Experts Integrate Explicit Contextual Priors and Environmental Information to Improve Anticipation Efficiency

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Abstract

Our understanding of how experts integrate prior situation-specific information (i.e., *contextual priors*) with emergent visual information when performing dynamic and temporally constrained tasks is limited. We use a soccer-based anticipation task to examine the ability of expert and novice players to integrate prior information about an opponent's action tendencies with unfolding environmental information such as opponent kinematics. We recorded gaze behaviours and ongoing expectations during task performance. Moreover, we assessed their final anticipatory judgements and perceived levels of cognitive effort invested. Explicit contextual priors biased the allocation of visual attention and shaped ongoing expectations in experts, but not in novices. When the final action was congruent with the most likely action given the opponent's action tendencies, the contextual priors enhanced the final judgements for both groups. For incongruent trials, the explicit priors had a negative impact on the final judgements of novices, but not experts. We interpret the data using a Bayesian framework to provide novel insights into how contextual priors and dynamic environmental information are combined when making decisions under time pressure. Moreover, we provide evidence that this integration is governed by the temporal relevance of the information at hand as well as the ability to infer this relevance.

Keywords: Bayesian; decision making; probabilistic information; visual attention; sport.

Public Significance Statement

This study suggests that soccer experts are superior to novices at combining explicit contextual priors with unfolding environmental information in order to efficiently predict future events. These novel findings elucidate the processes by which expert anticipators may assimilate multiple dynamic information sources in order to make rapid and accurate judgements in naturalistic contexts.

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In many domains, we make predictive judgements about the world around us, often on the basis of ever-changing and partial information (Griffiths, Kemp, & Tenenbaum, 2008). In order to do so, we combine current environmental information with previously acquired situation-specific information, termed *contextual priors,* to formulate our decisions (Körding, 2007; Torralba, 2003). However, the use of these two information sources have typically been examined in isolation and consequently, the impact of contextual priors on the use of current environmental information, and the associated cognitive demands of doing so, has largely been ignored (Vilares & Körding, 2011). Furthermore, due to the use of simple generic tasks and homogeneous groups of participants, the role that domain-specific expertise may play when integrating different sources of complex and evolving information has been overlooked (Brouwer & Knill, 2009; Miyazaki, 2005; Tassinari, Hudson, & Landy, 2006) . In the current study, we use a dynamic domain-specific simulation task to assess the impact of explicitly provided contextual priors on the processes and strategies used by expert and novice performers when anticipating the actions of others.

We are frequently required to make accurate estimates about the state of an uncertain world that only provides probabilistic information about its actual state (Brunswik, 1952). A fundamental question therefore for human perception and cognition is how do we make inductive inferences that inform our subsequent behaviour from typically incomplete information? In recent years, researchers have tried to answer this question using a Bayesian framework for probabilistic inference (for a review, see Rottman & Hastie, 2014). The fundamental concept behind the Bayesian approach is that the human brain combines confirmatory and conflicting pieces of ambiguous information to build abstract models of the world (Clark, 2013). It is suggested that each informational variable provides a probability value referring to the state of a *hidden variable*, and people must effectively infer the resulting uncertainty to make accurate estimations about the hidden variable of interest (Knill & Pouget, 2004). For example, consider a doctor who is tasked with detecting a clinical disease (the hidden variable) on the basis of specific symptoms from a patient (the informational variables). A symptom is associated with a certain probability for and against potential diseases, which generates a joint probability distribution that informs the doctor's diagnosis.

Using Bayesian probabilistic inference, the individual strives to maximally reduce the total uncertainty associated with the hidden variable (Vilares & Körding, 2011). It is thought that the joint probability distribution is derived from a weighted integration of the informational variables at hand. This process suggests that, if one informational variable is associated with greater uncertainty than another, the joint probability distribution should be biased toward the 'less uncertain' variable (Knill & Pouget, 2004). For example, the doctor may consider visually salient symptoms (e.g., swelling) to be more relevant than the patient's self-reported symptoms (e.g., pain). While both information sources should be taken into account, the lower uncertainty associated with the former should be reflected in a more accurate estimate of the patient's clinical state.

Such weighted probabilistic inference has been explicitly demonstrated in simple spatial-location tasks (e.g., Alais & Burr, 2004; Battaglia, Jacobs, & Aslin, 2003; van Beers, Sittig, & van der Gon Denier, 1999) and perceptual-judgement tasks (e.g., Hillis, Watt, Landy, & Banks, 2004; Jacobs & Fine, 1999; Knill & Saunders, 2003). In more applied contexts, such as driving (Underwood, 2007), radiology (Krupinski, 2000), and when playing soccer (Savelsbergh, Williams, Kamp, & Ward, 2002) it has been reported that players draw upon pertinent informational variables according to their relevance to the task at hand. Furthermore, it has been suggested that this weighted acquisition of information is contingent upon the individual's level of domain-specific expertise (Krupinski, 2000; Savelsbergh et al., 2002; Underwood, 2007). In other words, the relative uncertainties associated with the informational variables seem to depend both on their relationship with the hidden variable and the individual's ability to extract meaningful information from those variables. However, we do not typically make inductive judgements about the world from current environmental information alone; we also use contextual priors – the prior probability distribution that informs our estimate of the hidden variable (Griffiths, Vul, & Sanborn, 2012). For example, the doctor may study their patient's medical records before meeting them face-to-face. This information is successfully integrated by expert doctors with the presenting symptoms to optimise diagnosis accuracy.

While expertise and experience can endow the individual with contextual priors, such information can also be introduced into experimental designs (Seriès & Seitz, 2013). For example, contextual priors have been applied to simple arm-reaching (Brouwer & Knill, 2009), pointing (Tassinari et al., 2006), and event-timing (Miyazaki, 2005) tasks. In all of these studies, the participants combined prior and current information in a fashion that is predicted by Bayesian models. That is, they relied more on priors when the current environmental information was associated with greater uncertainty, and vice versa. Furthermore, it is suggested that the addition of contextual priors biases the individual's allocation of attention by inducing a top-down, context-driven, selection of environmental information (Torralba, 2003). This procedure has been demonstrated in law enforcement, where contextual priors biased not only participants' anticipatory judgements, but also their allocation of visual attention toward context-relevant environmental information (Eberhardt, Goff, Purdie, & Davies, 2004).

However, the integration of contextual priors does not necessarily generate greater certainty of the joint estimate or enhance task performance; the priors may either conflict with environmental information or be invalid with regard to the hidden variable. In dynamic and changing performance environments, as encountered in many sports, our prior beliefs may lead us toward non-optimal behaviours and judgements (Vilares & Körding, 2011). For example, using a video-based anticipation task, Loffing, Stern, and Hagemann (2015) showed that exposure to an opponent’s previous action patterns biased anticipation of the opponent’s next action in volleyball. The players’ awareness of the opponent’s action tendencies was only beneficial when the to-be-anticipated action was congruent with the preceding pattern (i.e., valid priors), but detrimental when it was incongruent (i.e., invalid priors). Such dependency on congruent contextual priors has been demonstrated by exposing handball goalkeepers to the action tendencies of a penalty taker, before they were required to predict the direction of a penalty throw (Mann, Schaefers, & Cañal-Bruland, 2014). In both studies, the information about the opponent’s tendencies was accrued in an implicit manner (i.e., the players did not receive explicit instructions or guidance). However, researchers have provided explicit information about the action tendencies of opponents to baseball batters (Gray, 2015) and soccer goalkeepers (Navia, Van der Kamp, & Ruiz, 2013). In line with previous findings (Loffing et al., 2015; Mann et al., 2014), the explicit provision of contextual priors seems to be beneficial when the to-be-anticipated event is congruent with the prior information, but detrimental when it is incongruent (Gray, 2015; Navia et al., 2013).

Loffing and colleagues (2015) reported that the congruence effect was more pronounced for expert than novice volleyball players. It may be that experts were superior to novices in utilising available contextual information (cf. Farrow & Reid, 2012), but because the video footage was occluded 360 milliseconds prior to hand-ball contact, they may not have been able to update their prior expectations with confirmatory or conflicting kinematic information from the opponent (cf. Loffing & Hagemann, 2014). Navia and colleagues (2013) found that prior information about the opponent’s action tendencies had greater impact on goalkeepers who spent relatively less time attending to the opponent's kinematics. These findings collectively suggest that the impact of contextual priors, whether they are explicitly provided or acquired in a more implicit manner, is subject to the individual's use of confirmatory or conflicting environmental information during task performance. The process by which this unfolds in a dynamic environment is yet to be examined (Cañal-Bruland & Mann, 2015). By furthering understanding of the anticipatory process and how it is informed by the congruence between contextual priors and evolving environmental information, we may extend the utility of a Bayesian framework when explaining how people weight available information sources in naturalistic and dynamic performance contexts. Moreover, knowledge of how this congruence effect interacts with the individual's ability to utilise available information sources may be used to inform adequate instructional approaches for practitioners at different skill levels.

In the current study, we use a dynamic performance context to provide unique insights into expertise-related differences in the ability to adapt one's judgements over time by integrating explicitly provided contextual priors with current environmental information (Loffing & Cañal-Bruland, 2017). The findings from this applied domain are discussed in line with a Bayesian framework for probabilistic inference to offer a novel insight into the underlying perceptual and cognitive processes employed (Körding, 2007). Specifically, we use a 2-versus-2 video-based soccer task to examine how expert and novice players integrate contextual priors about an opponent's action tendencies with environmental information when anticipating the direction of an oncoming opponent's imminent actions. We record gaze behaviours and unfolding expectations to explore the perceptual and cognitive processes that underpin the anticipatory judgements. Also, we assess the efficiency of the ultimate anticipatory judgement, as well as the perceived level of cognitive effort invested in the task.

We predict that the explicit provision of contextual priors will increase visual dwell time on the players off the ball during the first half of the trial, as their positioning at this stage of the trial contains context-relevant information (see Methods section for detailed explanation; cf. Torralba, 2003; Eberhardt et al., 2004). This process will bias the online expectations when no other pertinent environmental information is available (cf. Brouwer & Knill, 2009; Miyazaki, 2005; Tassinari et al., 2006). This effect will be expressed by an increase in expectation accuracy when the opponent carries out the most likely action given his action tendencies (i.e., congruent trials) and a decrease in expectation accuracy when the opponent performs the least likely action (i.e., incongruent trials). We hypothesise that these biasing effects of explicit contextual priors will improve the efficiency of the ultimate anticipatory judgement on congruent trials but will impair the efficiency on incongruent trials (cf. Loffing et al., 2015).

Furthermore, we predict that these effects will be moderated by expertise. We hypothesise that the effects on visual dwell time and online expectations will be more pronounced in experts compared to novices, due to the former group's superior ability to utilise context-relevant information compared to the latter group (Farrow & Reid, 2012). We predict that the impairment of anticipation efficiency on incongruent trials will be less pronounced in experts as they will more effectively use evolving kinematic information from the player in possession to update expectations and inform their ultimate anticipatory judgement (cf. Savelsbergh et al., 2002). Consequently, we predict that, due to better integration of contextual priors and environmental information, experts will anticipate more efficiently than novices on both congruent and incongruent trials. These predictions are in line with a Bayesian framework for probabilistic inference as players try to minimise the uncertainty of their final judgements by combining prior and current information, according to the relative uncertainty associated with the different sources of information (Körding, 2007). Finally, in line with previous suggestions (Green & Flowers, 2003), we predict that the explicit provision of contextual priors will increase the perceived cognitive effort in all players.

Methods

Participants

A total of 16 expert (M_{age} = 20 years, *SD* = 2) and 15 novice (M_{age} = 21 years, *SD* = 3) male soccer players participated. A spreadsheet for estimating sample size for magnitude-based inferences (Hopkins, 2006a) was used to calculate the number of participants needed to find a clear effect (i.e., chances of the true effect to be substantially positive and negative < 5%; Hopkins, 2006b) on our main dependent measure (anticipation efficiency). We used data from a previous study (Roca, Ford, McRobert, & Williams, 2013) to calculate the minimum required sample size (Hopkins, Marshall, Batterham, & Hanin, 2009). This sample size is comparable to those employed in previous studies examining the perceptual and cognitive mechanisms that underpin anticipatory performance across expert and novice athletes (e.g., Jackson, Warren, & Abernethy, 2006; Murphy et al., 2016; Roca et al., 2013). The expert players had a mean of 11 years (*SD* = 2) of competitive experience in soccer and took part in an average of 8 hours (*SD* = 3) of practice or match-play per week. The novice players were not currently playing at a competitive level and had an average of 2 years (*SD* = 2) of competitive experience. Research ethics committee approval was gained from the lead institution and informed consent was obtained from all participants.

Test stimuli

The video sequences were filmed on an artificial turf soccer pitch using a wide-angle converter lens (Canon WD-H72 0.8x, Tokyo, Japan) attached to a high-definition digital video camera (Canon XF100, Tokyo, Japan). The video camera was attached to a moving trolley, at a height of 1.7 meters, to closely replicate the perspective of a central defender in a typical match situation (i.e., facing oncoming opponents while simultaneously moving backwards).

The sequences represented 2-versus-2 counter attacking scenarios in soccer. In each sequence, there was one attacking player in possession of the ball, a second attacker off the ball, and one defender marking the second attacker. Participants viewed all sequences from a first-person perspective, as if they were the second defender (see Figure 1). This scenario rapidly unfolds and presents a high level of perceived threat, which requires athletes to make frequent anticipatory behaviours (Triolet, Benguigui, Le Runigo, & Williams, 2013) and to increase their use of prior expectations (Roca et al., 2013), when compared to less pressured situations.

At the start of each sequence, the player in possession of the ball was positioned three meters inside the halfway line, approximately seven meters in front of the participant. The attacker off the ball and the marking defender started approximately three meters behind, either on the left, or the right, side of the player in possession. As players in a soccer match are normally aware of the relative positions of the ball and other players when they perform such tasks, each sequence started with a one-second freeze-frame, to allow the participant to determine this information (cf. Roca, Ford, McRobert, & Williams, 2011). When the sequence started, the attackers approached the participant and, after approximately one-and-a half-seconds, the attacker off the ball made a direction change towards either the left or the right. At the end of the sequence, the player in possession was positioned approximately three meters in front of the participant. The attacker off the ball was level with the player in possession, either to his left or right. The marking defender followed the attacker off the ball throughout each sequence. At the end of each sequence, the player in possession either passed the ball to his teammate (33% of trials) or dribbled the ball in the opposite direction (67% of trials). The final position of the player off the ball was therefore informative with regard to the direction of the final action (i.e., if the players off the ball were on the left side, 67% of the opponent in possession's final actions were to the right and vice versa). A sequence lasted 4,960 milliseconds and was occluded 120 milliseconds after the player in possession's final action.

The footage was edited using Pinnacle Studio software (v15; Pinnacle, Ottawa, Canada). In total, 130 video simulations were created. Two qualified soccer coaches (UEFA A Licence holders) independently selected the clips that they considered to be representative of actual game play. Only the clips that were selected by both coaches were included in the final test footage, making a total of 48 clips. These clips were projected on to a 4.1 x 2.3 m projection screen (AV Stumpfl, Wallern, Austria) using an NEC PE401H projector (NEC, Tokyo, Japan).

****Figure 1 near here****

Task design

The task for the participant was to predict the direction (left or right) of the player in possession's final action quickly and accurately. Also, over the course of each trial, participants were required to indicate their ongoing expectations with regard to the direction of the final action. At the start of each trial, the participant was positioned four meters from the projection screen holding a bespoke response device in each hand (see Figure 2a). The device was equipped with two response buttons; one to record the participant's online expectations throughout the trials and one to record their final prediction (see Figure 2b). Participants were instructed to indicate their expectations as soon as they started to feel that one direction was more likely than the other, and that they could change their expectations throughout the trial. The participant was instructed to execute their final prediction as soon as they were certain enough to carry out an action based on their prediction; they were told that they could not change this response. The response time for their final prediction was displayed on-screen after each trial. As the sequence was occluded 120 milliseconds after the player in possession's final action, the participant was able to see whether their response was correct or incorrect. Participants were free to move as they preferred during the task performance in order to maximise the real-world representativeness of the task (cf. Roca et al., 2011).

****Figure 2 near here****

Procedure

Prior to testing, the participant was given an overview of the experimental protocol and was presented with two blocks of six trials in order to familiarise themselves with the experimental setup and the response requirements. The participant was then fitted with a lapel microphone and a body-pack transmitter that was wirelessly connected to a compact diversity receiver (ew112-p G3; Sennheiser, Wedemark, Germany) and a recording device (Zoom H5; Zoom Corporation, Tokyo, Japan), so that self-report data could be recorded. Eye-tracking glasses (Applied Science Laboratories, Bedford, MA, USA) were subsequently fitted onto the participant's head. The glasses were connected to a recording device that was worn by the participant in a small backpack. The eye-tracking system was calibrated using a 9-point grid that covered the entire display. Calibration was checked between conditions and recalibration was performed where necessary.

After the calibration of the eye-tracking system, the 48 test trials were presented under two informational conditions (i.e., 96 trials in total). Each condition of 48 trials was divided into six blocks and each block comprised eight trials. In one condition, information about the player in possession's action tendencies (*contextual priors*; dribble = 67%, pass = 33%) was explicitly announced prior to each block, both verbally and on-screen. In the other condition, no contextual priors were explicitly provided; however, the proportion of actions was the same as in the condition with explicit contextual priors (i.e., dribble = 67%, pass = 33%). The order in which conditions were presented was randomised and counterbalanced across skill groups (i.e., half of the expert group and half of the novice group began with the condition containing explicit contextual priors while the other half began without priors). To eliminate the influence of trial-specific characteristics, the same 48 trials were presented in both informational conditions. However, to avoid any potential familiarity between conditions, the trial order in each condition was randomised. Upon completion of each block, the participant was asked to indicate their perceived level of cognitive effort when completing the trials in the preceding block, using the RSME (Zijlstra, 1993). In order to minimise the influence of the experimental manipulations on data collected in the subsequent condition, a *washout* condition comprising three blocks of six trials was carried out between each test condition. Prior to each of the three washout blocks, novel information about the opponent’s action tendencies was explicitly provided (dribble = 40%, pass = 60%; dribble = 60%, pass = 40%; dribble = 50%, pass = 50% in this order). This information corresponded to the proportion of dribbles and passes that the player in possession performed within each block of the washout condition. The entire test session was completed in 60 minutes.

Dependent measures

Visual dwell time. We characterised the overt allocation of visual attention as the relative distribution of visual dwell time across two interest areas: the player in possession of the ball; and the players off the ball (see Figure 2). Dwell time distributions have previously been used as an index of visual attentional allocation (e.g., Bayliss et al., 2012; Cavanagh, Wiecki, Kochar, & Frank, 2014; Fox, Russo, Bowles, & Dutton, 2001). The three most discriminating congruent and incongruent trials based on combined within-group differences for efficiency scores, making it six trials for each condition and participant (i.e., 372 trials in total), were subjected to gaze analysis[1]. We selected only the most discriminating trials based on performance outcomes in order to provide the most sensitive measure of how well the variable of interest (in our study: visual dwell time) predicts the performance measure of interest (in our study: anticipation efficiency; Ericsson & Smith, 1991). This is a well-established approach when assessing the perceptual or cognitive mechanisms behind certain performance effects (e.g., Martins, Garganta, Oliveira, & Casanova, 2014; Murphy et al.,2016; Roca et al., 2013). The data were analysed frame-by-frame using Windows Media Player version 12 (Microsoft Corporation, WA, USA). Since we predicted that attentional allocation would evolve as the player in possession's kinematics became more informative, visual dwell time was analysed for each trial in its entirety (0-4960 milliseconds), as well as for the first (0-2479 milliseconds) and second (2480-4960 milliseconds) halves of the trial, separately. Visual dwell time outside the classified Areas of Interest (< 0.6%) and missing data due to equipment failure (< 1.1%) or trials in which invalid button presses were made (< 2.5%) were excluded from the gaze analysis. Also, trials for which more than 20% of the data were missing (< 2.2%) were excluded. The first author analysed all trials. A random sample containing 10% of all data was reanalysed to obtain intra- (96%) and interobserver (92%) reliability. In the later instance, the data were re-coded by an independent researcher.

Expectation accuracy. The accuracy of online expectations was expressed as the correspondence of participant's button presses to the direction of the final action. All expectation responses that the participant made over the course of a trial were included in the average accuracy score that was calculated for each informational condition. As we predicted a congruence effect for expectation accuracy, both combined and separate analyses of congruent and incongruent trials were carried out. Trials for which response times differed by more than three *SD*s (< 0.3%) from the participant's mean response time were deemed to be

[1]Gaze data from the trials chosen for analysis may not be representative of all trials (see the Discussion section for further comments on this).

invalid button presses and were excluded from the analysis. In the condition without explicit contextual priors, the average accuracy score from the first three blocks was compared to the average score from the final three blocks, to check whether information about the opponent's action tendencies was learnt over time, according to the opponent's preceding actions.

Anticipation efficiency. To account for inevitable speed-accuracy trade-off, anticipatory performance was expressed as an *efficiency score* for each informational condition (cf. Bishop, Kuhn, & Maton, 2014). The efficiency score was calculated by multiplying the mean response time by the proportion of inaccurate trials for the participant's final predictions; *lower efficiency scores indicated superior anticipatory efficiency*. As we predicted a congruence effect for anticipation efficiency, both combined and separate analyses of congruent and incongruent trials were carried out. Responses executed after video occlusion (i.e., 120 milliseconds after foot-ball contact) were recorded as inaccurate since too little time would have been afforded for the participant to carry out a successful defensive action in response to the attack. Trials for which response times differed by more than three *SD*s from the participant's mean response time (< 1.2%) were deemed to be invalid button presses and were excluded from the analysis. In the condition without explicit contextual priors, the average efficiency score from the first three blocks was compared to the average score from the final three blocks, to check whether information about the opponent's action tendencies was learnt over time, according to the opponent's preceding actions.

Cognitive effort. Perceived levels of cognitive effort were expressed by the RSME ratings. The scale ranges from 0 to 150 and contains nine descriptors (e.g., 2 = absolutely no effort; 58 = rather much effort; 113 = extreme effort). The RSME has been successfully used to assess levels of cognitive effort across various informational conditions (Cocks, Jackson, Bishop, & Williams, 2016).

Statistical analysis

Descriptive statistics are reported as means and *SD*s. Magnitudes of observed effects are reported as standardised units (*d*) and uncertainties in true effects as 90% confidence limits. The between-group effect in each informational condition was assessed by dividing the mean difference between the groups by the pooled *SD*. The within-group effect between the condition without explicit contextual priors and the condition with priors was assessed by dividing the mean difference between the conditions by the *SD* from the condition without explicit priors (cf. Cumming, 2012). The observed effect was interpreted against the following scale: $0.2 > |d|$, trivial; $0.2 \leq |d| < 0.5$, small; $0.5 \leq |d| < 0.8$, moderate; $0.8 < |d|$, large (Cohen, 1988). Cohen's standardised unit for the smallest substantial effect (0.2) was used as a threshold value when estimating the uncertainty in the true effect to have the same sign as the observed effect. The following scale was used to convert the quantitative chances to qualitative descriptors: 25-75%, possible; 75-95%, likely; 95-99.5%, very likely (Hopkins, 2002). If the lower and upper bounds of the confidence interval exceeded the thresholds for the smallest substantial negative and positive effect, respectively, then the effect was deemed unclear. All other effects were reported as the magnitude of the observed value and were evaluated probabilistically as described above. We chose against using traditional null-hypothesis significance testing (Neyman & Pearson, 1933) in favour of magnitude-based inference (Batterham & Hopkins, 2006). The latter approach was chosen as it is more informative to report magnitude of observed effects and precision of estimates than whether observed effects are statistically significant according to a specified alpha level (e.g., p <.05; Cumming, 2014; Wilkinson, 2014).

Results

Figure 3 shows the within-group effects of the explicit provision of contextual priors on our main dependent measures.

****Figure 3 near here****

Visual dwell time

The group means and difference between expert and novice players in visual dwell time for each informational condition are presented in Table 1. As shown in Figure 3, experts decreased the time they spent looking at the player in possession of the ball (d = −0.43 ± 0.28) and increased the time spent looking at the players off the ball (d = 0.48 ± 0.27) when contextual priors were explicitly provided, relative to when they were not. Separate analyses of the first and second half of trial showed that these differences emerged over the first half of the trial (d = −0.42 ± 0.27 and d = 0.45 ± 0.25, respectively), while no clear effects were found over the second half of the trial. The explicit provision of contextual priors had no clear effects on gaze behaviours in the novice group.

****Table 1 near here****

Expectation accuracy

Group means and the difference between groups in expectation accuracy for each informational condition are presented in Table 2. The expert players increased their accuracy when contextual priors were explicitly provided, compared to when they were not (d = 1.01 ± 0.50). No clear effect of the provision of contextual priors was reported on accuracy for the novice players. Figure 3 shows that for the expert players, accuracy increased during congruent trials (d = 0.93 ± 0.52) and decreased during incongruent trials (d = −0.73 ± 0.58) when contextual priors were explicitly provided, compared to when they were not. The provision of contextual priors had no clear effects on novices during either congruent or incongruent trials. No clear effects were obtained, for experts or novices, when the average accuracy score for the initial three blocks in the condition without explicit contextual priors was compared to the average score for the final three blocks in the same condition.

****Table 2 near here****

Anticipation efficiency

The descriptive statistics for response times and accuracy scores that were used to calculate the efficiency scores are shown in Table 3. As shown in Figure 4, when compared to their less skilled counterparts, efficiency scores were lower (i.e., they were more efficient) in the expert group both without (overall, $d = -1.01 \pm 0.60$; congruent, $d = -0.63 \pm 0.60$; incongruent, $d = -0.51 \pm 0.60$) and with (overall, $d = -0.71 \pm 0.59$; congruent, $d = -0.39 \pm 0.60$; incongruent, $d = -0.77 \pm 0.59$) explicit contextual priors. Both experts and novices improved their overall efficiency when contextual priors were provided, compared to when they were not ($d = -0.33 \pm 0.45$ and $d = -0.45 \pm 0.54$, respectively). As shown in Figure 3, explicit contextual priors exerted beneficial effects on congruent trials for both experts ($d = -0.42 \pm 0.39$) and novices ($d = -0.59 \pm 0.56$). However, on incongruent trials contextual priors yielded clear detrimental effects for novice ($d = 0.23 \pm 0.40$), but not expert players. No clear effects were obtained, for experts or novices, when the average efficiency score for the initial three blocks in the condition without explicit contextual priors was compared to the average score for the final three blocks in the same condition.

****Table 3 near here****

****Figure 4 near here****

Cognitive effort

The ratings of perceived levels of cognitive effort did not reveal any clear differences between experts and novices, either without (68 ± 21 [*M* ± *SD*] and 73 ± 18, respectively) or with (70 ± 25 and 69 ± 19, respectively) explicit priors. The provision of contextual priors had no substantial effects on either expert ($d = 0.09 \pm 0.16$) or novice ($d = -0.17 \pm 0.16$) players (see Figure 3).

Discussion

We examined the ability of expert and novice soccer players to integrate explicit contextual priors pertaining to an opponent's action tendencies with current environmental information, such as opponent kinematics, when anticipating the opponent's next action. We used visual dwell time as a process measure of their acquisition of current environmental information. Furthermore, we captured the accuracy of their online expectations and assessed the efficiency of the final anticipatory judgements. We predicted that the players would strive to reduce the joint uncertainty associated with their final judgements by adopting a Bayesian strategy for integration of contextual priors and current environmental information. In doing so, we predicted that the players would weight and combine available sources of information on the basis of their relative uncertainty (Körding, 2007). Furthermore, we believed that the uncertainties associated with the various sources of information would be assessed given their relevance as well as the player's ability to infer this relevance. It was predicted that experts, more so than novices, would use the explicit contextual priors to guide the allocation of visual attention (cf. Torralba, 2003) and to shape online expectations (cf. Loffing et al., 2015). However, we predicted that experts would update these expectations as new environmental information entered the display (cf. Clark, 2013) resulting in superior anticipation efficiency when compared to novices.

In line with our predictions, the explicit provision of contextual priors guided the experts' visual attention toward more context-relevant environmental information. It is worth noting that this finding refers to analysis of the six most discriminating trials for each participant, according to the effect of explicit contextual priors on anticipation efficiency (cf. Ericsson & Smith, 1991; Martins et al., 2014; Murphy et al., 2016; Roca et al., 2013). While comparing these gaze data to those from all trials would be interesting from a methodological perspective, this was beyond the scope of this study. The experts increased the time they spent looking at the players off the ball and decreased the time spent looking at the player in possession, relative to when no contextual priors were explicitly given; this effect was not found for novices. In the current study, the final positioning of the opponent off the ball (*left* or *right*) revealed information that enabled the participants to use the contextual priors more effectively (i.e., if the players off the ball were on the left side, 67% of the opponent in possession's final actions were to the right and vice versa). This information could be confirmed early in the trial as the opponent off the ball made his direction change ~1.5 seconds after trial onset. This finding supports the notion that contextual priors induce a more top-down, context-driven, selection of environmental information (Eberhardt et al., 2004; Torralba, 2003). Separate analyses revealed that the explicit contextual priors biased how experts allocated their visual attention over the first half of the trial only (i.e., the period during which the opponent off the ball changed direction). Over the latter half of the trial (i.e., closer to the point of action execution) the player in possession's kinematics became more revealing (cf. Farrow, Abernethy, & Jackson, 2005). This finding is in line with our prediction that the impact of explicit contextual priors would emerge predominantly over the first half of the trial, in which the direction change of the opponent off the ball occurred and the kinematic information from the opponent in possession was not relevant to the final action. The progressive unfolding of relevant environmental information complements previous research which has shown that the effect of contextual priors is mediated by the relative uncertainty associated with confirmatory or conflicting environmental information (Brouwer & Knill, 2009; Miyazaki, 2005; Tassinari et al., 2006). Furthermore, the expertise effect revealed in our study provides novel evidence that this relative uncertainty is subject to the temporal relevance of available information as well as the individual's ability to infer this relevance.

As predicted, the expertise effect on visual attention was mirrored in the online expectations expressed by players. With explicit priors, experts enhanced their expectation accuracy when the oncoming opponent carried out the most likely action given his action tendencies (i.e., congruent trials). When the least likely action was performed by the opponent (i.e., incongruent trials), the provision of priors decreased the accuracy of online expectations. However, we did not find these biasing effects for online expectations in novices. These findings are consistent not only with our dwell time data, but with previous published research showing that experts are superior to novices at using prior contextual information (Farrow & Reid, 2012). It is worth noticing that the expert players in our study were only biased by the opponent's action tendencies when information about these tendencies was explicitly provided. This finding suggests that, in contrast to previous research (Loffing et al., 2015; Mann et al., 2014), the players in our study were not able to utilise contextual information derived from task experience alone (i.e., from the opponent's actions in preceding trials).

An effect was also found for the explicit provision of contextual priors, but not for task experience alone, on the players' efficiency when making their final judgements. In line with our predictions, the explicit provision of priors enhanced anticipation efficiency on congruent trials in both experts and novices. We argue that combining the contextual priors and confirmatory kinematic information resulted in lower informational uncertainty and, consequently, superior anticipatory judgement, compared to when no contextual priors were explicitly provided. For experts, these findings correspond with our findings for visual attention and online expectations, as well as previous published reports that have emphasised the beneficial impact of contextual priors (Brouwer & Knill, 2009; Loffing et al., 2015; Miyazaki, 2005; Tassinari et al., 2006). It is noteworthy that the enhanced efficiency demonstrated by novices was not accompanied by any biases in their allocation of visual attention or online expectations. This finding suggests that novices ultimately used the contextual priors to guide their anticipatory judgements but did not integrate them with current environmental information to form and update their in-task expectations. As predicted by a Bayesian framework for probabilistic inference, novices employed a less optimal combination of available informational variables, when compared to experts, resulting in inferior final anticipatory judgement efficiency for congruent trials.

For incongruent trials, we predicted that the explicit priors would impair the efficiency of the final anticipatory judgement in experts and, to a greater extent, in novices. However, impaired performance on incongruent trials was only evidenced in novices, which contradict the expertise effect reported by Loffing and colleagues (2015). In the light of Bayesian theory, we speculate that the contrasting expertise effects could be due to the fact that Loffing and colleagues used a temporal occlusion paradigm. We argue that the experts in our study used their superior ability to interpret opponents' kinematics in the final stages of the action (cf. Krupinski, 2000; Savelsbergh et al., 2002; Underwood, 2007) to update their prior expectations. In contrast, important kinematic information may have been occluded in the study by Loffing and colleagues. This suggestion is supported by the notion that contextual priors have a greater impact on soccer goalkeepers, who spend less time attending to the kicker's kinematics (Navia et al., 2013).

These findings suggest that the impact of contextual priors is governed by both the availability of relevant environmental information and the performer's processing priorities of the information available in the environment. In support of Bayesian theory, we argue that, compared to novices, the expert players used a more optimal weighing of contextual priors and environmental information resulting in superior efficiency of their final anticipatory judgement on incongruent trials. These findings may have practical implications, as recent advancements in technology have enabled sophisticated analyses of forthcoming opponents' action tendencies/movement patterns; hence, the explicit provision of contextual priors has become a vital component of preparation in elite sport (Memmert, Lemmink, & Sampaio, 2017). Specifically, our study provides novel evidence that the impact of explicitly providing such information is subject not only to the availability of environmental information, but also the athlete's ability to use this information.

In contrast to what we predicted, the use of priors did not engender increased levels of perceived cognitive effort for experts or novices. This finding contradicts previous suggestions that remembering and applying prior probabilistic rules may induce greater cognitive demands (Green & Flowers, 2003). However, it is possible that the retrospective reports collected in our study did not accurately capture the fluctuation in demands over the course of a trial. The potential limitations of using retrospective subjective ratings as a measure of online cognitive effort suggests that researchers should explore this topic further using concurrent neuroscientific measures of cognitive effort (cf. Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2008) and/or by comparing performances across conditions with varying cognitive demands (cf. Runswick, Roca, Williams, Bezodis, & North, 2017). An increased understanding of this phenomenon may have practical implications for performance under cognitively demanding conditions; for example, in the presence of a secondary task (Abernethy, Maxwell, Masters, van der Kamp, & Jackson, 2007).

In summary, our novel findings suggest that the explicit provision of contextual priors biases anticipatory judgements and shapes the underlying perceptual and cognitive strategies employed by individuals. As prescribed by a Bayesian framework for probabilistic inference, the impact of explicit contextual priors seems to alter as a function of the relative uncertainties associated with the available sources of information (Körding, 2007). The temporal effects, together with the expertise effects reported in this paper, suggests that these uncertainties are governed by the temporal relevance of the information at hand as well as the individual's ability to infer this relevance. It appears that experts integrate contextual priors with environmental information more effectively than novices. This effect was highlighted in our data by the shifts in overt visual attention according to prevailing contextual information (cf. Torralba, 2003) and updating of expectations as new confirmatory or conflicting information emerged (cf. Clark, 2013). In keeping with Bayesian theory, this results in a more reliable joint estimate of future events and enables experts to anticipate with greater efficiency than their novice counterparts. Our novel findings have implications for the assessment and enhancement of anticipation across a multitude of professional domains.

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Table 1

Group Means and SDs for Visual Dwell Time (%) and Inference of Between-Group Effects

	Without explicit contextual priors			With explicit contextual priors		
	Experts	Novices	Δ (Expert-Novice)	Experts	Novices	Δ (Expert-Novice)
PiP						
Full trial	69 ± 19	66 ± 18	Trivial*	61 ± 20	65 ± 15	Small (−)*
1st trial half	62 ± 24	57 ± 22	Small (+)*	51 ± 23	53 ± 17	Trivial*
2nd trial half	78 ± 16	75 ± 25	Trivial*	77 ± 18	78 ± 17	Trivial*
PoB						
Full trial	28 ± 19	33 ± 19	Small (−)*	37 ± 19	34 ± 14	Small (+)*
1st trial half	35 ± 24	42 ± 22	Small (−)*	46 ± 22	44 ± 16	Trivial*
2nd trial half	20 ± 17	25 ± 25	Trivial*	22 ± 19	21 ± 17	Trivial*

Note. PiP = player in possession; PoB = players off the ball; Full trial = 0-4960 milliseconds; 1st trial half = 0-2479 milliseconds; 2nd trial half = 2480-4960 milliseconds; (−) = negative sign of effect; (+) = positive sign of effect. Inference of observed effect: $0.2 > |d|$, trivial; $0.2 \leq |d| < 0.5$, small. Inference of uncertainty in true effect: * unclear.

Table 2

Group Means and SDs for Expectation Accuracy (%) and Inference of Between-Group Effects

	Without explicit contextual priors			With explicit contextual priors		
	Experts	Novices	Δ (Expert-Novice)	Experts	Novices	Δ (Expert-Novice)
Overall	42 ± 9	47 ± 8	Moderate (−)***	51 ± 10	50 ± 13	Trivial*
Congruent	26 ± 20	39 ± 19	Moderate (−)***	45 ± 26	44 ± 30	Trivial*
Incongruent	71 ± 18	60 ± 24	Small (+)***	57 ± 28	60 ± 25	Trivial*

Note. (−) = negative sign of effect; (+) = positive sign of effect. Inference of observed effect: 0.2 > |*d*|, trivial; 0.2 ≤ |*d*| < 0.5, small; 0.5 ≤ |*d*| < 0.8, moderate; 0.8 < |*d*|, large. Inference of uncertainty in true effect: * unclear; *** likely (75-95%).

Table 3

Group Means and SDs for Response Time (ms) and Accuracy (%) of Final Predictions

	Without explicit contextual priors		With explicit contextual priors	
	Experts	Novices	Experts	Novices
Response time				
Overall	4,437 ± 583	4,761 ± 210	4,303 ± 576	4,768 ± 198
Congruent	4,413 ± 577	4,735 ± 209	4,283 ± 562	4,745 ± 188
Incongruent	4,486 ± 598	4,812 ± 217	4,342 ± 611	4,816 ± 227
Accuracy				
Overall	54 ± 9	48 ± 9	57 ± 10	53 ± 10
Congruent	66 ± 14	61 ± 15	72 ± 10	70 ± 12
Incongruent	31 ± 20	23 ± 18	28 ± 20	18 ± 14

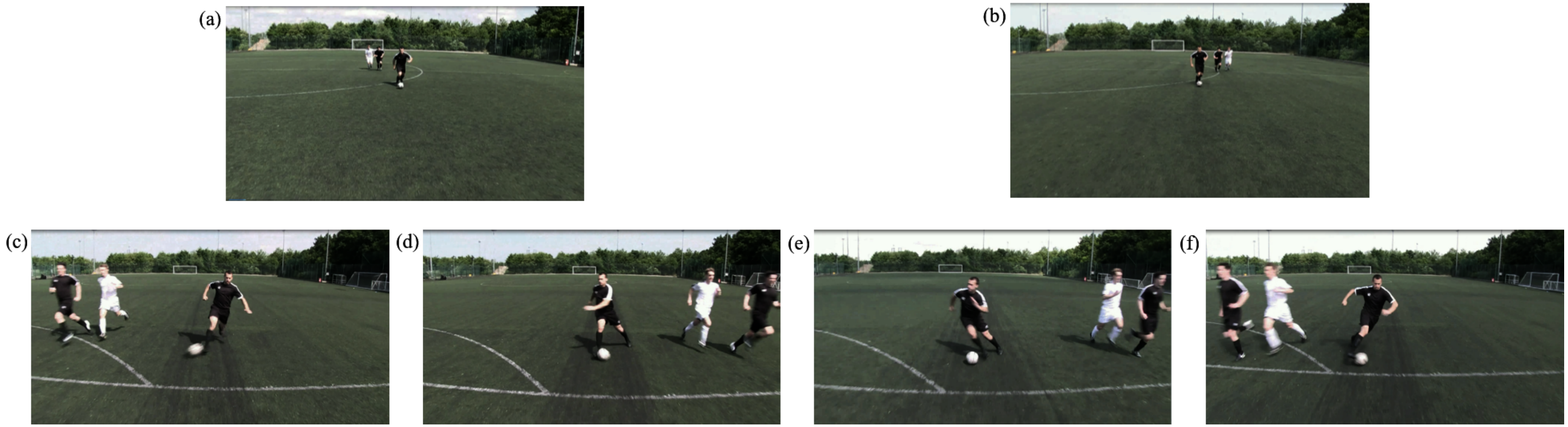

Figure 1. Test Stimuli. The two different positions that the players off the ball could have at the start of each sequence; left-hand side of the player in possession (a) and right-hand side of the player in possession (b). The four different ultimate actions that the player in possession could carry out at the end of each sequence; pass left (c), pass right (d), dribble left (e), and dribble right (f).

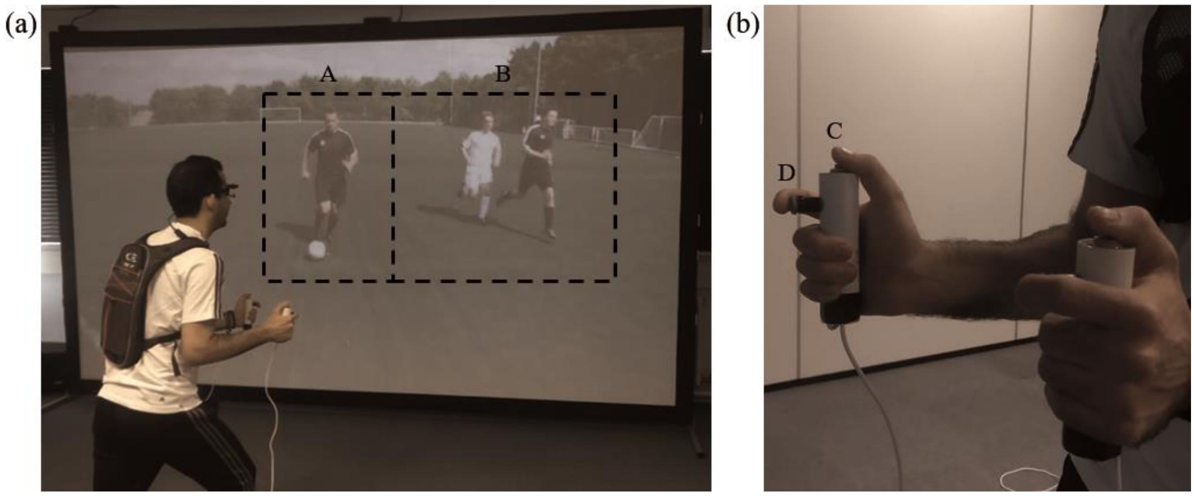

Figure 2. (a) Experimental Setup. A depiction of the experimental task with Areas of Interest superimposed (A = player in possession; B = players off the ball; Note: These markings were not visible to participants).

(b). Close-up of handheld devices with response buttons (C = online expectations; D = final prediction.

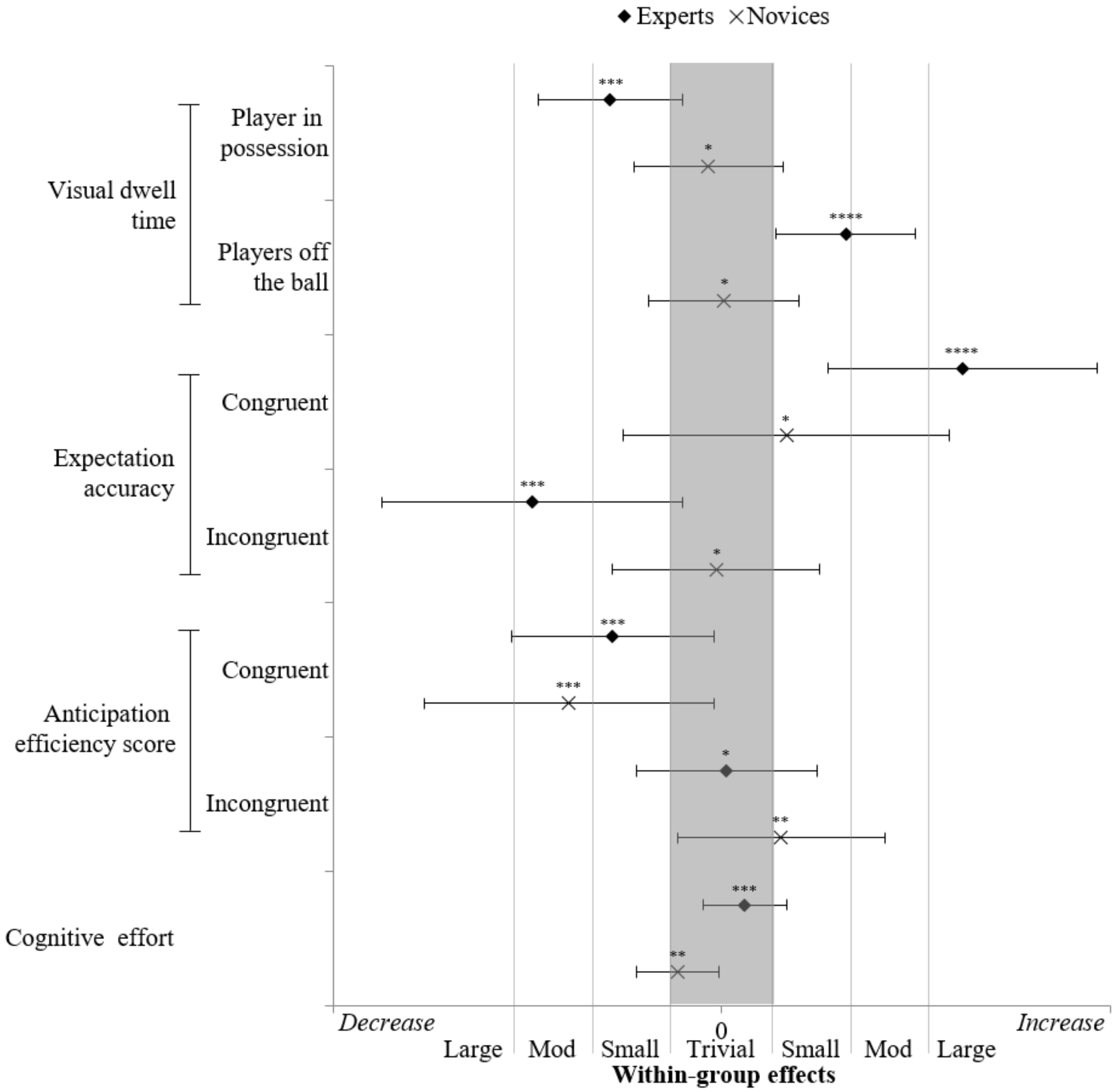

Figure 3. Within-Group Effects of Explicit Contextual Priors (with explicit contextual priors *vs* without explicit contextual priors). Standardised effects and 90% confidence limits for the effects of explicit contextual priors within each group, as well as inferences of observed and true effects within groups for our main dependent measures. The effects represent the *increase* or *decrease* in scores for when contextual priors where explicitly provided, relative to when no explicit contextual priors were provided. Note: *lower anticipation efficiency scores indicate superior efficiency*. Inference of observed effect: $0.2 > |d|$, trivial; $0.2 \leq |d| < 0.5$, small; $0.5 \leq |d| < 0.8$, moderate; $0.8 < |d|$, large. Inference of uncertainty in true effect: * unclear; ** possibly (25-75%); *** likely (75-95%); **** very likely (95-99.5%).

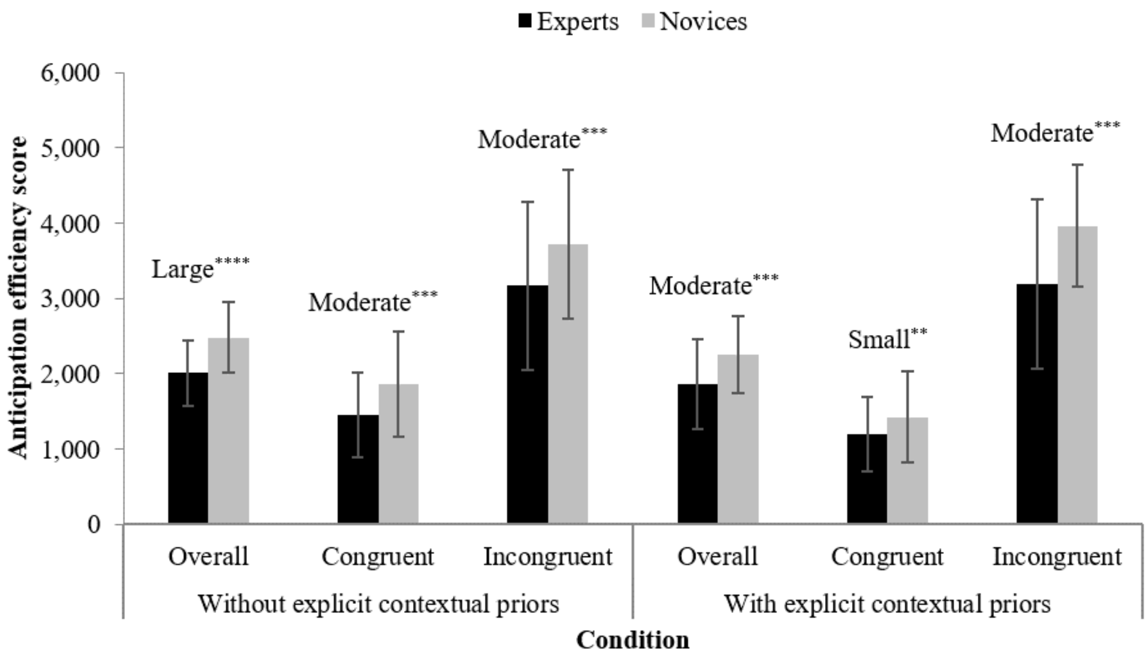

Figure 4. Between-Group Effects for Anticipation Efficiency. Group means and *SD*s for efficiency scores in each informational condition, as well as inferences of observed and true effects between groups. Note: *lower scores indicate superior anticipatory efficiency*. Inference of observed effect: $0.2 \leq |d| < 0.5$, small; $0.5 \leq |d| < 0.8$, moderate; $0.8 < |d|$, large. Inference of uncertainty in true effect: ** possibly (25-75%); *** likely (75-95%); **** very likely (95-99.5%).