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Article

To Cross or Not To Cross

Monitoring Decisions Based on Everyday Life Experience in a Simulated Traffic Task

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Abstract. Different theoretical accounts have attempted to integrate anterior cingulate cortex involvement in relation to conflict detection, error-likelihood predictions, and error monitoring. Regarding the latter, event-related potential studies have identified the feedback-related negativity (FRN) component in relation to processing feedback which indicates that a particular outcome was worse than expected. According to the conflict-monitoring theory the stimulus-locked N2 reflects pre-response conflict. Assumptions of these theories have been made on the basis of relatively simple response-mapping tasks, rather than more complex decision-making processes associated with everyday situations. The question remains whether expectancies and conflicts induced by everyday knowledge similarly affect decision-making processes. To answer this question, electroencephalogram and behavioral measurements were obtained while participants performed a simulated traffic task that varied high and low ambiguous situations at an intersection by presenting multiple varying traffic light combinations. Although feedback was kept constant for the different conditions, the tendency to cross was more pronounced for traffic light combinations that in reallife are associated with proceeding, as opposed to more ambiguous traffic light combinations not uniquely associated with a specific response. On a neurophysiological level, the stimulus-locked N2 was enhanced on trials that induced experience-based conflict and the FRN was more pronounced for negative as compared to positive feedback, but did not differ as a function of everyday expectancies related to traffic rules. The current study shows that well-learned everyday rules may influence decision-making processes in situations that are associated with the application of these rules, even if responding accordingly does not lead to the intended outcomes.

Keywords: performance monitoring, conflict monitoring, stimulus-locked N2, FRN

Posterior medial prefrontal cortex (pMFC) and in particular anterior cingulate cortex (ACC) have been implicated in a variety of cognitive functions related to attentional and motivational processes (see Bush, Luu, & Posner, 2000, for a review) with recent research mainly focusing on the role of the ACC in monitoring and optimizing behavior. The ACC has been associated with processes like error detection (Holroyd & Coles, 2002), conflict monitoring (Botvinick, Braver, Barch, Carter, & Cohen, 2001), and, more recently, error-likelihood prediction (Brown & Braver, 2005; Magno, Foxe, Molholm, Robertson, & Garavan, 2006). These theoretical accounts implicate increased pMFC activity in response to erroneous responses, response conflict, or increased error likelihood (Botvinick et al., 2001; Carter et al., 1998; Dehaene et al., 1994; Nee, Kastner, & Brown, 2011; Yeung, Botvinick, & Cohen, 2004).

Event-related potential (ERP) studies have contributed extensively to the formation of these theories by identifying different ERP components generated in pMFC, which are assumed to reflect different aspects of these processes. The first described ERP component associated with action monitoring and error detection was the so-called error negativity (Ne; Falkenstein, Hohnsbein, Hoormann, & Blanke, 1990), which occurs between 50 and 100 ms after an error has been made (also referred to as ERN; Gehring, Goss, Coles, Meyer & Donchin, 1993). Later research has identified a similar component emerging approximately 250 ms after negative performance feedback (Gehring & Willoughby, 2002; Miltner, Braun, & Coles, 1997), which is frequently called the feedback-related negativity (FRN). In addition, ERP studies have identified the stimulus-locked N2 component to be increased roughly 250 ms following stimuli that induce pre-response conflict (i.e., conflict between two competing response tendencies; Nieuwenhuis, Yeung, Van den Wildenberg, & Ridderinkhof, 2003; Yeung, Botvinick, & Cohen, 2004). For example,

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Nieuwenhuis and colleagues (2003) identified the stimulus-locked N2 in response to infrequent stimuli, independent of trial type (go, no-go).

Several theoretical accounts have provided useful frameworks for explaining the emergence of these ERP components. The Ne and FRN, for example, play a central role in the reinforcement-learning model of performance monitoring as proposed by Holroyd and Coles (2002). According to this view, both components reflect the same performance-monitoring process but occur at different time points, with the Ne generated immediately after internal feedback signaling that an error has been made, and the FRN in response to negative external feedback indicating incorrect performance. In both instances, the ACC detects when an outcome is worse than expected and uses this information to facilitate the development of adaptive behavior (Holroyd & Coles, 2002). Findings that the FRN is not sensitive to the absolute magnitude but rather to unexpected deviations from the reward value (Holroyd, Larsen, & Cohen, 2004; Holroyd, Nieuwenhuis, Yeung, & Cohen, 2003) are in line with this contention (see also Simons, 2010). In addition, functional MRI studies support the common origins of both ERP components in the ACC in response to internally and externally generated negative feedback (Holroyd et al., 2004; Mars et al., 2005).

On the other hand, the Ne and the stimulus-locked N2 play a central role in the conflict-monitoring theory (Botvinick et al., 2001), which states that the ACC evaluates the need for cognitive control by monitoring occurrences of conflict when multiple competing response tendencies are simultaneously activated (Botvinick, Cohen, & Carter, 2004; Nieuwenhuis et al., 2003; Yeung et al., 2004). In this view, both ERP components are reflections of the same process, but occurring at different time points, with the elicitation of the N2 when conflict that results from two competing response tendencies (i.e., left and right index finger) is detected before the actual response (resulting in correct trials) and the Ne reflecting detection of the same conflict after execution of an erroneous response (Carter et al., 1998; Van Veen & Carter, 2002; Yeung et al., 2004). Indeed, several ERP studies implicate that the N2 and Ne rely on the ACC as a common generator (Ladouceur, Dahl, & Carter, 2007; Liotti, Woldorff, Perez, & Mayberg, 2000; Nieuwenhuis et al., 2003; Van Veen & Carter, 2002). In addition, research using neuroimaging techniques such as functional magnetic resonance imaging (fMRI) has provided congruent evidence for this assumption. For example, Carter et al. (1998) showed that in addition to incorrect responses, the ACC was also activated in conditions of greater response competition preceding correct responses.

Importantly however, dissociations between N2 and Ne amplitudes may still occur, because these components are related to different aspects of task processing, namely target stimulus information (Ne) and irrelevant stimulus information (N2; Yeung & Cohen, 2006). In other words, the Ne depends on the degree of processing of the target stimulus whereas the N2 reflects activation of distracting, irrelevant stimuli. In addition, unlike the Ne, N2 latency has been found to relate to response selection processes, with shorter latencies being associated with faster responses, independent of level of conflict (Di Russo, Taddei, Apnile, & Spinelli, 2006; Gajewski, Stoerig, & Falkenstein, 2008).

Recently, Alexander and Brown (2011) have proposed a comprehensive model that unifies many of the above-mentioned theories of mPFC function into one single account, which they coined the predicted response-outcome (PRO) model. Simulations of this model showed that a single underlying mechanism may account for the generation of error signals, error-likelihood, conflict, etc., with maximum activity when expected events fail to occur, independent of the valence of the event (good or bad).

Up until now, most studies that investigated different ERP components have used speeded reaction-time tasks or reinforcement-learning paradigms, in which task-specific strategies and instructions minimally associated with real-life decision-making, have to be incorporated and applied for successful performance monitoring. However, many daily routines and choices people have to make are strongly coupled with particular outcome expectancies and conflict. For example, when you cross a road as soon as the traffic light has turned green, you expect other traffic from competing directions to wait, as their traffic light should be red. On the other hand, approaching an intersection while the traffic light turns orange may induce conflict, because depending on distance and speed, one has to decide to stop or proceed.

In the current study we wanted to investigate performance-monitoring processes and accompanying ERP components during more everyday life experience-based decision-making. To accomplish this, we designed a task in which, to a certain extent, everyday expectancies and conflict-inducing situations were integrated. Participants had to engage in a two-choice reaction-time traffic task, during which both behavioral and ERP measurements were obtained. On each trial, both the participant and another road user – controlled by the computer – had to concurrently decide whether to cross or not to cross an intersection. In addition, traffic lights colored green, orange, or red were positioned at the intersection next to each road user. To investigate whether knowledge of traffic lights and associated rules would influence the decision-making process independent of task conditions, all combinations of green, orange, and red were presented during the task. Obviously, this approach is somewhat artificial, as in real-life, the colors displayed by traffic lights from opposing directions are not visible (although probably implicitly inferred). This trade-off however was implemented to assure that participants based their decision-making on the same, explicit information. Also, the execution of the crossing was not displayed on screen. Instead, the outcome of this response (i.e., whether the crossing was successful or not) was indicated by the feedback. The frequency of positive and negative feedback was equally distributed within each condition, independent of traffic light colors. In this way, abidance of traffic rules was not explicitly hinted at nor rewarded during the execution of the task. Although in real-life road users usually abide by traffic rules, this approach allowed us to investigate if conflict and expectancies were induced by everyday knowledge of traffic light rules (i.e., a green light means cross, while an

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orange light indicates "prepare to stop" and a red light prohibits traffic to proceed) and whether these aspects of the decision-making process were still incorporated and consequently reflected in behavioral response patterns and the ERP components.

Based on previous work involving reinforcement learning (Holroyd & Coles, 2002; Nieuwenhuis et al., 2002), we hypothesized that the degree of unexpectedness based on real-life action-outcome coupling would be reflected in the negativity of the FRN. More specifically, we predicted that negative feedback in response to crossings that in real-life are expected to be successful (e.g., crossing an intersection with a green traffic light, while the other road user has a red light) would result in larger FRN components than to crossings that in real-life generally are unsuccessful (crossing an intersection with a red light, while the other road user has a green light) or ambiguous traffic light combinations (e.g., both traffic lights are orange). Likewise, in line with previous research on conflict monitoring (Barch et al., 2000; Yeung et al., 2004), we expected that ambiguous traffic light combinations are weakly associated with a particular response (e.g., both traffic lights have the same color and you have to decide to cross or not) and would result in more pre-response conflict compared to the situation in which traffic lights are strongly associated with a particular response (e.g., not crossing an intersection when your traffic light is red and the traffic light for the other road user is green), as reflected by an enhanced N2 component.

To summarize, the current study aimed at investigating performance-monitoring processes during everyday life experience-based decision-making. At a behavioral level, we expected daily-life knowledge and expectations to be reflected in an increased number of crossing responses for situations that are associated with allowed driving (i.e., a green traffic light while the traffic light for road users from competing directions is red) compared to situations that are associated with prohibited driving (i.e., a red traffic light while the traffic light for road users from competing directions is green) or are ambiguous (similar color displays for both traffic lights). Also, we expected reaction times (RTs) to be prolonged for ambiguous and hence, conflict-inducing traffic light combinations (e.g., Fan, McCandliss, Sommer, Raz, & Posner, 2002). On an electrophysiological level, we expected the FRN to be more pronounced for everyday unexpected outcomes (i.e., a collision while the traffic light color indicated right of way) compared to everyday expected outcomes (i.e., a collision while the traffic light color prohibits proceeding). Similarly, we predicted ambiguous traffic light combinations to result in more conflict before a decision was made, as reflected by an enhanced N2.

Methods

Participants

Fifteen participants were recruited at the Radboud University Nijmegen. Participants were compensated €10 per hour for their participation and had normal or corrected-to-normal vision. One participant was removed from the dataset because of excessive electroencephalogram (EEG) artifacts. As a result, data on the remaining 14 participants (12 women, mean age = 22.0, *SD* = 4.8 years) were analyzed and reported.

Design and Procedure

The aim of the task was to cover an as large as possible distance during a simulated traffic task. To engage participants in the task, they were told that of all participants, the three with the highest scores on total covered distance would receive an additional €5 for their performance. On each trial, an intersection was presented that displayed one rectangular shape at the lower end of the intersection, which represented the participant's vehicle, and another rectangular shape was either positioned at the right or left side of the intersection, representing the computer's vehicle (see Figure 1). In addition, on each trial traffic lights were displayed as colored circles, one at the right side of the participants' shape and one at the right side of the computers' shape. To be able to contrast behavioral and electrophysiological results associated with realistic and unrealistic traffic light combinations, all combinations of green, orange, and red display were possible, resulting in nine different traffic light combinations. Participants were instructed to decide on each trial whether they wanted to cross the intersection or not, while the other road user would concurrently make a similar decision. Participants had to respond by pressing one of two buttons on a button box with a response accuracy of 1 ms, which was developed by the technical support group at the social science faculty of the Radboud University. One designated response button was associated with the response to cross whereas another designated button was associated with the response not to cross. Participants were informed that, in case both the computer and the participant decided to cross at the same trial, this would result in a collision and hence, an unsuccessful crossing for the participant. Conversely, if the participant decided to cross the intersection while at the same trial the computer decided not to cross, this would result in a successful crossing for the participant. Importantly, without specifying the prerequisites for a successful crossing, participants were instructed to try to make as many meters as possible by crossing the intersection, while at the same time taking into account the presence of the other road user.

Unbeknownst to the participants, the task was programmed such that for each traffic light combination the participant decided to cross, the other road user was programmed to cross the intersection half of the trials and not to cross the intersection on the other half of the trials, counterbalanced over its position (right, left) and traffic lights colors (all possible combinations of green, orange, and red). In each condition, the presentation of positive and negative feedback was equally distributed over the crossing trials. This way, the occurrence of positive and negative feedback was 50% for each condition, so traffic light colors were in fact uninformative. Consequently, the

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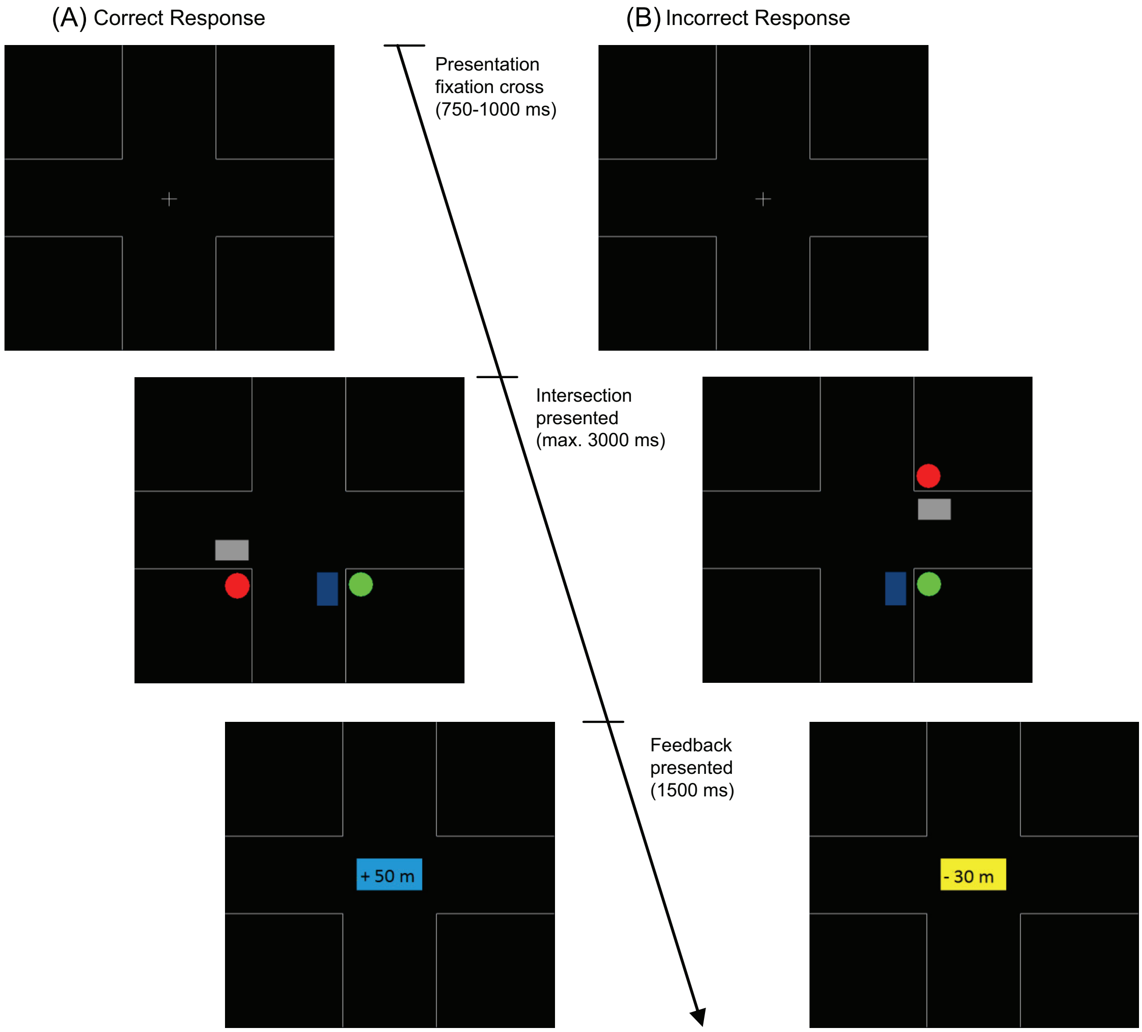

Figure 1. Setup of the two-choice traffic task with an example of a correct crossing (A) and an incorrect crossing (B). The participant was represented by the rectangular shape (blue) at the lower end of the intersection, whereas the other road user (computer) was represented by the rectangular shape (gray) at either the left or right side of the intersection. After presentation of the intersection (pictures depicted in the middle) participants had to press a designated button if they decided to cross the intersection and another designated button in case they decided not to cross the intersection. After a response associated with crossing, feedback indicated whether the response was correct (+50 m) or incorrect (–30 m). After a response associated with not crossing, feedback indicated that the covered distance remained unchanged (+0 m).

decision to cross or not should be equal over conditions if everyday based knowledge of traffic lights was not taken into account during the task. After each successful crossing response, feedback was presented indicating that 50 m were added to the total of covered distance. Conversely, after an unsuccessful crossing, feedback indicated that 30 m were subtracted from the total of covered distance. If the participant decided not to cross by pressing the designated button, feedback would display an addition of zero meters, indicating that the total covered distance did not change on that particular trial. The asymmetry between reward (+50 m) and penalties (–30 m) was necessary to ensure that the total covered distance after each block would be more than zero.

Each of the nine traffic light combinations occurred on a total of 42 trials, with the position of the other road user counterbalanced over these trials (21 trials positioned left, 21 trials positioned right), resulting in 18 different conditions (nine traffic light combinations, two positions of the other road user) which were evenly distributed over three blocks of 126 trials each, adding up to a total of 378 trials (for a schematic overview for all traffic light combinations, response options, and feedback types, see Figure 2). Intersections were displayed for a maximum duration of 3,000 ms. If participants failed to press a button within 3,000 ms, feedback would indicate that the response was too slow. Neutral, positive, and negative feedback were presented as follows: If participants pressed the button

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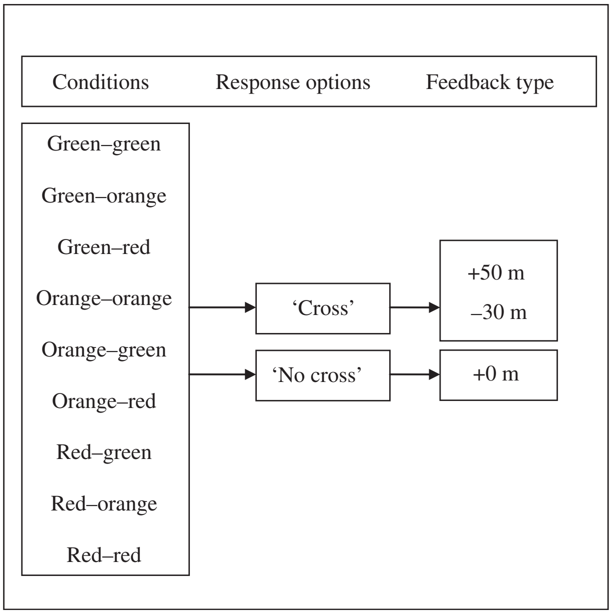

Figure 2. Schematic overview of all traffic light combinations, possible response options, and feedback types.

designated as the response not to cross, feedback was shown with the text: "+0 m." If participants choose to press the button designated as the response to cross, feedback would indicate "+50 m" for successful crossings and "–30 m" for unsuccessful crossings. After a button press, the intersection remained on screen unchanged for 1,000 ms before the feedback screen was presented by depicting the amount of added or subtracted meters at the center of the screen, positioned in the middle of an empty intersection. Feedback was displayed for 1,500 ms, after which the next trial would start with the presentation of a fixation cross. Trial duration ranged between a minimum of 4,250 ms and a maximum of 6,000 ms, depending on the RT of the participant. After each block with duration of approximately 10 min, progress on the task was indicated by displaying the cumulative amount of covered distance in meters for a duration of 5,000 ms, after which the participant could take a 5-min break before continuing with the next block. The total experiment lasted 1.5 hr, including preparation and breaks.

Please note that all possible traffic light combinations of green, orange, and red were included in the experiment. However, a first inspection of the data revealed that responses (cross, not cross) were not equally distributed over conditions, resulting in a number of conditions with too few responses of either type to conduct reliable separate ERP analyses. Considering power issues, we decided to restrict our ERP analyses to conditions with at least 10 cross response trials per participant. Three "crossing" conditions of interest met these requirements, with each participant having enough responses to cross for the intersection types green-red (M = 35.5, SD = 7.75, range: 20–42), green-orange (M = 35.5, SD = 5.43, range: 27–42), and orange-orange (M = 28.07, SD = 9.62, range: 10–40). However, for the FRN analyses these three conditions had to be further subdivided into feedback type (positive, negative), which resulted in three participants having less than 10 feedback trials to analyze. To resolve this issue, these three participants were included in the N2 analyses (N = 14) but excluded from FRN analyses (N = 11).

With regard to the "no cross" responses, only the conditions with a red traffic light for the participant appeared to reach the minimum number of trials to analyze, however, close inspection revealed that in each condition (red-green, red-orange, red-red) 1–4 participants had less than 10 "no cross" responses. Also, the involved participants were not always the same individuals for each "red traffic light" condition. In addition, since feedback for "no cross" responses (+0 m) did not reveal the decision the other road user had made (cross, not cross), expectations could not be formed on the basis of these trials, which made investigations of these trials also less interesting in the current task design. Based on these issues, we decided to do ERP analyses only on the crossing responses for the three above-mentioned crossing conditions, and to do behavioral analyses on both the response to cross and the response not to cross for the same three conditions. In this way, it was still possible to investigate response differences in conflict and expectancies as a function of traffic light ambiguity, ranging from unambiguous (green for the participant, red for the other road user) to semi-ambiguous (green for the participant, orange for the other road user) and ambiguous (orange for both the participant and the other road user[1]) combinations.

Electrophysiological Recordings and Data Analyses

The EEG was recorded with 27 active electrodes (Acticap, Brain Products, Munich, Germany) mounted in an elastic cap and arranged according to an extended version of the 10–20 system. Signal impedance was kept below 5 kΩ. All signals were referenced to the left mastoid and later offline re-referenced to the average of both mastoids. The vertical electrooculogram (EOG) was recorded with electrodes placed above and below the right eye. Horizontal EOGs were recorded with electrodes at the outer canthi of both eyes. All signals were digitized with a sampling rate of 500 Hz, and filtered offline with a .50 Hz high-pass filter and a slope of 24 dB/oct and a 20 Hz low-pass filter and a slope of 24 dB/oct. After removal of artifacts with signals that exceeded ±75 μV, the minimum number of segments per participant was 18 in the green-red condition, 26 in the green-orange condition, and 10 in the orange-orange condition (one participant). Eye movement artifacts were rejected using Independent Component Analysis (Jung

[1] Please note that an additional analysis on N1 amplitude at electrodes Fz, FCz, and Cz (latency range 100–200 ms) did not reveal any significant effect for the different ambiguity conditions, $F(2, 26) = 1{,}10$, $p = .35$.

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et al., 2000), with the built-in ICA toolbox of Brain Vision Analyzer.

EEG signals for trials with correct and incorrect feedback were time-locked to feedback onset and were analyzed separately for positive and negative feedback for each participant, relative to a 200 ms interval preceding feedback onset. FRN amplitude was determined by the difference between the most negative peak between 200 and 350 ms after feedback onset and the preceding most positive peak, and analyzed at the midline electrodes Fz, FCz, and Cz.

EEG signals for cross trials with different intersection setups were time-locked to stimulus onset and analyzed separately for each traffic light combination relative also to a 200 ms pre-stimulus baseline. The N2 was then defined as the most negative deflection between 200 and 350 ms after stimulus onset and analyzed at the midline electrodes Fz, FCz, and Cz.

Percentages of crossing responses between conditions were investigated by entering the difference scores of crossing percentages (cross, not cross) for each condition (green-red, green-orange, orange-orange) as within-subject variables in a 2 × 3 repeated-measures general linear model (GLM). To examine reaction-time patterns, a similar GLM was conducted with crossing response (cross, not cross) and intersection type (green-red, green-orange, orange-orange) as within-subject variables. Additionally, to investigate differences in response selection processes, correlations between N2 latencies and RTs for the three different conditions were investigated.

For the ERP analyses, N2 amplitudes were entered in a 3 × 3 repeated-measures GLM with the within-subject factors traffic light ambiguity (green-red, green-orange, orange-orange) and electrode position (Fz, FCz, Cz). FRN amplitudes were submitted to a 2 × 3 × 3 repeated-measures GLM with feedback (positive, negative), traffic light ambiguity (green-red, green-orange, orange-orange), and electrode position (Fz, FCz, Cz) as within-subject factors. Finally, if applicable, Greenhouse-Geisser corrections were used. For interpretation purposes, uncorrected degrees of freedom are reported in all cases.

Results

Behavioral Data

Frequencies

Figure 3 shows the mean percentages of crossing responses for the unambiguous, semi-ambiguous, and ambiguous conditions. The analyses on difference scores of the percentages of the crossing response (cross-not cross) for each intersection type (green-red, green-orange, orange-orange) showed a main effect of ambiguity, $F(2, 26) = 8.20$, $p = .002$. Tests of Within-Subjects Contrasts showed that the differences between crossing and not crossing response percentages were significantly smaller for the orange-orange intersection type compared to both the green-red intersection type, $F(1, 13) = 8.46$, $p = .012$, and the green-orange intersection type, $F(1, 13) = 10.88$, $p = .006$, indicating that crossing responses as opposed to responses not to cross occurred more frequently for the unambiguous green-red intersection type ($M = 70.29$, $SD = 36.16$) and the semi-ambiguous green-orange intersection type ($M = 69.71$, $SD = 25.97$) compared to the ambiguous orange-orange intersection type ($M = 34.14$, $SD = 45.59$).

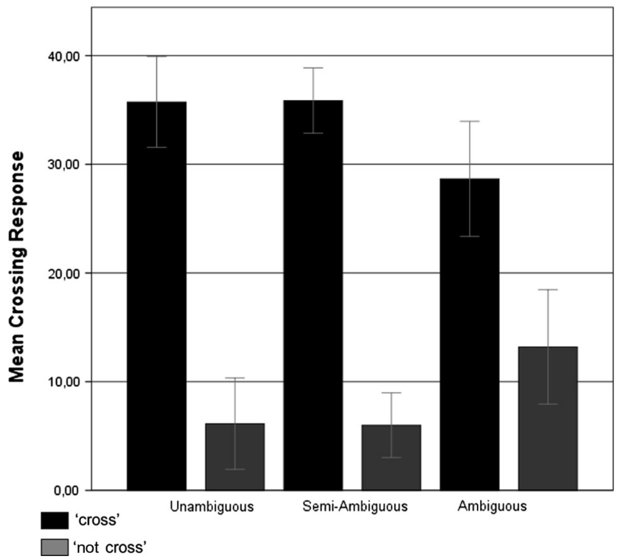

Figure 3. Mean percentages of crossing responses in the unambiguous (green-red), semi-ambiguous (green-orange), and ambiguous (orange-orange) condition.

Reaction Times

A main effect of crossing response was found: participants decided significantly faster to cross ($M = 839.65$, $SD = 70.52$) than not to cross ($M = 955.13$, $SD = 75.98$), $F(1, 9) = 56.98$, $p < .001$. Although the numerical values hinted at the expected pattern of slower cross responses in the ambiguous condition (810 ms) than in the semi-ambiguous (782 ms) and unambiguous conditions (773 ms, see Table 1), differences in RTs between conditions were nonsignificant $F(2, 18) = .79$, $p = .47$. RTs for the three different conditions were not significantly related to N2 latencies (all rs < .50, all ps > .08).

Electrophysiological Data

N2

The absence of a significant main effect for electrode indicated that N2 amplitude was not significantly different at the three midline electrode positions, $F(2, 26) = 2.21$, $p = .210$. Likewise, no significant interaction was found

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Table 1. Mean RTs for the ERP analyzed crossing conditions

Traffic light combination	Crossing RTs (ms) *M* (*SD*)	No crossing RTs (ms) *M* (*SD*)	Total RTs (ms) *M* (*SD*)
Unambiguous (green[a]-red[b])	773 (55)	898 (71)	809 (57)
Semi-ambiguous (green[a]-orange[b])	782 (59)	1,015 (92)	883 (71)
Ambiguous (orange[a]-orange[b])	810 (56)	952 (79)	881 (54)

Notes. [a]The color denotes the traffic light display next to the rectangular shape of the participant. [b]The color denotes the traffic light display next to the rectangular shape of the other road user.

between intersection type and electrode sites, $F(4, 52) = .22$, $p = .807$. Importantly however, a significant main effect of traffic light ambiguity on N2 amplitude was identified, $F\ (2, 26) = 3.71$, $p = .038$ (Figure 4). Contrasts showed that the N2 associated with the ambiguous intersection type (orange-orange; $M = -4.70$, $SD = 1.19$) was significantly more negative compared to the semi-ambiguous intersection type (green-orange; $M = -3.31$, $SD = 0.99$; $t(13) = 2.21$, $p = .045$) and the unambiguous intersection type (green-red; $M = -2.88$, $SD = .92$; $t(13) = 2.52$, $p = .025$).

FRN

Analyses on the FRN peaks revealed that overall, this component differed significantly between positive ($M = -3.86$, $SD = 0.69$) and negative ($M = -5.93$, $SD = 0.88$) feedback, $F(1, 10) = 5.80$, $p = .037$, in the expected direction with increased amplitudes for negative feedback (Figure 5). Neither the main effect for intersection type, nor the interaction between feedback type and intersection type (ambiguous, semi-ambiguous, and unambiguous) did interact, Fs < 1. The main effect of electrode site was not significant, $F(2, 20) = 4.34$, $p = .052$.

Please note that correlation analyses did not reveal any correlations between ERP measures and behavioral measures (RTs, frequencies of crossing responses; all ps > .075).

Discussion

In the current study, we investigated performance-monitoring processes during everyday life experience-based decision-making. Results of this study are partly consistent with our hypotheses that expectancies and conflicts based on real-life experience are reflected in behavioral outcomes and in ERP components known to be involved in action monitoring and control. First, although the valence of feedback was not dependent on the colors of traffic light combinations, percentages of crossing responses were higher when the traffic light color for the participant was green as compared to orange. Apparently, everyday experience with traffic situations influenced the decision-making process during the task, resulting in the tendency to cross the intersection in the presence of a signal which is strongly associated with this response. Second, as predicted, the

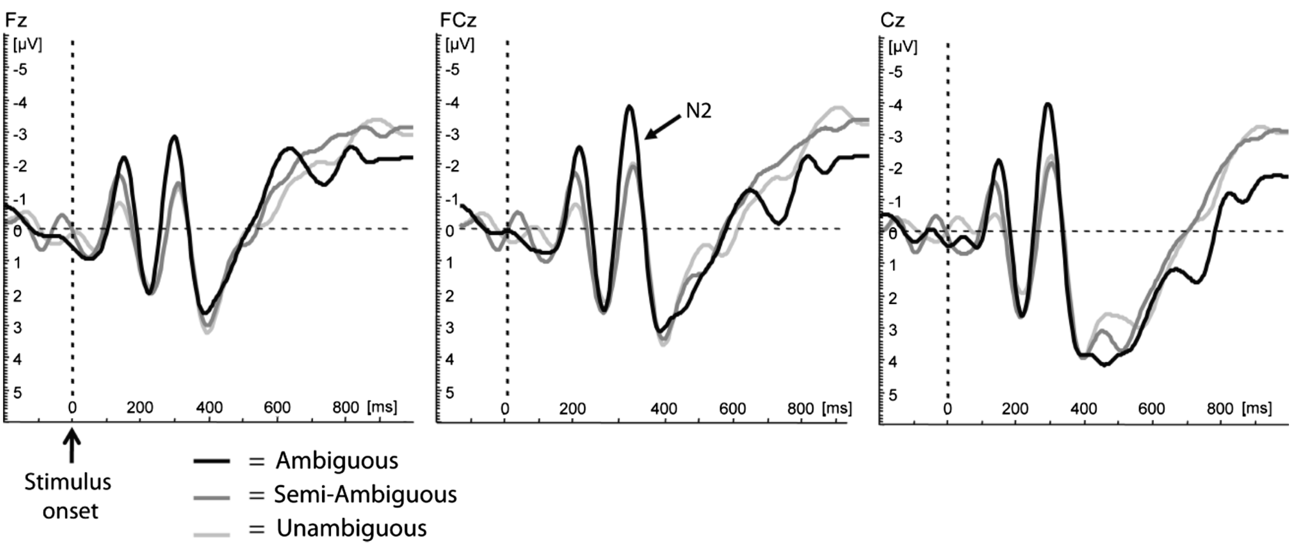

Figure 4. Grand average N2 waveforms ($n = 14$) time-locked to stimulus onset for unambiguous (green-red; dashed lines), semi-ambiguous (green-orange; gray solid lines), and ambiguous stimuli (orange-orange; black solid lines) separately. Midline electrodes Fz, FCz, and Cz are depicted.

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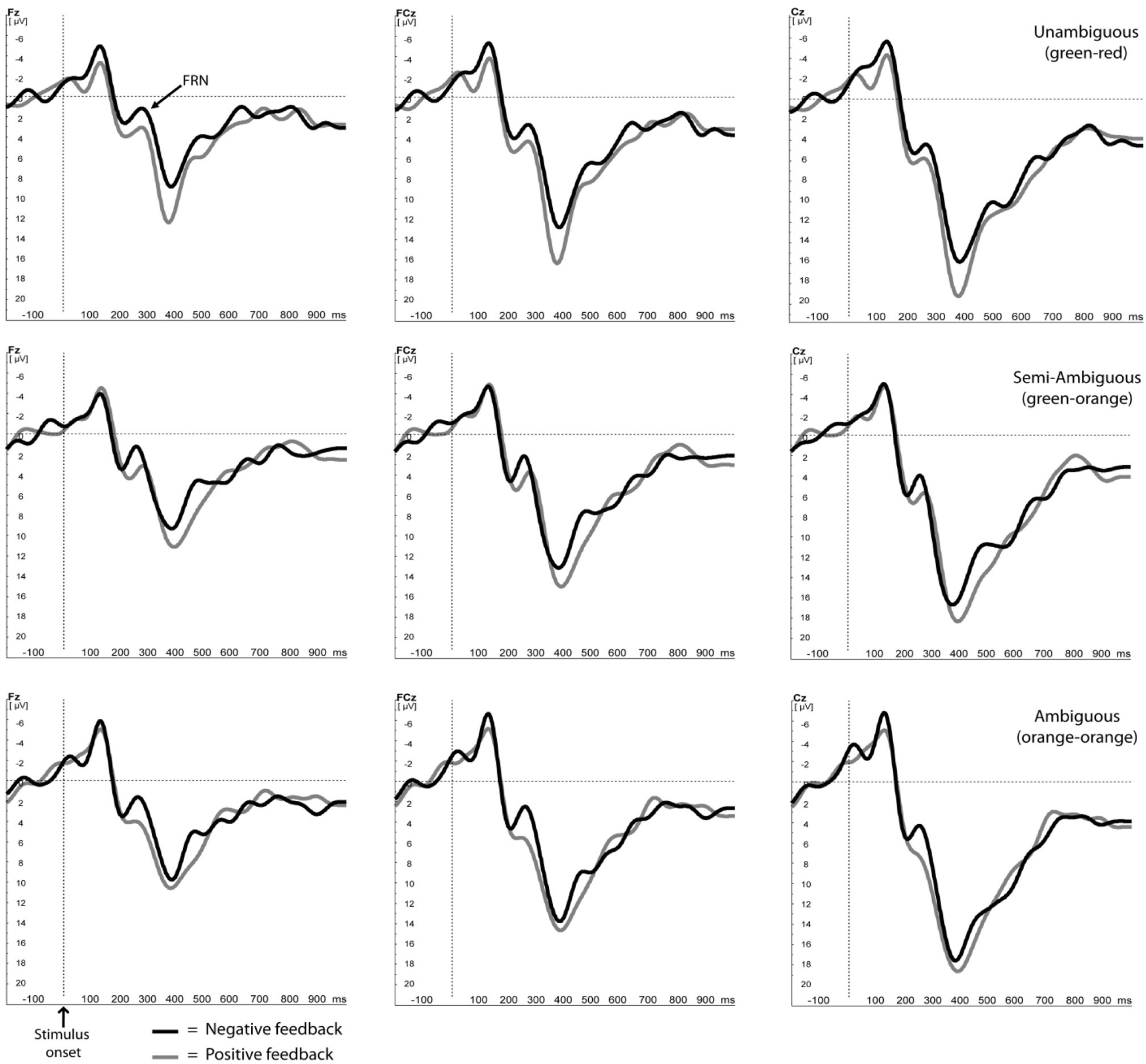

Figure 5. Feedback-locked ERPs (n = 11) measured at Fz, FCz, and Cz in the unambiguous (green-red), semi-ambiguous (green-orange), and ambiguous (orange-orange) conditions, for positive (gray lines) and negative (black lines) feedback separately.

amount of response conflict as reflected in the stimulus-locked N2 component was larger for the traffic light combination we thought was most ambiguous based on everyday experience (both traffic lights were illuminated orange) compared to both the semi-ambiguous combination (green-orange) and the unambiguous combination (green-red). Third, the FRN was larger for negative feedback as opposed to positive feedback, but was not modulated by expectancies based on the knowledge of traffic rules. In other words, the FRN was not larger for unsuccessful crossings that are unexpected in everyday life (a green traffic light while the traffic light for the other road user was red) compared to more ambiguous traffic light combinations (a green or orange traffic light while the traffic light for the other road user was orange).

Based on the results of the current study, we argue that the stimulus-locked N2 was enhanced as a function of more crosstalk or competition between alternative response options. These findings are also in line with the research of Barch and colleagues (2000), who demonstrated increased ACC involvement for nouns associated with more response options compared to nouns associated with less response options, and in response to verbs that were weakly associated as opposed to strongly associated with particular nouns. Similarly, in traffic, the orange light is associated with proceeding if close to the crossing, but signals one

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should stop if the distance is still very large. In contrast, green or red lights are uniquely associated with the response to drive or stop, respectively. Apparently, knowledge of traffic rules influenced the decision-making process, which must have become even more confusing when traffic lights for both directions were illuminated orange. This notion is strengthened by the finding that the N2 was most pronounced in response to ambiguous (orange-orange) traffic light combinations. Based on previous fMRI and ERP studies (see Van Veen & Carter, 2002, for a review), the current findings may suggest increased ACC activity with increased levels of conflict.

Although the current results indicate that conflict-monitoring processes account for both behavioral and electrophysiological observations, it is important to mention that these findings may alternatively reflect error likelihood predictions (Brown & Braver, 2005). According to this recent view, the ACC might not detect conflict or errors, but instead predict the probability of making an error. By conducting an fMRI study, Brown and Braver (2005) showed that the ACC was more active on trials associated with higher error likelihood compared to trials associated with low error likelihood, even if trials in which errors were committed were excluded from analyses.

In the present study, error likelihood was kept similar over conditions, which means that participants could not have made predictions of error likelihood based on task conditions. However, if it turns out that the ACC is involved in predicting error likelihood (Brown & Braver, 2005), our findings of a more pronounced stimulus-locked N2 in the ambiguous condition potentially reflect error-likelihood predictions based on knowledge of traffic rules. It is important to note that the current findings on the stimulus-locked N2 are equally interpretable in light of conflict-monitoring processes as error-likelihood predictions. To obtain more insight into the mechanisms underlying the generation of this component, it would be interesting to find out if well-learned everyday knowledge (such as knowledge of traffic rules) influences related decision-making processes either through conflict-monitoring processes reflecting response competition, or through error-likelihood predictions.

In line with our expectations based on the reinforcement model of performance monitoring as proposed by Holroyd and Coles (2002), the FRN was more pronounced for negative as compared to positive feedback. Note that this finding is hard to reconcile with the PRO model (Alexander & Brown, 2011) that holds that the underlying mechanism for error signals, conflict, and error-likelihood is insensitive to the valence of the outcome. Additionally, although on a behavioral level the decision-making process was guided by knowledge of traffic rules, the FRN was not modulated by expectancies based on traffic rules.

Several other studies have found difficulties with establishing a link between the FRN component and expectancy. Results from a study performed by Hajcak and colleagues (Hajcak, Moser, Holroyd, & Simons, 2007) showed that although behavioral responses revealed a reward bias, reward prediction errors did not result in FRN enhancement. In a second experiment (Hajcak et al., 2007), participants had to make predictions both before and after their response choice. The FRN was found to be more pronounced when losses were preceded by two separate lose/win predictions, compared to losses after win/lose predictions. This indicates that the focus on the second prediction overruled the impact of the first prediction and resulted in an increased action-outcome coupling.

In the current study, implicit predictions were probably only made before the decision to cross or not to cross and not considered thereafter, possibly resulting in a weaker action-outcome coupling and hence, an undifferentiated FRN as a function of everyday expectancies. An alternative explanation is that, although response patterns indicated that participants integrated their everyday knowledge of traffic situations in the execution of the task, expectancies and performance-monitoring processes were dominated by the task conditions after a response had been made (see, e.g., Nieuwenhuis, Nielen, Mol, Hajcak, & Veltman, 2005; Nieuwenhuis et al., 2002).

It is important to note that the design of the current study has several shortcomings. For example, the large number of conditions resulted in too few trials available to conduct solid analyses on. Therefore, we were unable to investigate the electrophysiological components in relation to responses not to cross. It would be interesting to find out though, if conflict also arises for responses not to cross in situations that in real-life are associated with successful crossings (e.g., when the traffic light is illuminated green). In addition, in a follow-up experiment, we aim to contrast experience-based decision-making with decisions solely based on task conditions, to get a better grasp on the influence of everyday experience. For example, conditions with "real" traffic light colors could be contrasted with conditions in which the traffic lights have, in this respect, meaningless colors (such as blue or purple), to isolate the effects of experience with traffic lights on the decision-making process.

Another limitation of the current study is that feedback presented on "no cross" trials did not indicate what the other road users' decision had been. The task was designed this way because we wanted to minimize the formation of expectancies on basis of the task, but instead investigate the influence of everyday-based expectancies and conflict on the decision-making process. The drawback of this approach, however, is that participants could not improve their performance, which might have reduced their motivation to do their best. To resolve this, we aim to include more informative feedback and restrict the number of conditions to the most crucial ones in a follow-up study. This approach, in combination with a larger sample size, will enable us to investigate if and how learning influences decision-making based on experience.

Finally, although we tried to integrate components (i.e., traffic rules) of everyday life in the simulated traffic task, the consequences of the decision-making process during this task were obviously very different from real-life consequences. In traffic, ignoring rules or making mistakes has far more serious consequences, which makes driving through red not a very likely action to undertake for most

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of us. Still, findings indicate that everyday well-learned elements influenced associated decision-making process to a certain degree, although behaving accordingly obviously did not yield the desired outcomes. Despite the mentioned limitations, we would like to emphasize that this study was, to our knowledge, the first one to integrate the influence of everyday knowledge in a controlled laboratory task and thereby contributes to the existing literature on decision-making.

To summarize, although the FRN was more pronounced in response to negative feedback as compared to positive feedback, real-life based expectancies did not influence post-response performance monitoring as reflected by this component. In contrast, pre-response conflict monitoring appeared to be affected by these everyday expectations, as reflected by the enhanced stimulus-locked N2 on "everyday" high conflict trials. This interpretation is also supported by the observed behavioral response patterns, which show that the bias toward the response to cross, as opposed to the response not to cross, was much smaller for ambiguous traffic light combinations compared to less ambiguous traffic light combinations. Moreover, crossing responses for the most ambiguous traffic light combination were numerically slower than for the less ambiguous traffic light combinations, although this difference did not reach significance.

To gain more insight into the underlying processes in the generation of the stimulus-locked N2, future ERP studies should attempt to disentangle the role of conflict and error-likelihood predictions in relation to this particular ERP component. In addition, findings on the FRN suggest that outcome predictions were based on task conditions instead of knowledge with regard to traffic rules, or alternatively, that outcome expectancies influenced decision-making before, but not after the response (Hajcak et al., 2007). Follow-up research is needed to investigate the specific role of experience-based expectancies both before and after a decision is made.

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