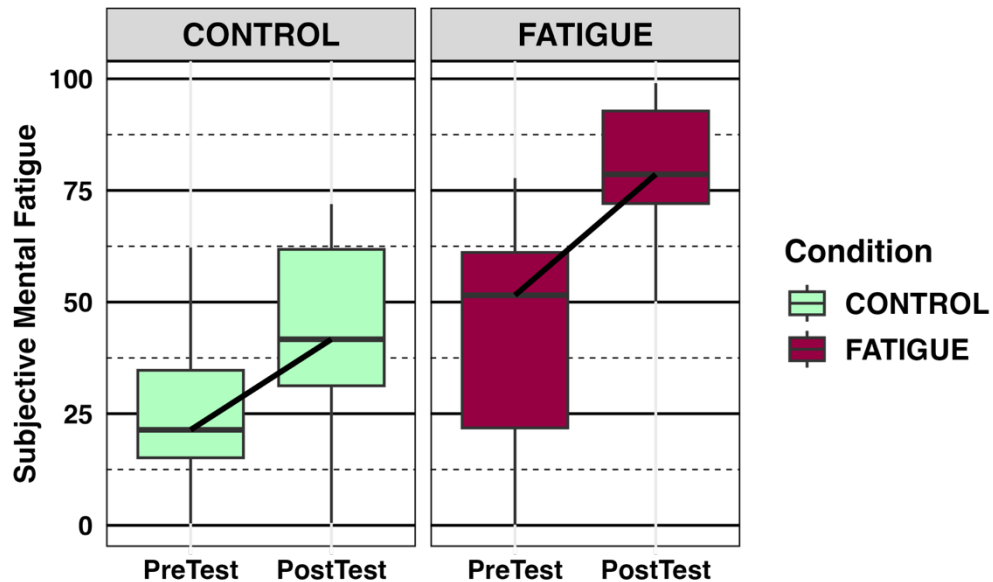
Subjective Measurements. We first controlled participants' initial subjective mental fatigue before each condition. Paired-samples t-test revealed that participants arrived with a higher feeling of mental fatigue during the fatigue condition, compared to the control condition (PreMentalFatigue = 44.05 $\pm$ 25.69; PreControl = 25.56 $\pm$ 17.62, $t(12) = -2.65$, $p = .021$, Cohen's $d = 0.73$).

We also computed Δ differential scores between pre- and post-task on the Visual Analogue Scale for the two conditions. Due to violation of assumption of normality, a non-parametric Wilcoxon signedrank test was performed and revealed that the difference of subjective rating of mental fatigue is higher in the fatigue condition than in the control condition (Δ Pre-PostMentalFatigue = 34.96 $\pm$ 20.26; Δ Pre-PostControl = 17.07 $\pm$ 16.93, $V = 17$, $p = .048$, $r = 0.55$).

Finally, we compared the states of mental fatigue perceived after each condition, and the paired samples t-test demonstrated that participants were significantly more mentally tired

after completing the cognitive task than after the control condition (PostMentalFatigue = 79.01 ± 13.93 ; PostControl = 42.63 ± 23.98 , $t(12) = -4.97$, $p < .001$, Cohen's $d = 1.38$) (see Figure 21).

Figure 21: Evolution of Subjective Mental Fatigue in Experiment 2

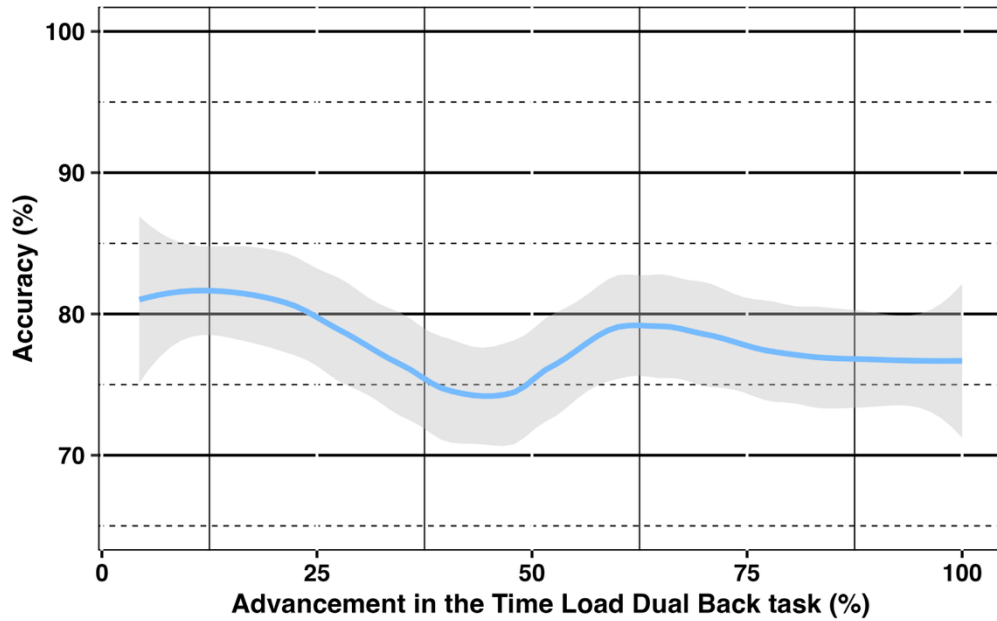


Note. Evolution of subjective mental fatigue (from 0 to 100 on the visual analogue scale) pre- and posttest in fatigue condition (before and after the Time Load Dual Back task - Purple) and in control condition (before and after viewing the emotionally neutral documentary - Light Green).

Pretest in the Cognitive Task. Minimal Stimulus Time Duration, in order to not perform the task under the threshold of 85% of accuracy, was measured for each participant. Mean Minimal Stimulus Time Duration was 815 ± 90 ms (range = 700-1000). The Shapiro-Wilk test demonstrated a normal distribution ($p = .078$).

Performance in the Cognitive Task. The linear mixed model revealed an effect of time (percentage of the cognitive task completed) on the performance achieved for each block of stimuli (30 letters and 30 digits, see Figure 22), $F(1, 245.06) = 4.617$, $p = .033$, $\eta^2 = 0.02$. The model showed an average decrease in overall performance of 0.04% for each percentage of the cognitive task performed.

Figure 22: Evolution of Cognitive Task Performance in Experiment 2



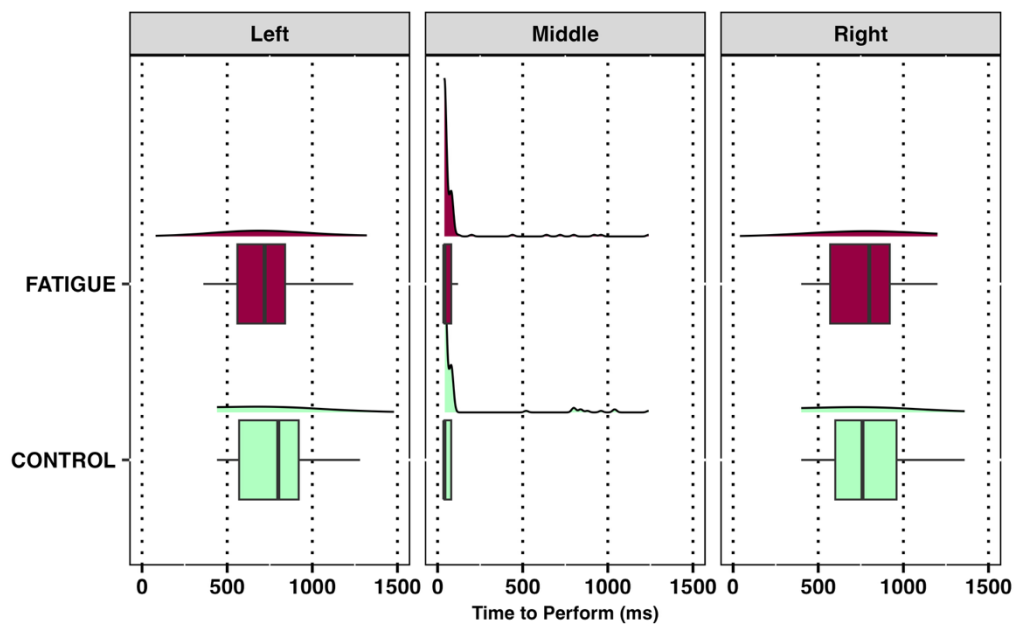
Note. Evolution of cognitive task performance (in % of accuracy) per block of stimuli (30 digits and 30 letters) throughout the Time Load Dual Back cognitive task (in %).

Football Task Performance

Decision Accuracy. Fisher's exact test didn't reveal a significant association between the fatigue condition and task success ($p = 1$), or a significant association between run direction and task success ($p = 1$). There was only 1 trial out of a total of 545 trials which was incorrectly performed, and it was a trial in the control condition, and the run direction was to the left.

Time to Perform the Task. The Linear Mixed Model (LMM) didn't reveal an effect of fatigue on the performance time, $F(1, 525.99) = 1.673$, $p = .196$, $\eta^2 = 0.003$, or an effect of the interaction between the fatigue condition and the run direction, $F(2, 526.00) = 1.734$, $p = .178$, $\eta^2 = 0.007$, but revealed an effect of run direction, $F(2, 526.00) = 364.650$, $p < .001$, $\eta^2 = 0.58$. Participants performed faster the task when run direction was on the middle, compared with the left ($M_{\text{Middle}} = 165$ ms, 95% CI [80, 251] ; $M_{\text{Left}} = 754$ ms, 95% CI [668, 839], $p_{\text{Mid-L}} < .001$), and also with the right ($M_{\text{Right}} = 776$ ms, 95% CI [691, 862], $p_{\text{MidR}} < .001$). However, there was no significant difference between the left and the right conditions ($p_{\text{L-R}} = 1$) (see Figure 23).

Figure 23: Time to Perform the Dual Task in Experiment 2



Note. Time (in milliseconds) to perform the task, from the reception of the ball until the last foot-ball contact, across run directions conditions (Left, Middle, Right), in fatigue condition (Purple) and in control condition (Light Green).

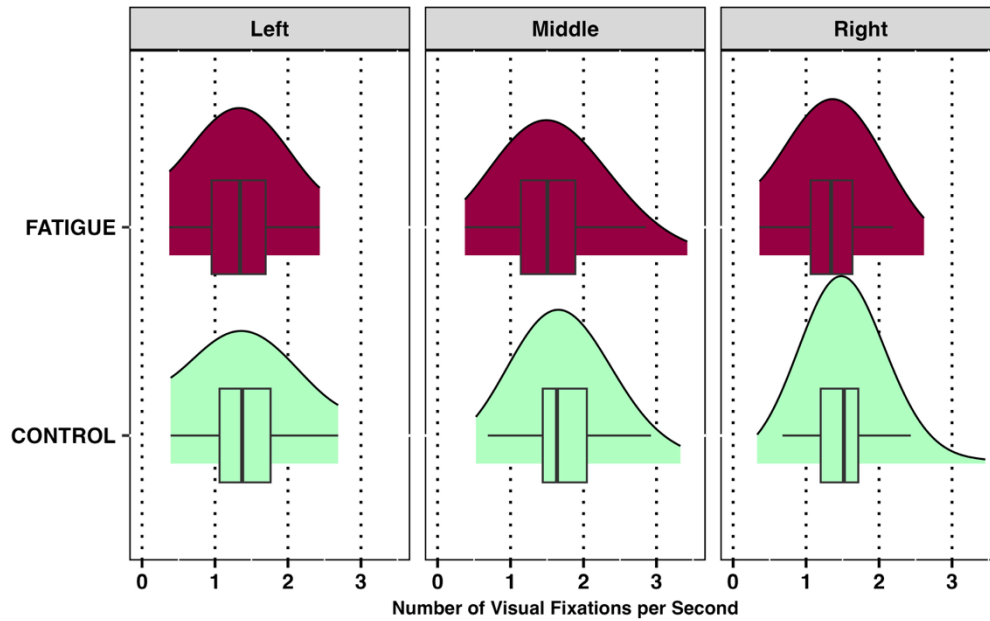
Eye-Tracking variables

Number of visual fixations per second. The LMM revealed an effect of the fatigue condition on the number of visual fixations per second, $F(1, 527.01) = 10.648$, $p = .001$, $\eta^2 = 0.02$. Participants performed more visual fixations per second in the control condition than in the fatigue condition ($M_{Control} = 1.55$ fixations / sec, 95% CI [1.43, 1.68] ; $M_{MentalFatigue} = 1.43$ ms, 95% CI [1.30, 1.55], $p_{Control-MentalFatigue} = .001$).

LMM also revealed an effect of run direction on the number of visual fixations per second, $F(2, 527.02) = 14.895$, $p < .001$, $\eta^2 = 0.05$. Participants performed more visual fixations when run direction was on the middle compared to the left ($M_{Middle} = 1.64$ fixations / sec, 95% CI [1.51, 1.77] ; $M_{Left} = 1.38$ fixations / sec, 95% CI [1.25, 1.52], $p_{Mid-L} < .001$), but also compared to the right ($M_{Right} = 1.45$ fixations / sec, 95% CI [1.31, 1.58], $p_{Mid-R} < .001$). No differences were observed between the left and the right condition ($p_{L-R} = .626$).

No association between the fatigue condition and run direction were observed by the LMM, $F(2, 527.02) = 0.485$, $p = .616$, $\eta^2 = 0.002$ (see Figure 24).

Figure 24: Number of Visual Fixations per second in Experiment 2



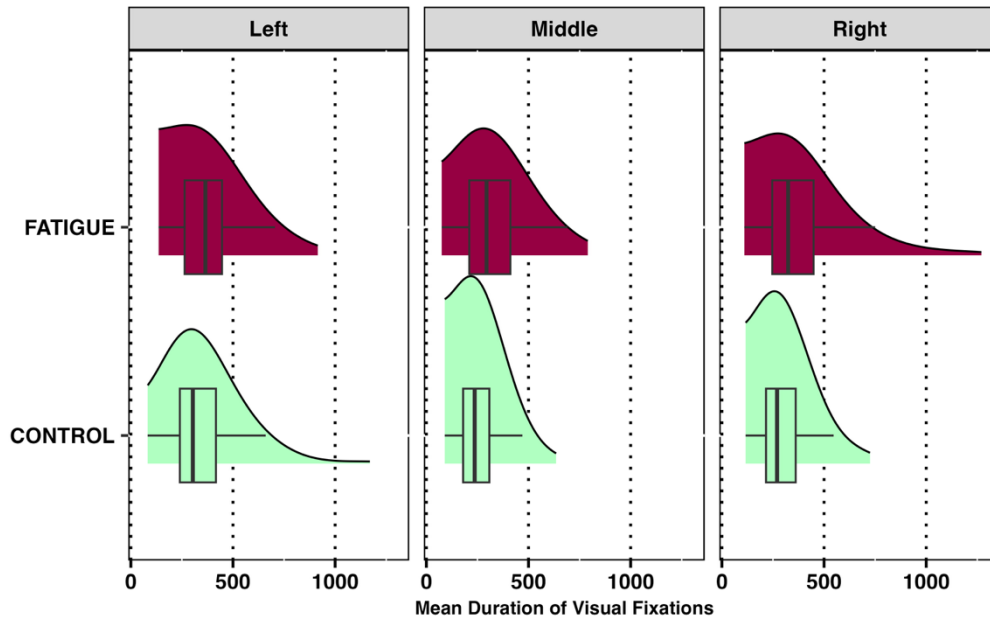
Note. Number of visual fixations per second performed by participants between the fatigue condition (Purple) and the control condition (light green) across run direction conditions (Left, Middle, and Right).

Mean Duration of Visual Fixations. The LMM revealed an effect of the fatigue condition on the mean duration of visual fixations, $F(1, 526.99) = 23.239$, $p < .001$, $\eta^2 = 0.04$. Participants performed longer visual fixations in the fatigue condition than in the control condition ($M_{Control} = 301$ ms, 95% CI [257, 345] ; $M_{MentalFatigue} = 359$ ms, 95% CI [315, 403], $p_{Control-MentalFatigue} < .001$).

The LMM also revealed an effect of run direction on the duration of visual fixations, $F(2, 527.00) = 11.953$, $p < .001$, $\eta^2 = 0.04$. Participants performed faster visual fixations when run direction was on the middle compared to the left ($M_{Middle} = 290$ ms, 95% CI [245, 335] ; $M_{Left} = 360$ ms, 95% CI [315, 405], $p_{Mid-L} < .001$), but also compared to the right ($M_{Right} = 339$ ms, 95% CI [294, 384], $p_{Mid-R} = .003$). No differences were observed between the left and the right condition ($p_{L-R} = .476$).

No association between fatigue condition and run direction were observed by the LMM, $F(2, 527.00) = 1.432$, $p = .240$, $\eta^2 = 0.005$ (see Figure 25).

Figure 25: Duration of Visual Fixations in Experiment 2



Note. Duration (in milliseconds) of visual fixations performed by participants between the fatigue condition (Purple) and the control condition (light green) across run direction conditions (Left, Middle, and Right).

Scan Characteristics

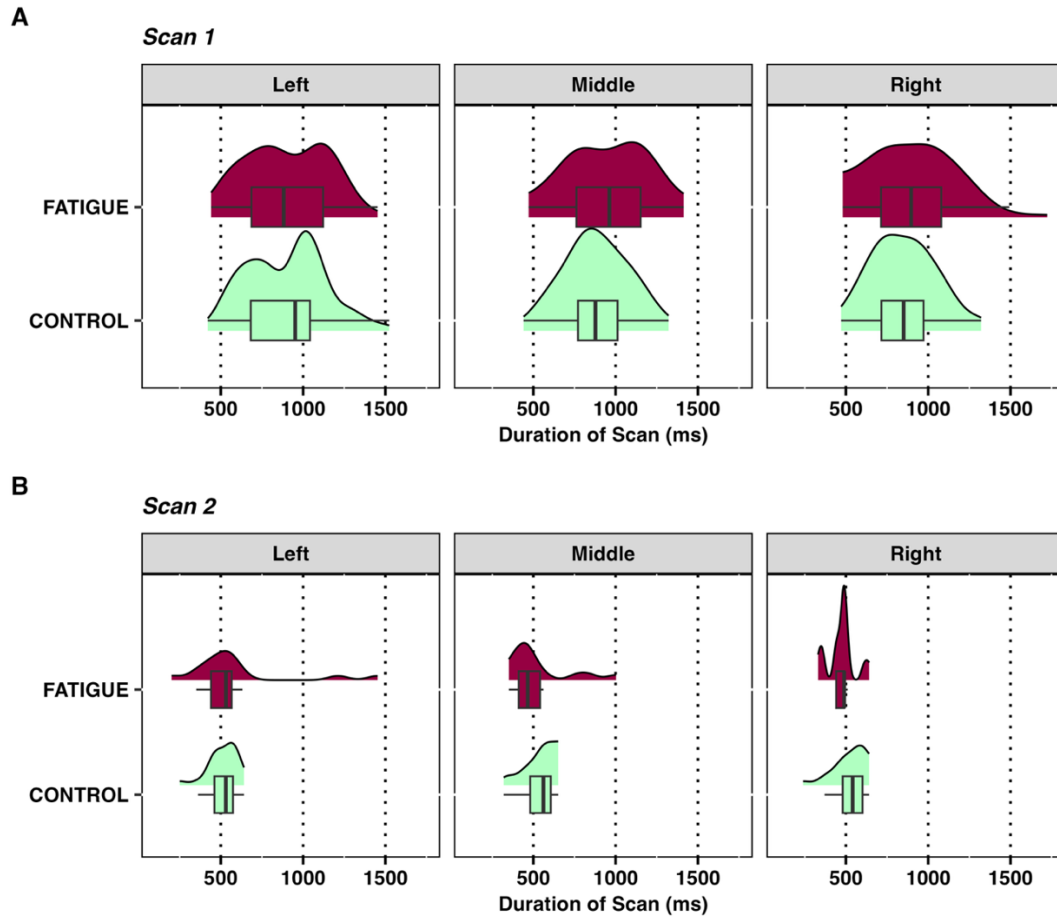
Number of Scans. The Generalized Linear Mixed Model (GLMM) didn't reveal a significant effect of fatigue condition, $\chi^2(1) = 0.80$, $p = .37$, nor an effect of run direction, $\chi^2(2) = 0.12$, $p = .94$, or an interaction between the fatigue condition and run direction, $\chi^2(2) = 0.10$, $p = .95$, on the number of scans performed during a trial.

Indeed, participants performed only 1 scan in 78.5% of the trials, 2 scans in 20.4% of the trials and 3 scans in 1.1% of the trials. These results are comparable to Experiment 1.

Duration of Scans. The LMM revealed an effect of fatigue on the duration of the first scan, $F(1, 527.00) = 7.276$, $p = .007$, $\eta^2 = 0.01$. Participants performed a longer first scan in the fatigue condition than in the control condition (MControl = 878 ms, 95% CI [786, 970] ; MMentalFatigue = 920 ms, 95% CI [828, 1011], $p_{\text{Control-MentalFatigue}} = .007$).

However, no effect of run direction, $F(2, 527.01) = 1.895$, $p = .151$, $\eta^2 = 0.007$) or of the association between the fatigue condition, $F(2, 527.01) = 1.617$, $p = .200$, $\eta^2 = 0.006$) were observed by the LMM on the duration of the first scan (see Figure 26A).

Figure 26: Duration of Scans in Experiment 2



Note. Duration (in milliseconds) of first scan (A) and second scan (B) performed by participants between the fatigue condition (Purple) and the control condition (light green) across run direction conditions (Left, Middle, and Right).

Concerning the duration of the second scan, the LMM didn't reveal any effect of fatigue condition, $F(1, 109.42) = 0.030$, $p = .863$, $\eta^2 = 0.0003$, or an effect of the run direction, $F(2, 107.39) = 1.005$, $p = .369$, $\eta^2 = 0.02$, or an effect of the interaction between the fatigue condition and run direction, $F(2, 106.36) = 1.777$, $p = .174$, $\eta^2 = 0.03$ (see Figure 26B).

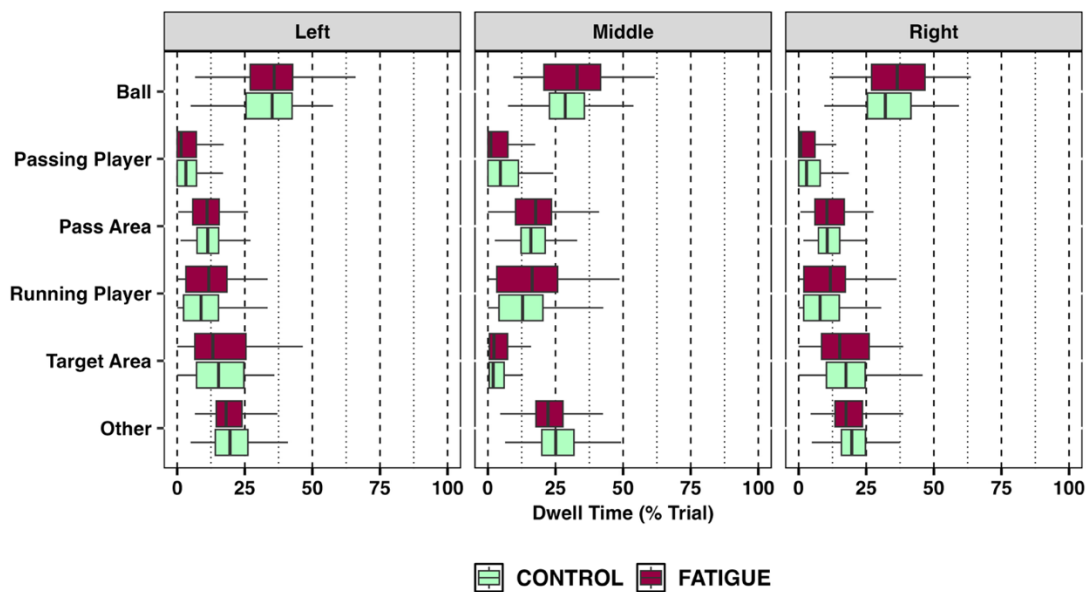
Gaze Dynamics

AOI Dwell Time. The multivariate ANOVA revealed significant effects of the fatigue condition (Wilk's $\Lambda = 0.964$, $F(1,534) = 3.32$, $p = .003$), of run direction (Wilk's $\Lambda = 0.630$, $F(2,1068) = 23.088$, $p < .001$), but no effect of the interaction between fatigue condition and run direction (Wilk's $\Lambda = 0.995$, $F(2,1068) = 0.244$, $p = .996$) (see Figure 27).

Post hoc tests revealed that, regardless of run direction, participants in the fatigue condition spent more time looking at the ball (MMentalFatigue = 34.4 %, 95% CI [33.0, 35.9] ; MControl = 32.3 %, 95% CI [30.9, 33.8], $p = .046$), and the running player (MMentalFatigue = 13.1 %, 95% CI [11.98, 14.3] ; MControl = 10.9 %, 95% CI [9.77, 12.1], $p = .009$). Rather, participants in the control condition spent more time looking at the passing player (MControl = 5.65 %, 95% CI [4.91, 6.39] ; MMentalFatigue = 3.93 %, 95% CI [3.19, 4.67], $p = .001$) and to the other areas (MControl = 22.4 %, 95% CI [21.4, 23.4] ; MMentalFatigue = 20.8 %, 95% CI [19.8, 21.8], $p = .027$).

Post-hoc tests didn't reveal any differences between the fatigue and control conditions for other areas of interest, pass area (MMentalFatigue = 13.40 %, 95% CI [12.5, 14.3] ; MControl = 13.7 %, 95% CI [12.8, 14.5], $p = .684$) and target area (MMentalFatigue = 12.90 %, 95% CI [11.7, 14.1] ; MControl = 13.7 %, 95% CI [12.5, 14.9], $p = .395$).

Figure 27: Dwell Time in Experiment 2

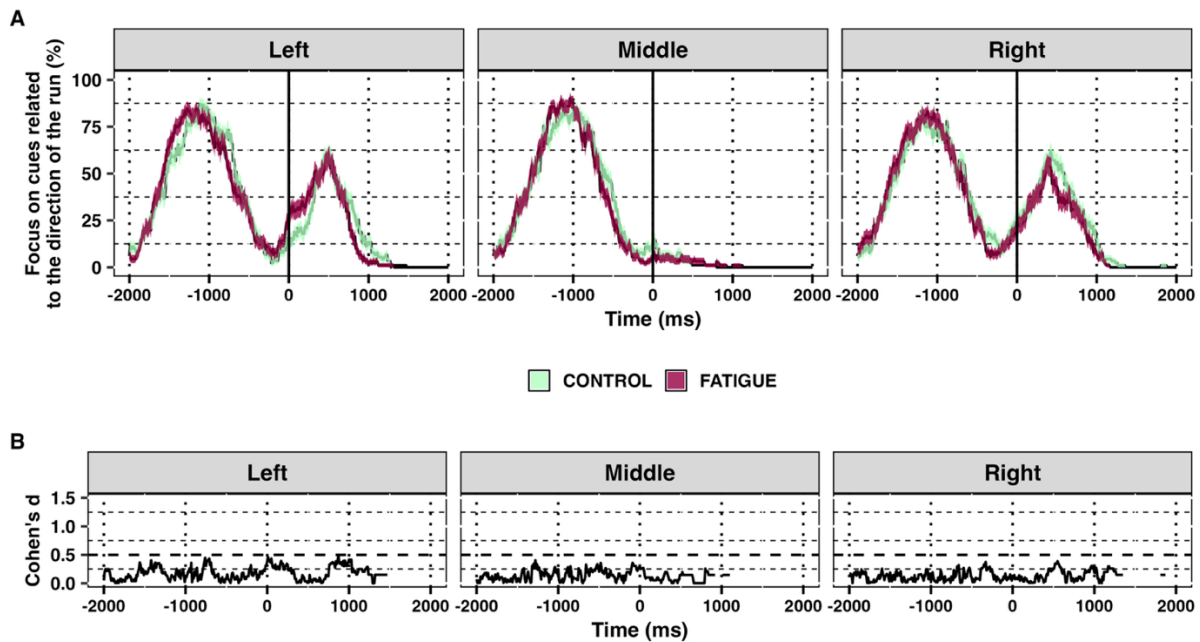


Note. Mean dwell time (% of trial duration) spent on each area of interest (ball, passing player, pass area, running Player, target area, other), for participants between the fatigue condition (Purple) and the control condition (light green) across run direction conditions (Left, Middle, and Right).

Gaze Dynamics. Examining the different gaze dynamics on the cues related to the direction of the run (i.e., running player, target area, also including the entirety of the scans performed) between the two conditions (see Figure 28), Cohen's d never reached the 0.5

threshold. However, we observe some trends whereby Cohen's d approached this threshold of 0.5, as we can see at approximately 700 ms before and also at approximately 700 ms after receiving the ball in conditions where the run direction of the running player was to the left or to the right.

Figure 28: Gaze Dynamics on Cues Related to the Direction of the Run in Experiment 2



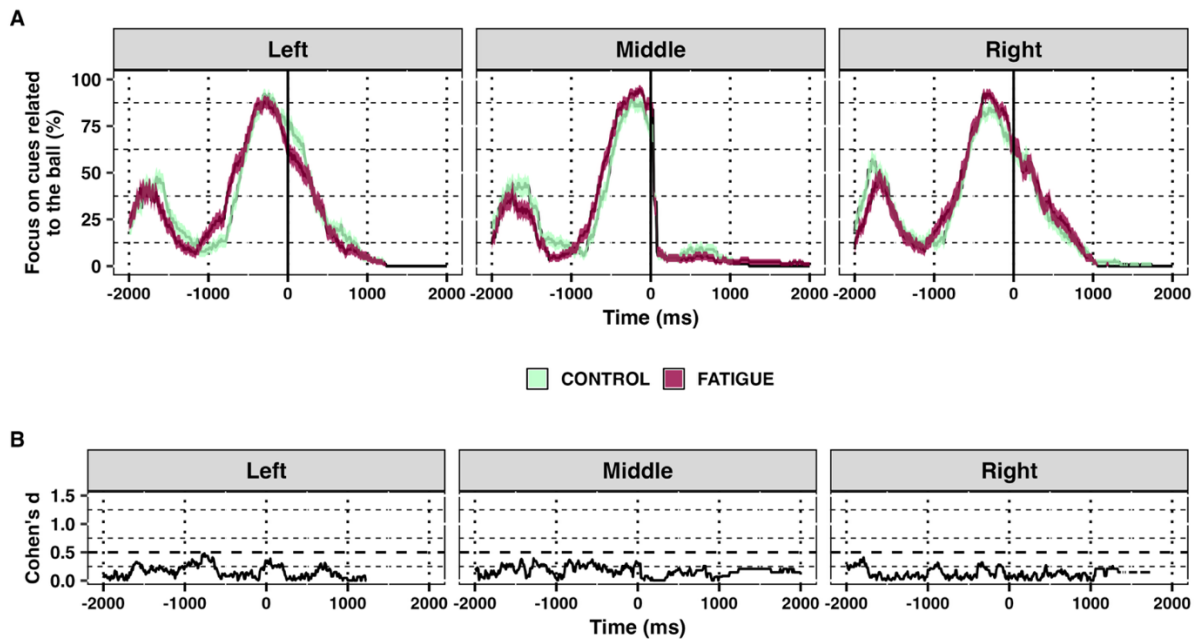
Note. Panel (A) shows, for Mental Fatigue (Purple) and Control (Light green) condition, the focus on cues related to the direction of the run (in %) over a period of time (in milliseconds) extending from 2000 ms before to 2000 ms after ball reception ($t = 0$ ms) of the return pass from the passing player. Panel (B) shows Cohen's d effect sizes comparing mental fatigue and control conditions' gaze patterns over the same time period. Dashed lines indicate medium effect size threshold ($d = 0.5$).

Specifically, whatever the condition, the participants focused their visual attention on the cues related to the run direction mainly between 1500 and 500 ms before receiving the ball in the three run conditions, and also between 300 ms and 800 ms after receiving the ball in the conditions where the run was directed to the left or to the right. The latter corresponds to the period in which participants had to control the ball and orient their bodies towards the running player, to successfully pass the ball. This pattern was absent when the run direction of the running player was to the middle, since in this case participants (who already knew the run

direction from their first scan) did not need to make the orienting actions - since their task was to pass the ball to the passing player.

Examining the different dynamics of gaze on the cues related to the ball between the two conditions (see Figure 29), Cohen's d never reached the 0.5 threshold. Participants allocated their visual attention to the ball predominantly between -700 ms before and 300 ms after receiving the ball, which corresponds to the moment when the participants had to collect sensory information about the ball to control it and perform the task appropriately.

Figure 29: Gaze Dynamics on Cues Related to the Ball in Experiment 2



Note. Panel (A) shows, for Mental Fatigue (Purple) and Control (Light green) condition, the focus on cues related to the ball (in %) over a period of time (in milliseconds) extending from 2000 ms before to 2000 ms after ball reception ($t = 0$ ms) of the return pass from the passing player. Panel (B) shows Cohen's d effect sizes comparing mental fatigue and control conditions' gaze patterns over the same time period. Dashed lines indicate medium effect size threshold ($d = 0.5$).

Summary of the Main Results of Experiment 2

Taken together, the results of Experiment 2 show that skilled participants with or without mental fatigue use similar, anticipatory VEAs to address our dual task: i.e. they look at the running player before they receive the ball. However, participants in the fatigue condition

made longer first scans in the fatigue condition. These results suggest that mental fatigue does not significantly affect the quality of the skilled participants' internal models and predictions, but only lower-level aspects of visual information processing, such as the time they require to extract information during visual scans.

General Discussion

Performing dual tasks in embodied contexts requires arbitrating between alternative actions with competing visual demands. In our football paradigm, players must look at the incoming ball to ensure good reception while also scanning the environment to infer the running direction of the teammate receiving the pass. This study analyzed players' performance and gaze patterns under this dual-task scenario. We aimed to address how people arbitrate between these two competing demands. We examined the effects of skill level and mental fatigue on the visual exploratory activities they adopt.

Our results reveal key differences in visual exploratory activity patterns between skilled and novice players. Skilled players demonstrate a significantly longer exploratory phase compared to novices. This phase lasts approximately 800 milliseconds for skilled players versus 600 milliseconds for novices. More importantly, skilled players exhibit anticipatory patterns of gaze exploration. They shift their gaze towards the running player's direction at an early stage of the task. This shift occurs approximately 1600 milliseconds before they receive the ball. They then look at the passing player before orienting themselves toward the player receiving their pass shortly before ball contact. We characterize this visual exploratory activity as "anticipatory" or "prospective". Skilled participants appear to prioritize collecting information about their second task before completing their first task.

Novices present a contrasting pattern. They exhibit longer gaze fixation on ball-related cues associated with their first task. They initiate scans towards the running player's direction only afterwards. We characterize novice participants' visual exploratory activity as "reactive". They appear to prioritize collecting information about their first task until completion. Only then do they attend to their second task. A plausible explanation for this difference involves the quality of internal generative models. Novices likely possess weaker models that generate uncertain predictions about the ball's trajectory and timing. This uncertainty necessitates continuous intake of sensory observations to afford correct ball reception.

The middle condition of our scenario provided particularly informative insights. This condition required passing the ball back to the initial passing player rather than the running player. It underscored additional differences in gaze dynamics and task performance between groups. Skilled players completed this task significantly faster in the middle condition. They

required approximately 450 milliseconds compared to 900 milliseconds in the left and right conditions. This efficiency improvement stemmed from a crucial insight. Skilled players already knew they had to pass the ball back to the passing player before receiving it. The exploratory phase of skilled players was approximately 75 milliseconds longer in the middle condition compared to lateral conditions. This represents about 850 milliseconds versus 775 milliseconds. This suggests they extended their exploratory activity to ensure confirmation of their teammate's movement direction.

Novices did not exhibit this behavioral flexibility. They performed the task in similar duration across all conditions. Task completion required approximately 1200 milliseconds regardless of condition. They maintained similar exploratory phase duration across conditions at about 590 milliseconds. This lack of adaptation reveals important constraints on novice attentional strategies.

Our second experiment addressed mental fatigue effects on these patterns. Skilled players adopted the same anticipatory visual exploratory activities even when mentally fatigued. The effects of mental fatigue manifested primarily on variables related to lower-level visual processing. The duration of visual fixations increased under fatigue. The length of the first scan also increased. These variables are plausibly more related to perceptual processing efficiency than strategic decision-making. Variables related to strategic aspects remained largely preserved. The decision to initiate a scan towards the running player before receiving the ball was maintained under fatigue. This dissociation strongly suggests that mental fatigue does not significantly degrade skilled participants' internal models and predictions. It affects primarily lower-level aspects of visual information processing.

These results can be understood within a computational framework. Participants facing dual tasks like ours arbitrate between two internal models. One model governs the receiving task. Another governs the passing task. Both models generate uncertain predictions and pose competing demands to visual attention. They require collecting information about different spatial locations. The key difference between skilled and novice players resides in the quality of their internal models. Skilled players generate confident predictions about the first task even with minimal evidence. They can rapidly turn their attention to the second task before completing the first. Novices possess weaker generative models. They require more visual

feedback to successfully complete the first task. They can only turn their attention to the second task after completing the first.

The observed differences in visual exploratory activities between groups therefore reflect differential uncertainty resolution dynamics. Resolving uncertainty about one task licenses allocating resources to the other task in an anticipatory manner. This principle has been observed in other visual exploration studies manipulating uncertainty levels. Our findings extend this principle to embodied dual-task contexts with real motor execution and temporal pressure.

Our study adds to the literature examining cognitive processing and visual exploration during naturalistic behavior. This includes sports contexts and the role of uncertainty and expertise. Compared to previous works, we specifically address a dual task in a real embodied setting with actual motor execution. We additionally manipulate participants' mental fatigue to examine robustness. An interesting finding concerns the frequency of head turns. Most trials in our paradigm involved only a single head turn. This occurred in 72.61% of trials. This contrasts with similar tasks where participants performed approximately two scans per second on average. This difference likely stems from the high time pressure of our dual-task paradigm. The second task involved relatively low uncertainty. Participants only needed to understand the running player's movement direction. Previous studies involved monitoring multiple screens to identify available teammates without controlling a real ball. This distinction underscores how time constraints and task demand shape visual exploration patterns.

Our findings revealed distinct visual exploratory patterns between skilled players and novices. These patterns highlight how experience supports optimization of action through efficient gaze allocation. Skilled players performed the task faster than novices. They made longer scanning movements before receiving the ball. They showed a more proactive exploratory strategy. They spent more time looking at cues related to future passing opportunities before completing the first task. Novices focused predominantly on ball-related cues rather than anticipating subsequent actions. This suggests a more reactive approach to task execution.

Mental fatigue results revealed that skilled participants maintain their anticipatory visual exploratory activities under cognitive load. They require more looking time as if the rate of information processing was lowered. These findings suggest that skilled visual exploratory activities may reside in perceiving optimal moments to shift visual attention between task-related cues. Expertise is not simply about scanning frequency. It concerns the strategic timing of attentional reallocation.

Future research could build upon these findings by increasing time pressure during task completion. Manipulating the level of uncertainty in task modules could further elucidate skilled players' gaze dynamics efficacy. Testing these principles in other dual-task domains would establish generalizability. Longitudinal studies tracking the development of anticipatory strategies could reveal learning mechanisms. These directions would advance our understanding of how expertise shapes the temporal orchestration of attention in complex dynamic environments.

CRedit authorship contribution statement

Aurélien Dehorne: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project administration.

Guillaume Hacques: Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Supervision, Project administration. **Téo Lépine:** Investigation, Resources, Data Curation, Project administration.

Riccardo Palumbo: Supervision. **Giovanni Pezzulo:** Conceptualization, Supervision, Writing – Original Draft, Writing – Review & Editing. **Pierpaolo Iodice:** Conceptualization, Methodology, Investigation, Resources, Writing

– Review & Editing, Supervision, Project administration.

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The two experimental studies presented in Chapter 2 provided answers to the first two research questions formulated in Chapter 1. First, we demonstrated that football expertise is characterised by distinct visual exploration strategies in dual-task situations. Expert players adopt anticipatory visual exploration strategies, shifting their attention to peripheral information approximately 1600 ms before receiving the ball, while novice players rely on sequential behaviours, i.e. they complete the first task before exploring opportunities for the second task, or more random behaviours. Then, in the second study, we showed that mental fatigue preserves the temporal structure of these anticipatory strategies in experts, but affects the efficiency of lower-level information processing, resulting in an increase in the duration of fixations and scans.

However, although the experimental approach in Chapter 2 successfully described these behavioral models and tested their robustness in the face of mental fatigue, it remained fundamentally observational. Indeed, our results present the differences between experts and novices, both quantitatively and qualitatively, with the study of gaze dynamics throughout the task, but the underlying computational mechanisms that generate these models remain implicit. The third major gap identified in Chapter 1, the absence of formal computational models capable of quantitatively predicting observed attentional allocation patterns, thus remains unaddressed.

Chapter 3 directly addresses this gap using a simulation-based approach founded on the principles of active inference. Rather than building a model from our empirical data, we adopted a different strategy: we took the classic T-Maze paradigm, well established in the active inference literature, and adapted it to the structure of our dual-task scenario in football. The goal was to examine whether this adapted model, when appropriately parameterized, could spontaneously generate visual exploration patterns similar to those observed in our experiments.

By systematically manipulating the model's matrices (prior precision, state transitions, reward structure), we performed simulations to test specific hypotheses. Can an agent with precise priors reproduce the early attentional reallocation characteristic of experts? Does the degradation of this accuracy lead to patterns more typical of novices? How do changes in task-related rewards affect the temporal dynamics of attention? The correspondence, or non-correspondence, between simulated and observed behaviors allows us to evaluate whether the

free energy optimization principle constitutes a sufficient explanatory mechanism for the results obtained in Chapter 2.

This computational approach brings theoretical precision to our understanding. It goes beyond simple descriptions by formalizing how uncertainty can influence the distribution of attentional, and it provides a unified framework in which differences between experts and novices can be interpreted as variations in specific model parameters rather than vague, simplistic ideas of “better attention”. If the model proves to be conclusive, it would also make it possible to identify concrete objectives for training interventions. If it fails, it would indicate that other mechanisms need to be taken into account, which in itself would constitute valuable theoretical progress.

4. Chapter 3: Computational Modeling of Attention Allocation in Dual-Task Contexts

The empirical studies presented in Chapter 2 revealed differences in the temporal dynamics of attention allocation between expert and novice soccer players, as well as specific effects of mental fatigue on these patterns. Expert players demonstrated anticipatory visual exploration strategies, reallocating their attention to peripheral information well before completing the task of receiving the ball. Mental fatigue preserved this temporal structure while increasing information processing time, suggesting that anticipatory strategies may be largely automated while remaining dependent on processing efficiency. These results provided crucial empirical constraints for theoretical understanding, but they raised a fundamental question: what computational principles generate these observed patterns?

Chapter 1 presented active inference and the Free Energy Principle as promising theoretical frameworks for understanding the allocation of attention in complex tasks. These frameworks propose that perception and action are guided by a unified optimization principle: minimizing prediction errors or, equivalently, minimizing free energy, a quantity that combines the accuracy of internal models' predictions and their complexity. Applied to the allocation of attention, this principle suggests that gaze is directed toward locations that would most effectively reduce uncertainty about task-relevant states, with this uncertainty being computed by internal predictive models maintained by the cognitive system.

However, it is not easy to translate these general theoretical principles into a concrete computational model that generates verifiable predictions for our specific dual-task paradigm. The model must formally specify how the system maintains and updates two competing internal models, one for receiving the ball and the other for identifying the teammate's running direction, while tracking the evolution of uncertainty within each model as observations accumulate. It must also define how the relative uncertainty between the models determines the distribution of attention at each moment. Beyond the architecture itself, the challenge is to set up the model so that differences in expertise emerge naturally from interpretable parameters, and to establish rigorous validation procedures that go beyond simple curve fitting to truly test whether the model accounts for the observed behavioral patterns.

This chapter addresses these challenges by presenting a formal computational model of attentional allocation in dual-task contexts, adapted specifically for our football paradigm

but with principles potentially generalizable to other domains involving competing informational demands. The model combines elements from several theoretical traditions: Bayesian inference for representing and updating uncertainty, optimal control theory for computing attentional allocation policies, and drift-diffusion models for capturing temporal dynamics of evidence accumulation. Critically, all these components are unified within an active inference framework where attentional shifts emerge from free energy minimization.

The work presented in this chapter constitutes a scientific article developed in collaboration with colleagues specializing in computational cognitive neuroscience. This collaboration brought together the empirical expertise in sport science and eye-tracking methodology developed through Chapters 1 and 2 with advanced competencies in computational modeling, Bayesian inference, and active inference formalization. The resulting article follows standard structure for computational neuroscience publications and addresses a central question: can a model based solely on uncertainty-driven attentional allocation reproduce the anticipatory versus sequential behaviors observed empirically in Chapter 2? Beyond this core validation, we examine whether estimated model parameters differ systematically between experts and novices in theoretically meaningful ways, particularly regarding the precision of internal predictive models. The article also explores the model's capacity to generate novel predictions for experimental conditions not yet tested and considers how alternative architectures or optimization principles compare in their explanatory power, insights that directly relate to the nature of the underlying cognitive mechanisms.

Beyond these specific questions, the mathematical modeling work presented in this chapter contributes more widely to the theoretical integration of the various components of this doctoral thesis. Chapter 1, Part 1 presented the theoretical frameworks focusing on predictive models and uncertainty; Part 2 synthesized the empirical data while identifying critical gaps; Part 3 formulated specific hypotheses to fill these gaps. Chapter 2 tested these hypotheses empirically and characterized behavioral models with unprecedented temporal resolution. Chapter 3 now completes this work by mathematically formalizing the theoretical principles and demonstrating that they quantitatively explain the observed models while generating verifiable predictions for future work.

The following article is currently being submitted to an international journal. The main contribution of this chapter lies in demonstrating that formal computational modeling can successfully fill the gap between abstract theoretical principles and concrete empirical findings, providing mechanistic explanations for observed differences in expertise, while opening up new directions for basic research and applied interventions in the field of perceptual-cognitive training.

An Active Inference Modelling of Visual Exploration and Decision Making in a Football Task

Guillaume Hacques¹, Giovanni Pezzulo², Aurélien Dehorne^{3,4}, Riccardo Palumbo^{3,4} and Pierpaolo Iodice¹

¹ Le Mans Université, Movement – Interactions – Performance, MIP, UR 4334

² Institute of Cognitives Sciences and Technologies, National Research Council, Rome, Italy

³ Center for Advanced Studies and Technology, University G. d'Annunzio of Chieti – Pescara

⁴ Department of Neuroscience, Imaging and Clinical Sciences, University G. d'Annunzio of Chieti–Pescara

Correspondence concerning this article should be addressed to Guillaume Hacques, Le Mans Université, Movement – Interactions – Performance, MIP, UR 4334, Avenue Olivier Messiaen, 72085 Le Mans Cedex 09, France. Email: guillaume.hacques@univ-lemans.fr

ORCID:

Guillaume Hacques <https://orcid.org/0000-0002-9760-6556>

Giovanni Pezzulo <http://orcid.org/0000-0001-6813-8282>

Aurélien Dehorne <https://orcid.org/0009-0002-5248-9429>

Riccardo Palumbo <https://orcid.org/0000-0003-4230-5817>

Pierpaolo Iodice <https://orcid.org/0000-0001-7167-8917>

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Abstract

Performing sequences of actions in dynamic environments often requires optimizing gaze shifts toward task-relevant sources of information. We studied this issue using a football-based decision-making task in which participants had to receive a ball from a first teammate and pass it to a second teammate moving behind them. Successful performance required managing two sources of visual information that could not be accessed simultaneously: information about ball reception (e.g., is the ball coming to the left or right foot?) and information about the teammate’s running direction (e.g., is she running to the left, or right?). Participants therefore had to actively select when and where to sample visual information in order to guide action.

We adapted a partially observable Markov decision process (POMDP) model within an active inference framework to simulate this task and to reproduce the sequences of actions observed in an experiment comparing two groups of participants: experts and novices. The model was designed as an extension of a classical T-maze task, allowing agents to gather informative cues before committing to action. We manipulated three candidate factors that could explain the observed group differences in policy selection: (i) the reward structure associated with action outcomes, reflecting prior preferences over these outcomes (i.e., how much the agent values being in a particular state at a given time); (ii) the precision of the agents’ beliefs about action consequences; and (iii) the reliability of sensory information.

Our results indicate that the reward structure of the task influenced policy selection, suggesting that expert agents place greater value on rapid task resolution than novices. This reward structure is likely learned through practice and shaped by specific performance constraints. Increasing noise in the agents’ beliefs altered policy selection and could lead to the adoption of novice-like strategies under high uncertainty. Similarly, degrading sensory signals induced a transition from expert to novice strategies, but only when the reward associated with rapid task resolution was sufficiently low. In this latter case, agents selected a policy that involved gathering information related to the ball location and, then passing the ball without acquiring cues about the teammate’s movement. This strategy resulted in a substantial drop in decision accuracy. Overall, these findings suggest that expert decision-making relies on more precise generative models and on different intentions than those of novices, which influenced when and where visual information is acquired.

An Active Inference Modelling of Visual Exploration and Decision Making in a Football Task

Introduction

Acting efficiently in dynamic environments requires more than fast motor execution, it requires knowing when and where to look. In many real-world tasks, the information necessary to guide action is distributed across space and time, and no single gaze position can capture it all. Agents must therefore actively sequence their visual sampling, allocating attention toward the sources that are most informative at each moment, while remaining committed to the ongoing motor demands of the task. This problem is not merely one of perceptual efficiency: it reflects a deeper challenge of decision-making under uncertainty, in which the value of gathering additional information must be continuously weighed against the cost of delayed action.

Team sports offer a particularly clear window onto this challenge. In football, for example, a player receiving a pass must simultaneously manage various competing sources of visual information: the trajectory of the incoming ball, which determines how to control reception, and the movement of teammates and opponents, which determines where to direct the subsequent action. These sources cannot be attended to simultaneously, forcing the player to make implicit decisions about when to shift gaze from one to the other. Research using mobile eye-tracking in ecological settings has consistently shown that expert players handle this allocation differently from novices. Rather than monitoring the ball until reception is complete before scanning the environment, experts shift their gaze toward the pass target earlier in the action sequence, sometimes before the ball has even been received, suggesting that they operate with a qualitatively different internal representation of the task (Jordet et al., 2013; McGuckian et al., 2018; Dehorne et al., 2025).

Despite these empirical advances, the computational basis of expert–novice differences in visual exploration remains poorly understood. The existing literature does not formally specify whether anticipatory reallocation reflects more precise internal models of ball trajectory, enabling earlier uncertainty resolution about the ongoing task, a stronger preference for rapid action that leads experts to accept higher residual uncertainty in exchange for temporal efficiency, or more reliable perceptual signals that make each observation more informative. These three candidate explanations, differences in generative model precision, in outcome preferences, and in sensory reliability, are not mutually exclusive, but they are

computationally distinct, and distinguishing between them requires moving beyond behavioral description toward explicit formal modelling.

Active Inference, grounded in the Free Energy Principle (Friston, 2010; Parr et al., 2022), provides exactly such a framework. Under Active Inference, agents maintain a probabilistic generative model of their environment and select actions so as to minimize expected free energy, a quantity that jointly reflects the epistemic value of reducing uncertainty and the pragmatic value of securing preferred outcomes (Friston et al., 2015, 2016). Crucially, this framework formalizes visual sampling as an active, goal-directed process: gaze shifts are not reactive responses to salient stimuli but prospective actions selected because they are expected to resolve uncertainty about task-relevant hidden states. This is an explanation why Active Inference is particularly well-suited to modelling the kind of strategic, anticipatory visual exploration that characterizes expert performance. Harris et al. (2022) were among the first to articulate the theoretical alignment between Active Inference and skilled anticipation in sport, outlining the conceptual foundations upon which the present work builds.

Concretely, Active Inference can be formalized as a Partially Observable Markov Decision Process (POMDP), in which an agent selects among candidate policies, sequences of actions, based on their expected free energy (Friston et al., 2016; Parr et al., 2022). A widely used instantiation of this framework is the T-maze task, in which an agent must choose whether to gather an informative cue before committing to a terminal action. The balance between information-seeking and direct action in this paradigm depends on three model components: the agent's prior preferences over outcomes, the precision of its beliefs about how actions lead to state transitions, and the reliability of its sensory observations. Manipulating these components produces interpretable, qualitatively distinct behavioural signatures, making the T-maze an ideal simulation for formalizing the expert–novice contrast in our football task.

Here, we extend the T-maze POMDP to a football-based dual-task paradigm in which participants must receive a ball from one teammate and pass it to another whose movement direction is initially unknown (Dehorne et al., 2025). The task requires managing two informationally independent sources of uncertainty, one about ball reception, one about the movement of the second teammate, that must be resolved through sequential visual sampling. We simulated this task using virtual agents and systematically varied three parameters drawn directly from the theoretical distinctions above: (i) prior preferences over action timing,

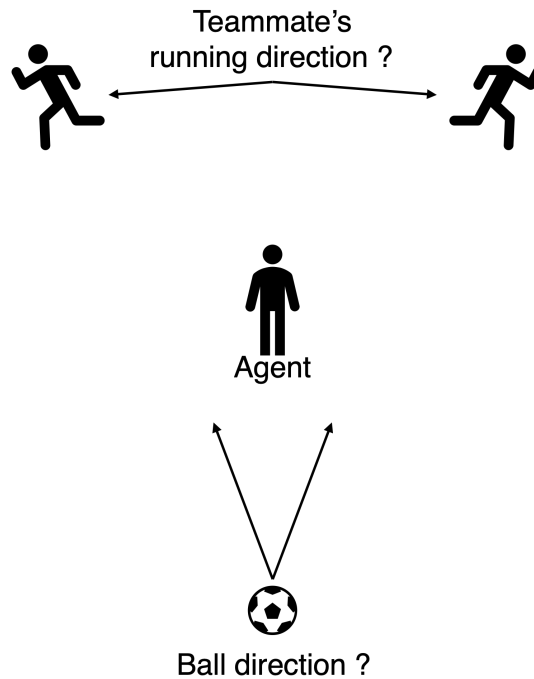
operationalized as the relative value assigned to passing at different timesteps; (ii) the precision of beliefs about action-dependent state transitions; and (iii) the reliability of exteroceptive sensory signals. By examining how each manipulation shifts policy selection between anticipatory and sequential strategies, the simulations aim to identify the specific computational parameters that distinguish expert from novice decision-making in ecologically valid sport contexts.

Methods

Task and Simulation

In the real-world experiment that we address (Dehorne et al., 2025), the task consisted of receiving a football from a first teammate and then passing it to a second teammate. This task required participants to perceive how to receive the ball (e.g., on the right or left foot) and to determine the movement of the second teammate (e.g., running to the right or to the left) (Figure 30). Thus, participants could be confronted with four possible conditions (i.e., two sides for receiving the ball and two possible running directions), for which they had no prior information. Importantly, participants could actively gather information about how to receive the ball (by looking at the first teammate) and to determine the movement of the second teammate (by looking at the second teammate), but they could not do both simultaneously. Therefore, the participants must decide whether to gather information (to reduce uncertainty before receiving and passing the ball) and which information to gather (about the first or second teammate, or both).

Figure 30: Representation of the experimental task addressed in this study.

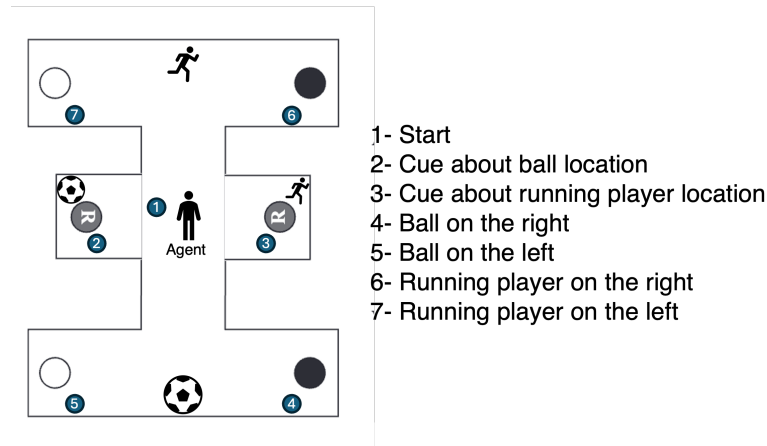


Note. The participant (in the central position) has to receive the ball from a first teammate and then pass it to a second teammate; for this, it can acquire information about the first or second teammate, or both.

We constructed a simulation of this decision-making task as an extension of the T-maze task (also known as the three-arm maze) and its associated partially observable Markov decision process (POMDP) model (K. Friston et al., 2016; Parr et al., 2022).

Our football decision-making task can be conceptualized in a similar way, except that the agent must act to identify both the ball reception side and the running direction of the teammate. These ambiguous decisions (actions) can be solved by acquiring cues related to the ball location and the teammate’s movement. This requires extending the original T-maze structure from four possible states to a more complex task comprising seven possible states for the agent, including the starting state in both cases (Figure 31).

Figure 31: Conceptualization of the football task as a more complex form of the T-maze.



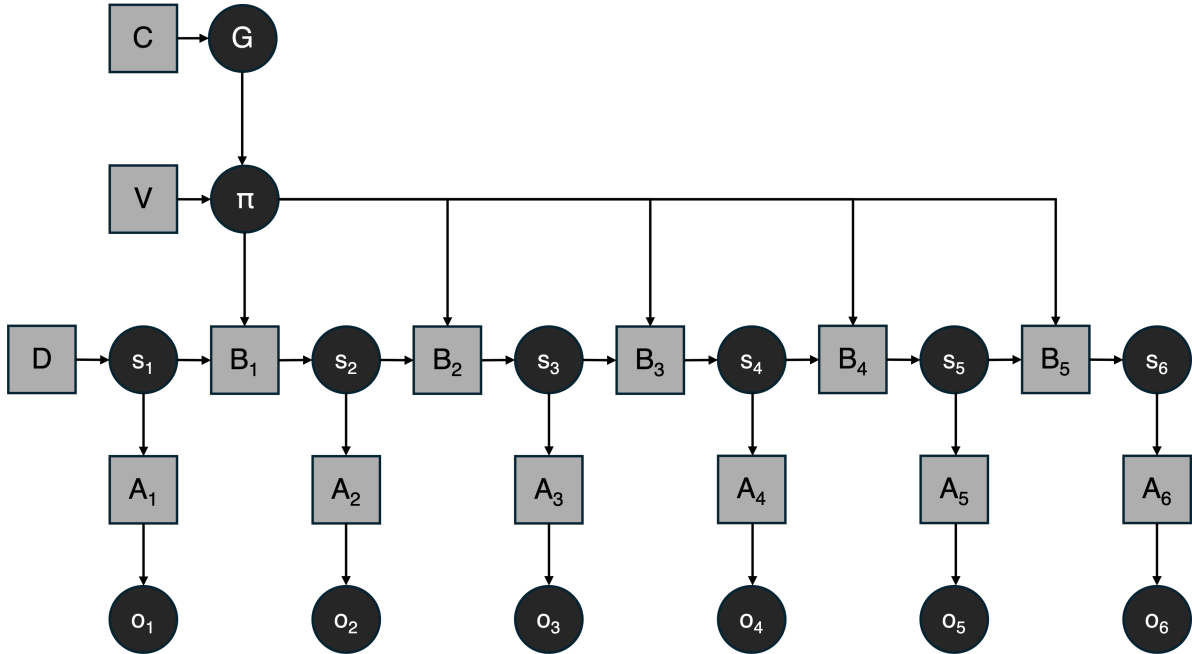
To solve the task, we endowed the agent with five possible policies (i.e., sequences of actions). The first is a novice strategy that consists in picking the cue related to the ball twice (to increase confidence in the inferred state), then receiving the ball, sampling the cue related to the direction of the teammate’s run, and finally passing the ball toward the running teammate. This policy corresponded to the strategy predominantly used by novice participants in the experiment (Dehorne et al., 2025). The second policy reflected the strategy used by expert players. It consisted in sampling one cue about the ball and one about the running teammate, before receiving the ball and passing it to the running teammate. The remaining three policies were not empirically observed, but they were included in the model as plausible alternatives. The third and fourth policy consisted of sampling only one of the two available cues (either the ball cue or the run-direction cue), followed by receiving the ball and directly passing it. The fifth was a purely pragmatic strategy, involving no cue sampling: the agent

directly received and passed the ball. These five policies were encoded in the V^1 -matrix. Their prior probabilities were defined in the V^2 -matrix, with all policies assigned equal prior probability at the beginning of each trial.

Initial Setup of the POMDP

Each trial was modeled as a Partially Observable Markov Decision Problem (POMDP) comprising six timesteps. The structure of the generative model for one trial is presented in Figure 32. The first timestep corresponded to the beginning of the trial. During the next two timesteps, the agent could visit informational cues. Timestep four was the only time point at which the agent could receive the ball and obtain the associated reward. The final two timesteps allowed the agent either to pass the ball to the running teammate or to sample a cue regarding the direction of the teammate's run. If the ball was passed at timestep five, the agent returned to the starting state at timestep six. In our simulation, the agent could not update their prior beliefs from trial to trial.

Figure 32: Structure of the partially observable Markov decision process model (POMDP) used for the football task



Note. The circular nodes represent random variables, whereas squares represent parameters of the generative model. Hidden state (s) generate observations (o) at each of the six timesteps of the trial. A represents the likelihood mapping between states and observations. B specifies the beliefs about state transitions, which encodes action-dependent state dynamics. D contains the

priors about initial states. Policies (π) are sequence of actions, defined by V , that are selected based on their expected free energy (G). C contains the prior preferences over observations that influence policy selection through G .

The D vectors present the probability of starting in a given state and the probability of being in a given context. In our task, agents were always starting in the starting position, for which the first state was associated. Thus, the first D vector take the following form:

$$D^1 = [1, 0, 0, 0, 0, 0, 0]^T$$

We also set the second D vector so that the four contexts had the same probability of occurrence and could not be updated from trial to trial:

$$D^2 = [1, 1, 1, 1]^T$$

A -matrices encode the likelihood mapping between states and observations, that is, the probability of observing an outcome given a hidden state. In our model, this mapping included both exteroceptive (A^1 -matrices) and interoceptive (A^2 -matrices) modalities (Figure 33). Depending on the context of the trial, the hidden states related to attending to the ball or to the teammate's run generated distinct observations. These observations could then inform action selection, enabling the agent to correctly receive the ball and pass it in the appropriate direction. We hypothesized that reducing the precision of the likelihood mapping would capture novice behavior. In this framework, lower likelihood precision corresponds to increased perceptual uncertainty, that is, making observations that are less reliable for inferring the underlying hidden state. For example, this would correspond to a novice player visually tracking the ball but using ambiguous or noisy cues about its trajectory. To test this hypothesis, we manipulated the precision of the likelihood mapping by adding noise in the A -matrices. We expected that increasing perceptual uncertainty would bias policy selection toward the sequential strategy previously associated with novice participants.

Figure 33: Example of A-matrices for one of the 4 contexts

$$\begin{array}{l}
 \begin{array}{c}
 \text{Start} \quad \text{Cue ball} \quad \text{Cue player} \quad \text{Ball location R} \quad \text{Ball location L} \quad \text{Player location R} \quad \text{Player location L} \\
 A^1 = \begin{bmatrix}
 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 1
 \end{bmatrix}
 \end{array}
 \begin{array}{l}
 \text{Cue start} \\
 \text{Cue ball location R} \\
 \text{Cue ball location L} \\
 \text{Cue player location R} \\
 \text{Cue player location L} \\
 \text{Ball location R} \\
 \text{Ball location L} \\
 \text{Player location R} \\
 \text{Player location L}
 \end{array} \\
 \\
 A^2 = \begin{bmatrix}
 1 & 1 & 1 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 1 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 1 & 0 & 1
 \end{bmatrix}
 \begin{array}{l}
 \text{Reward neutral} \\
 \text{Reward positive} \\
 \text{Reward negative}
 \end{array}
 \end{array}$$

Note. The context represents the ball coming on the right and the running player going to the right. The first matrix presents the probability mapping of states with exteroceptive cues (A^1), and the second with interoceptive cues (A^2).

B^1 -matrices encodes the state transition probabilities, that is, the probability of transitioning to a subsequent hidden state given the current state and the selected action (Figure 34). These matrices therefore reflect the agent's beliefs about how actions influence state dynamics. By introducing noise into B^1 -matrices, we increased uncertainty about action-dependent state transitions, that is, uncertainty regarding the consequences of the agents' actions. We hypothesized that a lower transition precision would capture key aspect of novice performance. In behavioral terms, novice participants lower technical skill may render action outcomes less predictable. For example, the direction of their pass could occasionally deviate from the intended one. To test this hypothesis, we manipulated the precision of the transition probabilities and predicted that increasing uncertainty about action outcomes would bias policy selection toward the sequential strategy associated with novice behavior.

Figure 34: Example of B-matrices for two of the seven possible actions.

$$\begin{aligned}
 B_{\pi(\tau)=1}^1 &= \begin{array}{c} \begin{matrix} \text{Start} & \text{Cue ball} & \text{Cue player} & \text{Ball location R} & \text{Ball location L} & \text{Player location R} & \text{Player location L} \end{matrix} \\ \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{l} \text{Start} \\ \text{Cue ball} \\ \text{Cue player} \\ \text{Ball location R} \\ \text{Ball location L} \\ \text{Player location R} \\ \text{Player location L} \end{array} \\
 B_{\pi(\tau)=2}^1 &= \begin{array}{c} \begin{matrix} \text{Start} & \text{Cue ball} & \text{Cue player} & \text{Ball location R} & \text{Ball location L} & \text{Player location R} & \text{Player location L} \end{matrix} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{l} \text{Start} \\ \text{Cue ball} \\ \text{Cue player} \\ \text{Ball location R} \\ \text{Ball location L} \\ \text{Player location R} \\ \text{Player location L} \end{array}
 \end{aligned}$$

Note. The matrices present the transition probabilities for transition between the possible states. The first matrix corresponds to moving to the starting location ($B^1\pi(\tau)=1$). The second matrix corresponds to obtaining cue about the ball location ($B^1\pi(\tau)=2$). In both cases, agents are certain to be in a particular state on the next timestep due to their action.

A second B-matrix encodes the probability of transitions between contexts from one timestep to the next within a trial (Figure 35). In our task, context remained constant over time, such that this matrix was an identity matrix.

Figure 35: Presentation of the B-matrix about context transition.

$$B_{\pi(\tau)}^2 = \begin{array}{c} \begin{matrix} \text{Context 1} & \text{Context 2} & \text{Context 3} & \text{Context 4} \end{matrix} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array} \begin{array}{l} \text{Context 1} \\ \text{Context 2} \\ \text{Context 3} \\ \text{Context 4} \end{array}$$

Note. It shows that context stays constant over time.

The C-matrices encode the prior preferences over observations across the six timesteps of each trial (Figure 36). These preferences specify the relative value assigned to different outcomes and shape policy selection through the minimization of expected free energy, primarily via its pragmatic (reward-seeking) component. In the first C matrix (C^1 in Figure 7), we specified a strong preference for receiving the ball at timestep four. This constraint was introduced to simulate the requirement that the agent commit to a decision regarding the ball reception at that specific time point, and prior to pass the ball. The goal was to approximate the temporal structure of the real-world task. Then, the agents had two possible timesteps (five and six) to pass the ball. This temporal window enabled two distinct strategies: acting immediately (as generally observed in skilled players) or sampling additional information about the teammate’s position before passing the ball (as more generally observed in the novices).

We hypothesized that skilled performers would exhibit a stronger preference for rapid action, reflecting their capacity to operate efficiently under the spatiotemporal constraints imposed by opponents in real-game situations. Within the Active Inference framework, increasing the reward value associated with passing at time step five raises the expected utility of immediate action. In this sense, higher positive reward values can be interpreted as promoting a form of risk-seeking behavior, as the agent becomes more inclined to commit to an early pass without fully resolving uncertainty about the teammate’s position. Conversely, lower reward values reduce the incentive for immediate action and relatively increase the contribution of epistemic value, thereby favoring information-seeking strategies. To test this hypothesis, we manipulated the value of the reward at time step five in the second preference matrix (C^2 in Figure 36), expecting that it would shift the balance between rapid, skilled-like performance, and sequential, information-seeking (novice-like) behavior.

Figure 36: Presentation of the two C-matrices.

$$\begin{array}{l}
 \begin{array}{c} \tau=1 \quad \tau=2 \quad \tau=3 \quad \tau=4 \quad \tau=5 \quad \tau=6 \\
 C^1 = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{array}{l} \text{Cue start} \\ \text{Cue ball location R} \\ \text{Cue ball location L} \\ \text{Cue player location R} \\ \text{Cue player location L} \\ \text{Ball location R} \\ \text{Ball location L} \\ \text{Player location R} \\ \text{Player location L} \end{array} \\
 C^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 3 & 1 \\ -1 & -1 & -1 & -1 & -1 & -1 \end{bmatrix} \begin{array}{l} \text{Reward neutral} \\ \text{Reward positive} \\ \text{Reward negative} \end{array}
 \end{array}
 \end{array}$$

Note. The C^1 matrix presents the prior preferences over outcomes. Agent does not like to be at the starting position at timesteps 1-5. The agent likes to be at the ball locations at timestep 4, and at the player locations at timesteps 5-6. The C^2 matrix presents the prior preferences for neutral, attractive and aversive stimuli. The positive stimulus becomes attractive at timesteps 4,5 and 6. But, its higher value on timestep 5 compared to 6 should promote passing the ball at timestep 5.

Procedure of the Simulations

We used the generative model described above to simulate policy selection in the football task. For each parameter configuration, simulations were run with 50 virtual agents, each performing 40 trials (10 trials in each of the four contexts, presented in randomized order).

In a first set of simulations, we manipulated the prior preferences over outcomes (C^2 -matrix). Specifically, we progressively increased the reward value at timestep five. The reward value was varied from 1 (indicating no preference between passing the ball at timestep five or six) to 6 (strong preference for passing the ball immediately after receiving it). Based on the results of this set of simulations, three representative levels of prior preferences were selected for subsequent simulations related to (i) beliefs about action consequences and, (ii) perceptual uncertainty.

Transition precision was progressively reduced by introducing noise into the B^1 -matrices. We began with maximal precision, corresponding to the deterministic transition structure

shown in Figure 34. We then reduced the probability of the most likely state transition by .02 across four steps (i.e., probabilities of 1 were replaced by .98, .96, .94, and .92, respectively). The remaining probability was distributed across alternative transitions such that each column of the transition matrices continued to sum to one.

Perceptual uncertainty over exteroceptive signal was progressively increased by introducing noise in the A^1 -matrices. As with the transition matrices, we began with a noise-free likelihood mapping (Figure 33) and applied the same procedure as described for the B^1 -matrices, reducing the probability of the most likely observation and redistributing probability across alternative outcomes.

For each parameter configuration, we recorded (i) the sequence of action performed by the virtual agent (i.e., the selected policy on each trial), (ii) decision accuracy (i.e., whether the agent successfully received the ball and passed it to the teammate) and (iii) the total reward accumulated over the 40 trials, expressed relative to the maximum achievable reward under the specified prior preferences.

Results

Manipulation of Prior Preferences over Observations

We progressively increased, in the C^2 matrix, the reward value for passing the ball at timestep five. With respect to policy selection, we observed a clear threshold at a reward value of 3 (Figure 37A). For reward values of 1 and 2, virtual agents exclusively selected the sequential (novice-like) strategy. In contrast, for reward values ranging from 3 to 6, agents exclusively selected the expert strategy, characterized by rapid passing following ball reception.

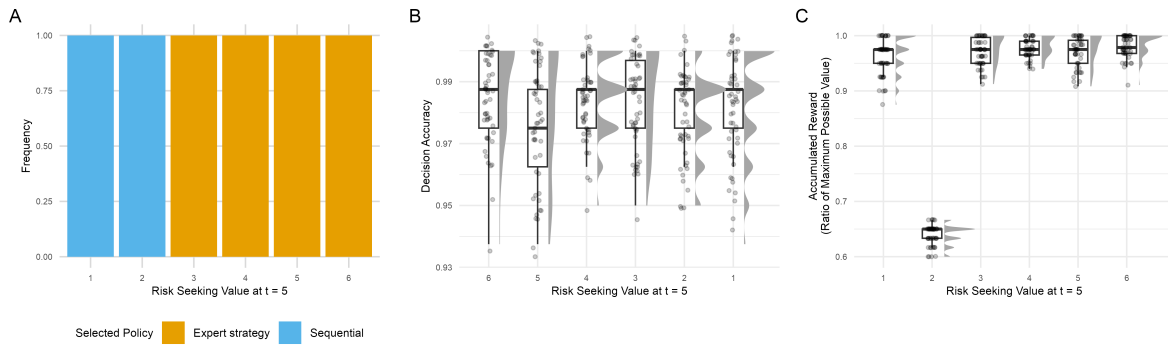
The shift in strategy did not significantly affect decision accuracy across conditions (Figure 37B), $F(5,294) = 1.64$, $p = .149$, $\eta^2 = .03$. Overall, agents successfully received the ball and passed it in the correct direction in the vast majority of trials ($M = 98.1\%$, $SD = 1.5\%$).

However, when the reward value at time step five was set to 2, selection of the sequential strategy was suboptimal in terms of total reward obtained relative to the maximum achievable reward ($M = 63.9\%$, $SD = 1.8\%$, Figure 37C). This performance was significantly lower than in all other conditions, $F(5,294) = 1617$, $p < .001$, $\eta^2 = .97$ (all post hoc comparisons between

the reward value of 2 and other conditions: $ps < .001$ and $ds > 13$). Two additional, comparatively small post hoc differences were observed between the reward value of 1 and reward values of 4 ($p = .017$, $d = 0.66$) and 6 ($p = .002$, $d = 0.79$). Detailed results of the post hoc tests are provided in the Supplementary Material.

Based on these results, we selected three representative levels of prior preferences for subsequent simulations: (i) a constant reward value across timesteps, (ii) a medium reward value at timestep five (value of 3), promoting rapid performance and consistent selection of the expert strategy, and (iii) a high reward value at timestep five (value of 5), strongly favoring immediate passing and the expert-like behavior.

Figure 37: Policy selection (A), decision accuracy (B) and reward obtained (C) under different values of positive reward at timestep five.



Manipulation of Beliefs about Transition Dynamics

For the three selected levels of positive reward at timestep five, we progressively reduced transition precision by introducing noise into the B^1 -matrices. When reward values were held constant across timesteps, the sequential strategy remained the dominant policy, even at the highest levels of transition noise (Figure 38A). However, increased noise induced occasional stochastic selection of alternative policies across trials, suggesting reduced confidence in action-dependent state transitions.

Under medium and high reward values at time step five, reducing transition precision induced a clear shift in policy selection (Figure 38D and 38G, respectively). Specifically, agents initially selected the expert strategy under high precision, but progressively reverted to the sequential strategy as transition noise increased. Notably, this transition occurred at higher noise levels under the high-reward condition compared to the medium-reward condition

(Transition precision of .96 and .98, respectively), indicating that stronger prior preferences for rapid passing partially compensated for reduced confidence in action outcomes.

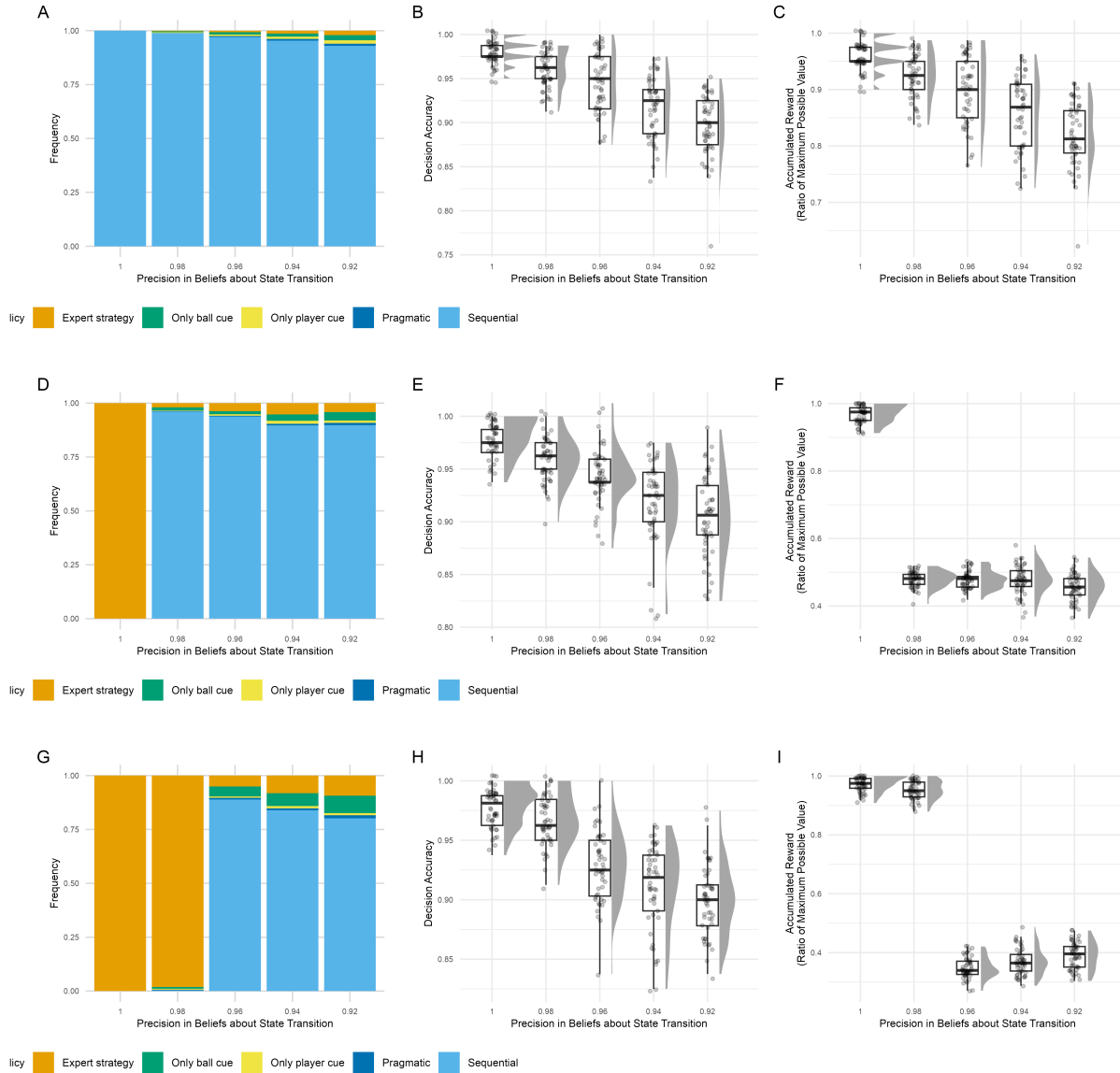
Increasing transition noise significantly impaired decision accuracy, irrespective of the level of reward manipulation (Figure 38B, 38E and 38H). Accuracy declined monotonically as noise increased, dropping from approximately 98% in the absence of noise to 90% at the lowest level of precision (.92). Detailed statistics of the ANOVAs are provided in Table 7, and results of the post hoc tests are provided in the Supplementary Material.

Table 7: One-way analyses of variance in decision accuracy and proportion of reward collected under the three levels of prior preferences for passing at timestep 5.

Measure and Level of Prior Preference at $\tau = 5$	$F(4,245)$	p	η^2
Decision Accuracy			
Constant reward	68.6	< .001	.53
Medium reward	50.3	< .001	.45
High reward	81.1	< .001	.57
Proportion of Reward Collected			
Constant reward	58.7	< .001	.49
Medium reward	2294	< .001	.97
High reward	3909	< .001	.99

With constant reward values, the proportion of reward collected decreased as transition noise increased (Figure 38C), consistent with the observed decline in decision accuracy. In contrast, under medium and high reward conditions (i.e., when risk-seeking was promoted), reward collection exhibited a sharp decline when agents shifted away from the expert strategy toward the sequential strategy (Figure 38F and 38I, respectively). This reduction reflects the temporal structure of outcome preferences: under these conditions, passing at timestep six remained rewarding but yielded a lower value than passing at timestep five. Consequently, deviations from rapid action were disproportionately penalized in high reward contexts. Results also revealed that the proportion of reward collected significantly increased from transition precision value of .96 to .92. This appeared also related to increased proportion of selection of policy related to rapid action.

Figure 38: Policy selection, decision accuracy and reward obtained under different level of noise in beliefs about action consequences.



Note. Panels A, B and C present results under constant value of positive reward. Panels D, E and F show results under medium reward value at timestep five. Panels G, H and I show results under high reward value at timestep five.

Manipulation of Perceptual Uncertainty

When introducing noise into the A^1 -matrices across the three levels of risk-seeking at timestep five, a distinct pattern of policy selection emerged compared to the manipulation of transition precision. Under constant value of reward, the sequential strategy remained the dominant policy regardless of the level of perceptual uncertainty (Figure 39A). However, increasing perceptual uncertainty up to .94 led to a progressive decline in decision accuracy

(Figure 39B) and in the proportion of reward collected (Figure 39C), consistent with reduced reliability of sensory evidence for inferring hidden states. Detailed statistics of the ANOVAs are provided in Table 8, and results of the post hoc tests are provided in the Supplementary Material.

Table 8: One-way analyses of variance in decision accuracy and proportion of reward collected under the three levels of prior preferences for passing at timestep 5.

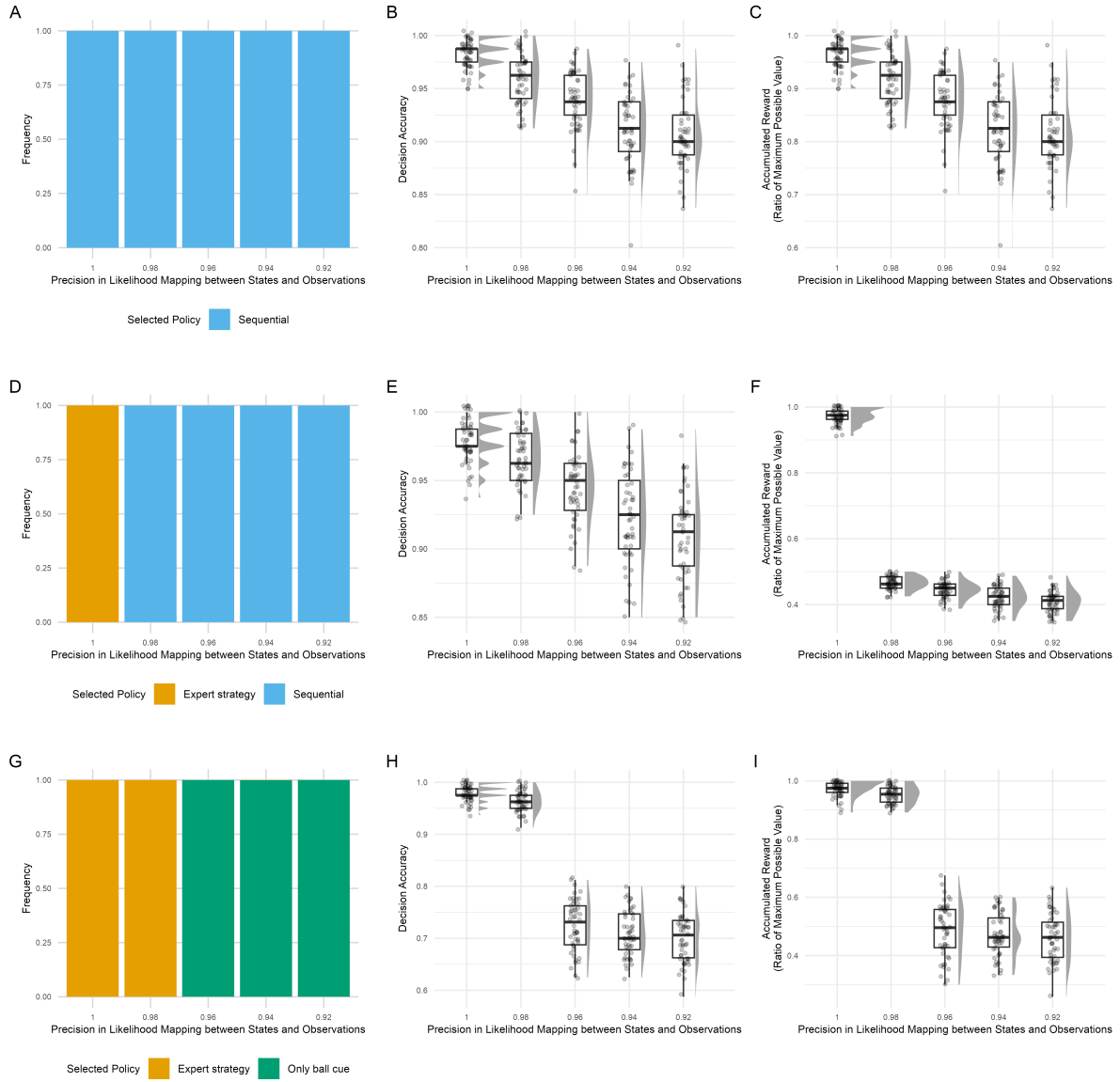
Measure and Level of Prior Preference at $\tau = 5$	$F(4,245)$	p	η^2
Decision Accuracy			
Constant reward	71.3	< .001	.54
Medium reward	62.7	< .001	.51
High reward	726	< .001	.92
Proportion of Reward Collected			
Constant reward	71.3	< .001	.54
Medium reward	3875	< .001	.98
High reward	3909	< .001	.99

Under the medium reward condition, even the lowest level of perceptual noise tested was sufficient to induce a shift from the expert strategy to the sequential strategy (Figure 39D). This transition in policy selection was accompanied by a marked decrease in the proportion of reward collected (Figure 39F). After this transition, the proportion of reward collected continued to decrease as the perceptual uncertainty increased, but with a lower magnitude. Decision accuracy also progressively declined as perceptual uncertainty increased (Figure 39E).

Finally, under the high risk-seeking condition, increasing perceptual noise also led to a transition away from the expert strategy (Figure 39G). However, in this case, the alternative policy selected was not the fully sequential strategy. Instead, agents adopted an intermediate strategy: sampling only the cue related to ball trajectory prior to receiving the ball, and then passing immediately at timestep five without sampling information about the teammate's running direction. This shift suggests a reconfiguration of the exploration–exploitation balance under high preference for immediate passing. As perceptual precision decreased, agents appeared to preserve rapid action (to secure the higher reward at time step five) while reducing information sampling related to the teammate's movement. This change in strategy

was associated with a significant drop in both decision accuracy (Figure 39H) and proportion of reward collected (Figure 39I), particularly at the noise level corresponding to the policy transition.

Figure 39: Policy selection, decision accuracy and reward obtained under different level of perceptual uncertainty.



Note. Panels A, B and C present results under constant value of positive reward. Panels D, E and F show results under medium reward value at timestep five. Panels G, H and I show results under high reward value at timestep five.

Discussion

The present study examined whether a POMDP model developed within the Active Inference framework could reproduce the qualitative difference in visual exploration strategies observed between expert and novice football players, and identify the computational parameters responsible for this difference. Three sets of simulations focused on prior preferences over outcomes, the precision of beliefs about action-dependent state transitions, and the reliability of exteroceptive sensory signals. Results showed that the expert strategy of anticipatory exploration emerges when agents combine a strong preference for rapid task resolution with sufficiently precise generative models. Each of these components contributes independently to policy selection, but their interactions reveal a richer account of expertise than any single parameter could provide.

The most relevant result of the first simulation set was the importance of the transition in policy selection as a function of the reward value assigned to passing at timestep five. Below a threshold of 3, agents exclusively adopted the sequential strategy characteristic of novices; above it, they exclusively adopted the proactive strategy characteristic of experts. This threshold-like behaviour suggests that the expert–novice distinction is not a matter of degree but of qualitatively different attractor states in the policy space, a finding that aligns with the observation that expert and novice players in the empirical study (Dehorne et al., 2025) showed largely non-overlapping distributions of gaze behaviour rather than a continuum. Crucially, the strategy shift had minimal impact on decision accuracy, which remained high across all reward levels, but carried substantial consequences for total reward collected: agents at reward value 2 didn't collected the maximum achievable reward, a cost that does not result from incorrect decisions but from the temporal inefficiency of the sequential strategy itself. This dissociation between accuracy and reward efficiency is theoretically important, in fact it implies that novice strategies are not simply less accurate, but less adapted to the temporal structure of the task, a structure that in real competitive contexts is regulated by the constraints imposed by opponents, pressing, and time pressure. Under this interpretation, the higher C-matrix values that produce expert-like behaviour in the model are not innate but learned, reflecting the internalization of competitive constraints through extensive practice, gradually raising the subjective cost of delayed action until rapid passing becomes the dominant policy.

The second set of simulations revealed that degrading the precision of beliefs about action-dependent state transitions was sufficient to shift agents from expert to novice strategies, but only when prior preferences already favoured rapid action. When reward values were held constant, that is, when the model was oriented in a novice-like configuration, increasing transition noise had no qualitative effect on policy selection. This asymmetry is theoretically meaningful, it implies that uncertainty about action consequences is not, by itself, a sufficient explanation for novice behaviour. Rather, transition noise interacts with prior preferences in a multiplicative fashion, it degrades the expert strategy from within, but only if that strategy was already being selected. The additional finding that agents under high reward conditions tolerated higher transition noise before reverting to sequential behaviour than those under medium reward conditions further supports this interpretation, stronger outcome preferences partially buffer against motor uncertainty, effectively extending the range of conditions under which the expert strategy remains viable. In behavioural terms, this suggests that the well-documented superiority of expert motor execution, more consistent passing trajectories, more reliable body positioning, may function not merely as a performance advantage but as a stabilizing force that protects the anticipatory gaze strategy from collapsing under uncertainty.

The third simulation set produced the most theoretically new result of the study. Under medium reward conditions, even the smallest level of perceptual noise tested was sufficient to shift agents away from the expert strategy, suggesting that the anticipatory parallel-sampling policy is particularly sensitive to the reliability of sensory information. This sensitivity reflects the epistemic logic of the model, the expert strategy commits to sampling one cue about each information source in rapid succession, which is only advantageous if each observation reliably reduces uncertainty about the corresponding hidden state. When sensory signals become noisy, a single observation is no longer sufficient to infer the hidden state with confidence, making the additional sampling steps of the sequential strategy relatively more attractive. More surprisingly, under high reward conditions, perceptual noise did not drive agents toward the fully sequential strategy but toward a qualitatively distinct intermediate strategy, sampling only the ball-related cue before receiving and passing immediately, without acquiring any information about the teammate's running direction. This reconfiguration reveals an important asymmetry in how the two sources of uncertainty are weighted under strong preferences for rapid action, when the pragmatic pressure to act quickly is high, agents prioritize resolving the uncertainty most directly coupled to the proximal motor demand while sacrificing information about the more distal component of the task. The consequence is a

marked drop in decision accuracy, as agents commit to a pass direction without having sampled the information needed to make that decision correctly. This pattern resonates with observations from the sport science literature on performance under extreme time pressure, and raises the possibility that certain failures in expert behaviour observed under fatigue or high-pressure conditions may reflect rational reconfigurations of information-seeking under altered cost functions, rather than simple failures of attention or motor control.

Taken together, these results support a multi-component account of perceptual-cognitive expertise in which prior preferences, transition precision, and sensory reliability make distinguishable and partially independent contributions to policy selection. Within the Active Inference framework, these three components map onto distinct aspects of the generative model. The C-matrices encode what the agent wants, the B-matrices encode what the agent believes its actions will do, and the A-matrices encode what the agent expects to perceive. The present findings suggest that expert behaviour requires all three components to be sufficiently well-calibrated, and that degradation in any one of them can be partially compensated by the others, but only up to a point. This picture is more nuanced than accounts that attribute expertise primarily to superior perceptual sensitivity or to more efficient motor execution alone, and it highlights the role of outcome preferences, arguably the most underexplored dimension in the existing computational literature on sport expertise, as a central organizing principle of skilled behaviour.

Conclusion

The present study demonstrates that a POMDP model within the Active Inference framework can successfully reproduce the qualitative contrast between expert and novice visual sampling strategies in an ecologically valid football task. Expert-like behaviour emerged when agents combined high prior preferences for rapid action with sufficiently precise beliefs about both sensory observations and action consequences. Importantly, perceptual noise and transition uncertainty did not produce equivalent effects. In fact, degrading sensory reliability under high reward pressure led to a novel intermediate strategy not observed under transition noise, revealing a systematic reconfiguration of the exploration-exploitation balance with direct implications for understanding expert performance under adverse conditions. More broadly, these findings suggest that the computational signature of motor expertise cannot be reduced to a single parameter but reflects the joint calibration of preferences, motor beliefs, and perceptual models, a conclusion that points toward new directions for both basic research and applied interventions in perceptual-cognitive training.

The computational modelling work presented in Chapter 3 provided answers to the third research question formulated in Chapter 1, namely, whether the visual exploration patterns observed empirically in Chapter 2 can be formally reproduced and explained within a principled computational framework. By adapting the classic T-maze POMDP to the structure of our football dual-task, we demonstrated that an Active Inference agent, when appropriately parameterized, spontaneously generates the qualitative contrast between expert and novice gaze strategies without requiring those strategies to be explicitly programmed. The expert pattern of proactive strategy emerged when agents combined a strong preference for rapid task resolution with sufficiently precise generative models, while the sequential strategy characteristic of novices appeared naturally under lower reward values or degraded model precision.

Beyond this core validation, the simulations revealed a richer picture than a simple binary opposition between expert and novice behaviour. The three manipulated parameters, prior preferences over outcomes, transition precision, and sensory reliability, produced distinguishable and partially independent effects on policy selection, and their interactions generated qualitatively novel predictions. In particular, degrading perceptual precision under high reward pressure did not merely shift agents toward the novice strategy but induced a distinct intermediate strategy in which ball-related information was sampled at the expense of information about the teammate's movement, a reconfiguration of the exploration-exploitation balance that suggests certain failures in expert performance may be better understood as rational adaptations to altered cost functions than as attentional failures. This finding was not anticipated from the empirical data alone and illustrates the generative power of formal modelling: by making the underlying assumptions explicit and manipulable, the model produces predictions that go beyond what observation can directly reveal.

Taken together, the three chapters of this thesis form a coherent and progressive argument. Chapter 1 identified the theoretical framework and the empirical gaps motivating the present work. Chapter 2 filled the first two gaps by characterizing, with fine temporal resolution, the dynamics of attentional allocation in expert and novice footballers and by demonstrating the specific effects of mental fatigue on these strategies. Chapter 3 addressed the third gap by formalizing, through simulation, the computational principles that generate the observed behavioural patterns. Each layer of analysis, descriptive, experimental, and computational, has both answered specific questions and raised new ones, the most important of which concern

the extent to which the present findings generalize beyond the specific task and population studied here, and what they imply for the design of perceptual-cognitive training interventions. These questions structure the general discussion that follows.

5. General Discussion

This doctoral thesis set out to address three interconnected gaps that a systematic meta-analysis of 90 studies had identified as structuring the current literature on perceptual-cognitive expertise in sport. The first was the near-total absence of temporal characterization of attentional allocation in ecological dual-task situations, a gap that rendered the existing literature descriptively rich, but unable to say not merely where experts look but when they redirect their gaze relative to the unfolding demands of the task. The second was the absence of experimental investigation of mental fatigue effects on sophisticated perceptuo-cognitive strategies in ecological contexts. This gap that was, in retrospect, surprising given the centrality of fatigue to competitive performance and the theoretical questions it could resolve about the cognitive architecture of expertise. The third was the absence of formal computational models capable of generating quantitative mechanistic predictions about observed attentional allocation patterns, leaving the field in a position of describing what experts do without being able to specify, in mathematically precise terms, how and why they do it.

What is perhaps most important to recognize, before examining each contribution individually, is that these three gaps were not independent. They formed a coherent set of lacks that together prevented the field from moving beyond phenomenological description toward mechanistic understanding. The temporal gap meant that even the most ecologically valid behavioral studies could not identify the cognitive decision that distinguishes expert from novice performance, the decision of when to switch attention from an ongoing task before its completion. The fatigue gap meant that the nature of the cognitive resources underlying this decision remained untested. One could postulate that expertise involved more precise internal models, but without knowing whether the strategies survived resource depletion, one could not determine whether those models operated automatically or required continuous executive engagement. And the computational gap meant that even if both empirical gaps were filled, the resulting behavioral data would remain open to multiple competing theoretical interpretations, each consistent with the observations but none formally adjudicated.

The three chapters of this thesis addressed these gaps in sequence. The temporal characterization of Chapter 2's first study generated the behavioral results that Chapter 2's second study then probed for robustness, and that Chapter 3 then sought to explain. The

mental fatigue dissociation between preserved timing and degraded processing efficiency constrained the space of viable computational accounts, ruling out models in which the timing decision is controlled and resource-dependent while pointing toward models in which it is at least partially automatized. And the computational model of Chapter 3 provided the formal machinery to distinguish between candidate explanations that the behavioral data alone could not separate, in particular, the respective contributions of prior preferences, motor beliefs, and sensory reliability to the emergence of expert-like policy selection. Read as a whole, the thesis constitutes an argument rather than a collection of studies, in fact, each chapter answers a question that the previous chapter had opened, and the general picture that emerges is more than the sum of its parts.

That general picture can be stated as follows. Expert performance in visually guided dual-task situations reflects the joint calibration of three computational components: an internal preference structure that assigns high value to temporal efficiency, sufficiently precise beliefs about the consequences of one's own motor actions, and reliable sensory models that extract meaningful information from each observation. When all three components are adequately calibrated, as they are in expert performers shaped by thousands of hours of competitive practice, the system naturally selects proactive strategies that optimize both decision quality and temporal efficiency. When any one of these components is degraded, the system reconfigures, sometimes gracefully and sometimes with substantial costs to accuracy and reward. The following sections develop this argument in detail, situating each layer of evidence within the broader theoretical context and drawing out the implications that could not have been reached from any single methodological perspective.

5.1. Temporal Dynamics of Attentional Allocation: Beyond Aggregated Metrics

Expert players in Experiment 1 shifted their attention from the incoming ball toward the running teammate approximately 1600 milliseconds before ball reception, an anticipatory reallocation that, in a substantial proportion of trials, occurred before ball reception had been completed. Novice players maintained visual contact with the ball until reception was secured, shifting attention toward the pass target only afterward in a reactive, sequential pattern. This temporal offset of approximately one second is not a trivial difference. In a dual-task scenario constrained by opponents, pressing, and the dynamics of the developing game, one second

represents the difference between a pass executed with full information about the target's movement and a pass executed without confirmatory evidence about where to direct it.

At a theoretical level, the temporal offset between expert and novice attentional reallocation is precisely what the active inference framework predicts. Agents equipped with more precise internal predictive models require fewer confirmatory observations before uncertainty about the ongoing task falls below the threshold at which redirecting attention becomes more valuable than continued monitoring. Experts, through thousands of hours of competitive practice, have refined their internal models of ball trajectory and timing to a point where early visual evidence is sufficient to constrain predictions with high confidence. They redirect attention earlier not because they process information faster, but because their predictions are more precise and therefore require less empirical confirmation. This interpretation aligns with work in computational motor neuroscience demonstrating that skilled movement depends critically on internal forward models predicting the sensory consequences of actions (Wolpert et al., 1995; Kawato, 1999; Shadmehr & Krakauer, 2008). The expert's ability to reallocate attention before ball reception is not a separate cognitive achievement superimposed on ball control, it is a consequence of the same predictive modelling that enables confident ball control in the first place, which is why technical expertise and sophisticated gaze behaviour co-develop rather than independently.

The middle condition of the paradigm, where the pass had to be directed back toward the initial passer, provided particularly revealing evidence. Expert players completed this condition significantly faster, approximately 450 milliseconds compared to 900 milliseconds in the lateral conditions, and extended their exploratory phase by approximately 75 milliseconds. When the pass target decision is resolved before ball reception, experts reallocate their additional visual capacity toward confirmation rather than discovery. Novices showed no significant difference across conditions, maintaining similar completion times and exploratory durations regardless of context, consistent with attentional strategies governed by habit rather than uncertainty-driven optimization.

5.2. Mental Fatigue and the Architecture of Expertise

Expert players under induced mental fatigue preserved the temporal structure of their anticipatory gaze strategies. In fact, they continued to initiate environmental scanning before ball reception, timing was not significantly delayed relative to the control condition, and the

fundamental distinction between anticipatory and sequential patterns was maintained. What changed under fatigue was processing efficiency: visual fixations became significantly longer, scanning durations increased, and total task completion time extended. The expertise advantage in temporal organization was preserved; the efficiency of information extraction within each attentional window was diminished.

This dissociation was not the only possible outcome. The timing degradation hypothesis, that mental fatigue would delay reallocation onset and reduce the temporal gap between groups, was grounded in substantial evidence that frontal executive functions are disproportionately sensitive to cognitive resource depletion (Boksem et al., 2005; Lorist et al., 2005). The efficiency degradation hypothesis required the stronger assumption that temporal coordination had been sufficiently automatized to operate independently of depleted resources. The empirical result unambiguously favoured the second hypothesis, providing direct evidence for a hierarchical architecture in which different levels of the same skilled behaviour show dissociable vulnerability to cognitive load.

This hierarchical structure extends the classic controlled-automatic processing distinction (Schneider & Shiffrin, 1977) in an important direction. The higher-level schema specifying when to reallocate attention has been sufficiently proceduralized to operate with minimal executive engagement, consistent with transfer to cortico-striatal habit systems across thousands of competitive encounters (Yin & Knowlton, 2006; Graybiel, 2008). Mental fatigue, associated with reduced prefrontal activation (Boksem et al., 2005), has limited impact on a decision no longer substantially dependent on those regions. Lower-level perceptual processing efficiency, however, retains resource sensitivity, degrading when sustained cognitive effort depletes the arousal systems supporting it.

This finding invites reconsideration of the deliberate practice framework (Ericsson et al., 1993). Practice does not merely accelerate existing processes, it transforms their computational substrate, transferring control from resource-dependent executive mechanisms to resource-independent procedural ones. The anticipatory gaze strategy has been sufficiently internalized to operate in a qualitatively different mode, one that survives the conditions of resource depletion under which effortful controlled processing breaks down.

The distinction between fatigue-induced slowing and pressure-induced reinvestment is equally important. The expert performance paradox (Beilock & Carr, 2001) proposes that under pressure, experts may reinvest attention in normally automatized processes, causing performance failure. Mental fatigue produces a qualitatively different profile, rather than disrupting strategic organization, it slows execution within a preserved strategic setting. These two forms of performance vulnerability call for distinct preparation strategies, and conflating them risks designing interventions that address the wrong mechanism.

5.3. A Computational Account of Expert Decision-Making

The behavioral findings of Chapter 2 established with considerable precision what expert and novice players do differently, and the mental fatigue results constrained the space of viable computational accounts by ruling out models in which the timing decision is purely resource-dependent. But behavioral data, however rich and temporally resolved, remain inherently ambiguous with respect to mechanism. The observation that experts shift gaze earlier is consistent with multiple underlying accounts: more precise internal models of ball trajectory, a stronger preference for temporal efficiency, more reliable beliefs about the consequences of actions, or some combination of these factors. Adjudicating between these accounts requires a formal modeling approach that can vary each candidate factor independently while holding others constant, something that experimental manipulation of human participants cannot cleanly achieve. This is the contribution of Chapter 3, and its results go considerably further than the validation exercise they might initially appear to be.

Active Inference (Friston, 2010; Parr et al., 2022) formalizes perception, action, and decision-making as processes of free energy minimization, in which agents maintain probabilistic generative models of their environment and select policies based on expected free energy. This quantity integrates the epistemic value of actions reducing uncertainty about hidden states and the pragmatic value of actions securing preferred outcomes. The distinction maps directly onto the dual challenge faced by players in the football task: balancing the epistemic value of gathering more information against the pragmatic value of acting quickly to secure the temporal reward associated with early passing. The POMDP extension of the T-maze paradigm developed in Chapter 3 translated this framework into a seven-state, dual-cue structure representing ball reception and teammate movement identification, a generalization

that required specifying the full generative model of the task and that gives the model its discriminative power.

The manipulation of prior preferences over outcomes revealed that the expert strategy emerges above a threshold in the reward assigned to early passing, and below this threshold, agents adopt the sequential novice strategy even with perfect sensory and motor precision. This threshold-like transition in policy space mirrors the distribution of visual exploration strategies documented in Experiment 1, suggesting that the expert-novice boundary observed on the field reflects a genuine bifurcation in the underlying preference landscape. A critical component of expertise is therefore not perceptual or motor but motivational, experts have internalized, through competitive practice, a preference structure that assigns substantially higher value to temporal efficiency, and this difference in what they want is sufficient to generate the qualitative strategy shift in the absence of any other parametric difference. The dissociation between decision accuracy, comparable across all reward levels, and reward efficiency, substantially lower at intermediate reward values, formalizes an intuition long held by elite sport practitioners. The difference between good and great performance in invasion sports is often not accuracy but timing, not whether the right action is eventually performed but whether it is performed at the right moment relative to the evolving constraints of the game situation.

The manipulation of transition precision revealed that motor uncertainty interacts with outcome preferences rather than acting as an independent driver of strategy selection. Degraded beliefs about action consequences shifted agents away from the expert strategy, but only when prior preferences already favoured rapid action. Under novice-level reward preferences, transition noise produced only stochastic variability without changing the dominant policy. Motor uncertainty is therefore not an independent explanation for novice behaviour. It destabilizes expert behaviour from within, but only when that behaviour is already being selected. Technical execution quality and attentional strategy are computationally coupled: improvements in motor reliability will stabilize expert-like gaze strategies across a wider range of challenging conditions.

The manipulation of sensory reliability produced the most theoretically new result of the thesis. Under medium reward conditions, even minimal perceptual noise was sufficient to shift agents toward the sequential novice strategy. Under high reward conditions, the same

degradation produced a qualitatively distinct intermediate strategy, ball-related information was sampled while information about the teammate's movement was entirely abandoned, with immediate passing at timestep five without any evidence about the target's running direction. This intermediate strategy was never observed in the empirical data and had not been predicted by any existing theoretical account. It demonstrates that the expert strategy, under conditions of strong preference for rapid action and degraded sensory reliability, does not simply fail, it reconfigures systematically, preserving the most proximal component of the task while sacrificing the most distal. This asymmetric information give up can be interpreted as a rational response to a cost function in which the penalty for delayed action outweighs the penalty for incomplete information, a cost function that arises in real competitive contexts when time pressure is extreme. Certain forms of performance failure observed in elite sport under fatigue or pressure may therefore reflect principled reconfiguration rather than attentional failure, with direct implications for how coaching interventions should be designed.

Taken together, the three simulation sets establish that perceptual-cognitive expertise is better understood as a configuration of attentional allocation than as a general increase in capacity. Rather than reflecting a single superior ability, better pattern recognition, faster processing, better anticipation, expert performance emerges from the joint calibration of preferences, motor beliefs, and sensory reliability, components that interact in specific ways and that are each independently vulnerable to degradation. This perspective also resolves a tension between Gibsonian ecological approaches, which rightly emphasize that perception in naturalistic contexts is active and tightly coupled to action, and predictive computational approaches, which specify the internal mechanisms regulating when and where that exploration is directed. These frameworks operate at different levels of analysis and should therefore be viewed as complementary rather than competing, the ecological paradigm constrains how performance should be studied, whereas active inference specifies how it is mechanistically explained.

5.4. Limitations and Future Directions

Like any empirical and modelling work, the present thesis involves a number of limitations that should be considered when interpreting its findings and that point to productive directions for future research.

The present findings are grounded in a specific sport, a specific task structure, and a sample of young male French players, which naturally raises questions about generalizability. Sample sizes, 23 expert and 21 novice players in Experiment 1, 13 experts in the mental fatigue study, were appropriate for the magnitude of the effects observed and consistent with standards in the sport expertise literature, but they do not allow examination of individual differences within expertise levels or potential moderating effects of gender, age, playing position, or cultural context. Whether the 1600 millisecond anticipation threshold, the specific fatigue-related changes, and the threshold reward value in the computational model hold across different populations and tactical systems represents a natural extension of this work rather than a fundamental constraint on its conclusions.

The computational model reflects deliberate modelling choices that future work can build upon. The five policies were defined to capture the strategies observed empirically, which was appropriate for the purpose of the present study but invites future work to test the model prospectively with a priori policy specifications and out-of-sample prediction. The absence of trial-by-trial learning dynamics means the model addresses the expression of expertise rather than its acquisition, a complementary question that longitudinal modelling approaches could address. Fitting model parameters to individual participant data rather than manipulating them systematically would further allow estimation of individual computational profiles and generate personalized predictions about performance vulnerability.

Several directions emerge naturally from these findings. Cross-domain validation is the most immediate priority, to test whether similar proactive strategies characterize expertise in other invasion sports, like basketball, rugby, hockey, handball, and whether the same computational framework accounts for cross-sport differences in timing and strategy would substantially strengthen the generality of the principles identified here. Beyond sport, the dual-task structure of the paradigm applies directly onto other domains involving competing informational demands under time pressure, including aviation, emergency medicine, and professional performance. The developmental trajectory of temporal attentional strategies represents a second important direction, the current cross-sectional design identifies the endpoint of expertise development but cannot characterize the path, whether the shift from reactive to proactive strategies is gradual or occurs in discrete qualitative reorganizations, and at what stages of competitive exposure it is most responsive to training. Finally, the hierarchical architecture suggested by the fatigue dissociation calls for direct neural

investigation. Combining mobile eye-tracking with portable neuroimaging approaches during natural task performance would allow identification of the neural signatures distinguishing the strategic timing decision from the perceptual processing operations it orchestrates, and would examine how each is affected by cognitive fatigue.

5.5. Practical Implications

The practical implications of this work are grounded in the specific mechanisms identified rather than in generic appeals to the importance of perceptual training, and this specificity is part of their value, because it generates testable predictions about which interventions should work and which should not.

The dominant approach to perceptual-cognitive training in sport has been to increase scanning frequency through instruction, video feedback, or task design rewarding exploration (Jordet, 2005; Pocock et al., 2019; Eldridge et al., 2023). The present results suggest that this quantitative emphasis misses the critical dimension, not how often players scan but when they redirect attention, and what internal conditions drive this decision. Interventions targeting frequency without addressing the underlying preference structure and predictive model precision that govern timing may produce players who scan more without scanning better, a distinction invisible to frequency-based measurement but clearly visible in temporally resolved analysis.

Effective training should instead target the three components identified by the computational model. Developing more precise internal predictive models requires exposing players to extensive variability in ball trajectories and contextual configurations under genuine time pressure, and not in simplified training exercises that separate ball control from environmental monitoring, but in representative dual-task scenarios that force simultaneous management of competing demands. Cultivating the preference for temporal efficiency requires repeated experience of the competitive consequences of delayed action, scenarios in which late passing is systematically penalized, rather than possession formats that reduce temporal pressure and remove the conditions making early commitment rewarding. Improving motor reliability in dual-task contexts simultaneously stabilizes attentional strategies by reinforcing the transition beliefs that protect against uncertainty, providing a mechanistic

account of why integrated technical and perceptual-cognitive training is more effective than training each component in isolation.

The findings on mental fatigue have similarly concrete implications for performance management. Players suffering from cognitive fatigue may appear strategically coherent whilst exhibiting slightly longer decision-making times, which could compromise their timing accuracy under extreme competitive pressure; this is a pattern that is invisible to conventional methods of monitoring physical load, but potentially detectable through high-temporal-resolution eye-tracking analysis. The implementation of gaze-based cognitive fatigue monitoring during training and competition could help identify players at risk of a decline in performance before this manifest as observable errors in results, thereby enabling proactive decisions regarding rotation and workload management.

For talent identification, assessing the temporal structure of gaze behaviour during representative dual-task scenarios offers a more sensitive and theoretically grounded methodology than accuracy-based video anticipation tests. Indeed, players showing early proactive strategies despite overall performance levels not yet matching experienced players demonstrate advanced perceptual-cognitive development that would justify specialized support. The computational model provides a principled basis for individualized assessment by identifying which specific parameter, preference structure, precision of motor belief or quality of the sensory model constitutes the main obstacle to each player's development.

These findings should be treated with a degree of caution. Training recommendations derived from a single experimental paradigm must be validated through randomized, controlled intervention studies before they can be widely adopted. This present work proposes a set of theory-based specific objectives, computational parameters that training aims to modify, as well as a formal framework for formulating verifiable predictions regarding the behavioural changes that should result.

6. Conclusion

This doctoral thesis was motivated by a deceptively simple observation: despite decades of research on perceptual-cognitive expertise in sport, the temporal dimension of attentional allocation during action had remained largely unexamined, the robustness of sophisticated gaze strategies under cognitive resource depletion had never been tested, and no formal computational model had been developed capable of generating quantitative mechanistic predictions about observed behavioral patterns. The systematic meta-analysis of 90 studies presented in Chapter 1 confirmed that these were not peripheral limitations of an otherwise complete field but structural gaps preventing progress from phenomenological description toward mechanistic understanding. The existing literature had accumulated rich knowledge about where experts look and how often, but the question of when they redirect their attention, and why, had not been formally addressed.

The three chapters of the thesis addressed these gaps in sequence. The first experimental study, conducted using mobile eye-tracking in an ecologically representative football dual-task, established that expert players reallocate their attention from the incoming ball toward the pass target approximately 1600 milliseconds before ball reception, while novice players adopt a reactive sequential strategy, waiting until reception is complete before scanning the environment. This temporal offset proved largely invisible to the aggregated metrics prevalent in the existing literature. The second experimental study showed that this anticipatory timing survives induced mental fatigue while lower-level processing efficiency degrades, a dissociation providing direct evidence for a hierarchical architecture in which the strategic timing decision has been sufficiently automatized through practice to operate independently of the executive resources depleted by fatigue. The third study developed and tested a Partially Observable Markov Decision Process model within the Active Inference framework, demonstrating that the expert-novice contrast emerges naturally from the joint configuration of prior preferences over action timing, precision of beliefs about action consequences, and reliability of exteroceptive sensory signals. Beyond reproducing observed behavioral patterns, the model generated a novel prediction, an intermediate strategy arising under high reward pressure combined with degraded sensory reliability, illustrating the generative capacity of formal computational modelling to produce predictions that behavioral research alone cannot reach.

The questions this work leaves open are as important as those it has answered. How these principles develop across competitive careers, whether they generalize beyond football to other high-stakes domains involving competing informational demands, and how they can be most effectively targeted through training interventions represent the natural next steps of a research programme that future research will need to address.

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Supplementary Materials

Appendix 1: Results of the post hoc tests for the proportion of reward collected when manipulating prior preferences over outcomes

Reward Value at $\tau = 5$		Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
condition	condition						
1	- 2	0.32200	0.00478	294	67.352	<.001	13.4705
	- 3	-0.00950	0.00478	294	-1.987	.718	-0.3974
	- 4	-0.01570	0.00478	294	-3.284	.017	-0.6568
	- 5	-0.00883	0.00478	294	-1.848	.985	-0.3695
	- 6	-0.01886	0.00478	294	-3.944	.002	-0.7889
2	- 3	-0.33150	0.00478	294	-69.340	<.001	-13.8679
	- 4	-0.33770	0.00478	294	-70.636	<.001	-14.1273
	- 5	-0.33083	0.00478	294	-69.200	<.001	-13.8400
	- 6	-0.34086	0.00478	294	-71.297	<.001	-14.2594
3	- 4	-0.00620	0.00478	294	-1.297	1.000	-0.2594
	- 5	6.67e-4	0.00478	294	0.139	1.000	0.0279
	- 6	-0.00936	0.00478	294	-1.957	.769	-0.3914
4	- 5	0.00687	0.00478	294	1.436	1.000	0.2873
	- 6	-0.00316	0.00478	294	-0.660	1.000	-0.1321
5	- 6	-0.01002	0.00478	294	-2.097	.553	-0.4193

Note. Comparisons based on estimated marginal means.

Appendix 2: Results of the post hoc tests for the decision accuracy when manipulating transition precision (under constant reward value).

Transition Precision								
condition	condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d	
0.92	- 0.94	-0.0225	0.00565	245	-3.98	<.001	-0.797	
	- 0.96	-0.0487	0.00565	245	-8.63	<.001	-1.726	
	- 0.98	-0.0635	0.00565	245	-11.24	<.001	-2.248	
	- 1.00	-0.0837	0.00565	245	-14.82	<.001	-2.965	
0.94	- 0.96	-0.0263	0.00565	245	-4.65	<.001	-0.929	
	- 0.98	-0.0410	0.00565	245	-7.26	<.001	-1.451	
	- 1.00	-0.0613	0.00565	245	-10.84	<.001	-2.168	
0.96	- 0.98	-0.0147	0.00565	245	-2.61	.096	-0.522	
	- 1.00	-0.0350	0.00565	245	-6.20	<.001	-1.239	
0.98	- 1.00	-0.0203	0.00565	245	-3.58	.004	-0.717	

Note. Comparisons based on estimated marginal means.

Appendix 3: Results of the post hoc tests for the proportion of reward collected when manipulating transition precision (under constant reward value).

Transition Precision		Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
condition	condition						
0.92	- 0.94	-0.0388	0.0101	245	-3.84	.002	-0.768
	- 0.96	-0.0783	0.0101	245	-7.75	<.001	-1.550
	- 0.98	-0.1050	0.0101	245	-10.40	<.001	-2.080
	- 1.00	-0.1395	0.0101	245	-13.82	<.001	-2.763
0.94	- 0.96	-0.0395	0.0101	245	-3.91	.001	-0.782
	- 0.98	-0.0662	0.0101	245	-6.56	<.001	-1.312
	- 1.00	-0.1007	0.0101	245	-9.98	<.001	-1.996
0.96	- 0.98	-0.0268	0.0101	245	-2.65	.086	-0.530
	- 1.00	-0.0613	0.0101	245	-6.07	<.001	-1.213
0.98	- 1.00	-0.0345	0.0101	245	-3.42	.007	-0.683

Note. Comparisons based on estimated marginal means.

Appendix 4: Results of the post hoc tests for the decision accuracy when manipulating transition precision (under medium reward value).

Transition Precision								
condition	condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d	
0.92	- 0.94	-0.0137	0.00596	245	-2.31	.219	-0.461	
	- 0.96	-0.0382	0.00596	245	-6.42	<.001	-1.283	
	- 0.98	-0.0547	0.00596	245	-9.18	<.001	-1.837	
	- 1.00	-0.0737	0.00596	245	-12.37	<.001	-2.474	
0.94	- 0.96	-0.0245	0.00596	245	-4.11	<.001	-0.822	
	- 0.98	-0.0410	0.00596	245	-6.88	<.001	-1.375	
	- 1.00	-0.0600	0.00596	245	-10.06	<.001	-2.013	
0.96	- 0.98	-0.0165	0.00596	245	-2.77	.061	-0.554	
	- 1.00	-0.0355	0.00596	245	-5.95	<.001	-1.191	
0.98	- 1.00	-0.0190	0.00596	245	-3.19	.016	-0.637	

Note. Comparisons based on estimated marginal means.

Appendix 5: Results of the post hoc tests for the proportion of reward collected when manipulating transition precision (under medium reward value).

Transition Precision		Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
condition	condition						
0.92	- 0.94	-0.02000	0.00652	245	-3.067	.024	-0.6134
	- 0.96	-0.02075	0.00652	245	-3.182	.017	-0.6364
	- 0.98	-0.02275	0.00652	245	-3.489	.006	-0.6977
	- 1.00	-0.50925	0.00652	245	-78.094	<.001	-15.6189
0.94	- 0.96	-7.50e-4	0.00652	245	-0.115	1.000	-0.0230
	- 0.98	-0.00275	0.00652	245	-0.422	1.000	-0.0843
	- 1.00	-0.48925	0.00652	245	-75.027	<.001	-15.0055
0.96	- 0.98	-0.00200	0.00652	245	-0.307	1.000	-0.0613
	- 1.00	-0.48850	0.00652	245	-74.912	<.001	-14.9824
0.98	- 1.00	-0.48650	0.00652	245	-74.606	<.001	-14.9211

Note. Comparisons based on estimated marginal means.

Appendix 6: Results of the post hoc tests for the decision accuracy when manipulating transition precision (under high reward value).

Transition Precision								
condition	condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d	
0.92	- 0.94	-0.0120	0.00534	245	-2.25	.256	-0.449	
	- 0.96	-0.0285	0.00534	245	-5.33	<.001	-1.067	
	- 0.98	-0.0667	0.00534	245	-12.49	<.001	-2.498	
	- 1.00	-0.0780	0.00534	245	-14.60	<.001	-2.920	
0.94	- 0.96	-0.0165	0.00534	245	-3.09	.022	-0.618	
	- 0.98	-0.0547	0.00534	245	-10.25	<.001	-2.049	
	- 1.00	-0.0660	0.00534	245	-12.35	<.001	-2.470	
0.96	- 0.98	-0.0382	0.00534	245	-7.16	<.001	-1.432	
	- 1.00	-0.0495	0.00534	245	-9.26	<.001	-1.853	
0.98	- 1.00	-0.0113	0.00534	245	-2.11	.363	-0.421	

Note. Comparisons based on estimated marginal means.

Appendix 7: Results of the post hoc tests for the proportion of reward collected when manipulating transition precision (under high reward value).

Transition Precision		Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
condition	condition						
0.92	- 0.94	0.0199	0.00735	245	2.71	.072	0.542
	- 0.96	0.0412	0.00735	245	5.61	<.001	1.123
	- 0.98	-0.5631	0.00735	245	-76.62	<.001	-15.324
	- 1.00	-0.5812	0.00735	245	-79.08	<.001	-15.816
0.94	- 0.96	0.0213	0.00735	245	2.90	.040	0.581
	- 0.98	-0.5830	0.00735	245	-79.33	<.001	-15.866
	- 1.00	-0.6011	0.00735	245	-81.79	<.001	-16.358
0.96	- 0.98	-0.6043	0.00735	245	-82.23	<.001	-16.446
	- 1.00	-0.6224	0.00735	245	-84.69	<.001	-16.938
0.98	- 1.00	-0.0181	0.00735	245	-2.46	.146	-0.492

Note. Comparisons based on estimated marginal means.

Appendix 8: Results of the post hoc tests for the decision accuracy when manipulating perceptual uncertainty (under constant reward value).

Precision in Likelihood Mapping								
condition		condition	Mean difference	Standard Error	dof	t	pbonferroni	Cohen's d
0.92	-	0.94	-0.00500	0.00534	245	-0.937	1.000	-0.187
	-	0.96	-0.03250	0.00534	245	-6.091	<.001	-1.218
	-	0.98	-0.05300	0.00534	245	-9.932	<.001	-1.986
	-	1.00	-0.07525	0.00534	245	-14.102	<.001	-2.820
0.94	-	0.96	-0.02750	0.00534	245	-5.154	<.001	-1.031
	-	0.98	-0.04800	0.00534	245	-8.995	<.001	-1.799
	-	1.00	-0.07025	0.00534	245	-13.165	<.001	-2.633
0.96	-	0.98	-0.02050	0.00534	245	-3.842	.002	-0.768
	-	1.00	-0.04275	0.00534	245	-8.012	<.001	-1.602
0.98	-	1.00	-0.02225	0.00534	245	-4.170	<.001	-0.834

Note. Comparisons based on estimated marginal means.

Appendix 9: Results of the post hoc tests for the proportion of reward collected when manipulating perceptual uncertainty (under constant reward value).

Precision in Likelihood Mapping								
condition		condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
0.92	-	0.94	-0.0100	0.0107	245	-0.937	1.000	-0.187
	-	0.96	-0.0650	0.0107	245	-6.091	<.001	-1.218
	-	0.98	-0.1060	0.0107	245	-9.932	<.001	-1.986
	-	1.00	-0.1505	0.0107	245	-14.102	<.001	-2.820
0.94	-	0.96	-0.0550	0.0107	245	-5.154	<.001	-1.031
	-	0.98	-0.0960	0.0107	245	-8.995	<.001	-1.799
	-	1.00	-0.1405	0.0107	245	-13.165	<.001	-2.633
0.96	-	0.98	-0.0410	0.0107	245	-3.842	.002	-0.768
	-	1.00	-0.0855	0.0107	245	-8.012	<.001	-1.602
0.98	-	1.00	-0.0445	0.0107	245	-4.170	<.001	-0.834

Note. Comparisons based on estimated marginal means.

Appendix 10: Results of the post hoc tests for the decision accuracy when manipulating perceptual uncertainty (under medium reward value).

Precision in Likelihood Mapping								
condition		condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
0.92	-	0.94	-0.0157	0.00524	245	-3.01	.029	-0.601
	-	0.96	-0.0355	0.00524	245	-6.78	<.001	-1.355
	-	0.98	-0.0582	0.00524	245	-11.12	<.001	-2.223
	-	1.00	-0.0712	0.00524	245	-13.60	<.001	-2.720
0.94	-	0.96	-0.0198	0.00524	245	-3.77	.002	-0.754
	-	0.98	-0.0425	0.00524	245	-8.11	<.001	-1.622
	-	1.00	-0.0555	0.00524	245	-10.59	<.001	-2.118
0.96	-	0.98	-0.0227	0.00524	245	-4.34	<.001	-0.868
	-	1.00	-0.0358	0.00524	245	-6.82	<.001	-1.365
0.98	-	1.00	-0.0130	0.00524	245	-2.48	.138	-0.496

Note. Comparisons based on estimated marginal means.

Appendix 11: Results of the post hoc tests for the proportion of reward collected when manipulating perceptual uncertainty (under medium reward value).

Precision in Likelihood Mapping								
condition		condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
0.92	-	0.94	-0.0157	0.00545	245	-2.89	.042	-0.578
	-	0.96	-0.0355	0.00545	245	-6.51	<.001	-1.302
	-	0.98	-0.0582	0.00545	245	-10.68	<.001	-2.137
	-	1.00	-0.5618	0.00545	245	-103.04	<.001	-20.607
0.94	-	0.96	-0.0198	0.00545	245	-3.62	.004	-0.725
	-	0.98	-0.0425	0.00545	245	-7.80	<.001	-1.559
	-	1.00	-0.5460	0.00545	245	-100.15	<.001	-20.029
0.96	-	0.98	-0.0227	0.00545	245	-4.17	<.001	-0.835
	-	1.00	-0.5263	0.00545	245	-96.52	<.001	-19.305
0.98	-	1.00	-0.5035	0.00545	245	-92.35	<.001	-18.470

Note. Comparisons based on estimated marginal means.

Appendix 12: Results of the post hoc tests for the decision accuracy when manipulating perceptual uncertainty (under high reward value).

Precision in Likelihood Mapping								
condition		condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
0.92	-	0.94	-0.00950	0.00749	245	-1.27	1.000	-0.254
	-	0.96	-0.02400	0.00749	245	-3.21	.015	-0.641
	-	0.98	-0.26350	0.00749	245	-35.19	<.001	-7.039
	-	1.00	-0.27850	0.00749	245	-37.20	<.001	-7.440
0.94	-	0.96	-0.01450	0.00749	245	-1.94	.539	-0.387
	-	0.98	-0.25400	0.00749	245	-33.93	<.001	-6.785
	-	1.00	-0.26900	0.00749	245	-35.93	<.001	-7.186
0.96	-	0.98	-0.23950	0.00749	245	-31.99	<.001	-6.398
	-	1.00	-0.25450	0.00749	245	-33.99	<.001	-6.798
0.98	-	1.00	-0.01500	0.00749	245	-2.00	.462	-0.401

Note. Comparisons based on estimated marginal means.

Appendix 13: Results of the post hoc tests for the proportion of reward collected when manipulating perceptual uncertainty (under high reward value).

Precision in Likelihood Mapping								
condition		condition	Mean difference	Standard Error	dof	t	p _{bonferroni}	Cohen's d
0.92	-	0.94	-0.00967	0.0131	245	-0.736	1.000	-0.147
	-	0.96	-0.02600	0.0131	245	-1.979	.490	-0.396
	-	0.98	-0.49033	0.0131	245	-37.314	<.001	-7.463
	-	1.00	-0.51000	0.0131	245	-38.811	<.001	-7.762
0.94	-	0.96	-0.01633	0.0131	245	-1.243	1.000	-0.249
	-	0.98	-0.48067	0.0131	245	-36.578	<.001	-7.316
	-	1.00	-0.50033	0.0131	245	-38.075	<.001	-7.615
0.96	-	0.98	-0.46433	0.0131	245	-35.336	<.001	-7.067
	-	1.00	-0.48400	0.0131	245	-36.832	<.001	-7.366
0.98	-	1.00	-0.01967	0.0131	245	-1.497	1.000	-0.299

Note. Comparisons based on estimated marginal means.