

Different strategies underlying uncertain decision making: Higher executive performance
is associated with enhanced feedback-related negativity

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Abstract

The aim of the present study was to investigate the role of executive functions (EFs) in different strategies underlying risky decision making. Adult participants from a nonclinical sample were assigned to low or high EF groups based on their performance on EF tasks measuring shifting, updating, and inhibition. ERPs were recorded while participants performed the Balloon Analogue Risk Task (BART). In this task, each balloon pump was associated with either a reward or a balloon pop with unknown probability. The BART behavioral measures did not show between-group differences. However, the feedback-related negativity (FRN) associated with undesirable outcomes was larger in the high EF group than in the low EF group. Since the FRN represents salience prediction error, our results suggest that the high EF group formed internal models that were violated by the outcomes. Thus, we provided ERP evidence for EFs influencing risky decision making processes.

Keywords: Balloon Analogue Risk Task; event-related brain potentials (ERPs); decision making; executive functions; feedback-related negativity; model-based learning; risk-taking behavior

Different strategies underlying uncertain decision making: Higher executive performance is associated with enhanced feedback-related negativity

The detection and evaluation of external feedback is a crucial factor of adaptive decision making (Baker & Holroyd, 2011; Warren & Holroyd, 2012). Converging evidence shows that executive functions (EFs) mediate decision making under explicit risk (Brand, Labudda, & Markowitsch, 2006; Schiebener, Wegmann, Pawlikowski, & Brand, 2012). However, the exact relationship between feedback processing and EFs is still unclear. Event-related brain potential (ERP) correlates of feedback processing, like the feedback-related negativity (FRN), could indicate the need to adjust performance during decision making, which is probably influenced by the EFs (Mushtaq, Bland, & Schaefer, 2011). Specifically, altered feedback processing and decision making have been shown in those clinical syndromes (e.g., ADHD, substance abuse, anxiety) that are associated with atypical EFs (Bari & Robbins, 2013; Gu, Huang, & Luo, 2010; Onoda, Abe, & Yamaguchi, 2010). Therefore, the aim of the present study was to investigate how individual differences in EF performance among healthy participants contribute to various strategies underlying uncertain decision making. To this end, ERPs were measured in a task that mimics real-life choice situations.

The feedback-related negativity (FRN) is a frontocentral negative deflection that occurs 200–300 ms after a negative feedback is presented (Holroyd & Coles, 2002; Talmi, Atkinson, & El-Dereby, 2013). The FRN is thought to mirror rapid feedback evaluation and phasic dopaminergic changes in activity between the basal ganglia and the anterior cingulate cortex, as proposed by the reinforcement learning theory (Holroyd & Coles, 2002). These neural structures together with the prefrontal cortex also underlie cognitive control (e.g., Arnsten & Rubia, 2012; Mushtaq et al., 2011). The FRN could express salience prediction errors, as well, since the component has been sensitive to both negative and positive

unexpected events in a recent study (Talmi et al., 2013). The FRN is usually followed by a P3, which is sensitive to cognitive control and represents a more elaborated evaluation of outcomes (Euser et al., 2013).

During reward-based learning the gating of new information necessarily involves activation of the prefrontal cortex (Chatham et al., 2011; Miyake & Friedman, 2012). As a common prefrontal function, the EFs is not a unitary construct, rather a set of goal-directed control mechanisms including inhibition, mental set shifting, and working memory as the three main subprocesses (Hofmann, Schmeichel, & Baddeley, 2012; Miyake & Friedman, 2012; Miyake et al., 2000). Behavior regulation in situations of emotional or motivational significance is often considered as an aspect of EFs measured by delay discounting tasks, probabilistic learning tasks, and gambling tasks (Lejuez et al., 2002; Zelazo, Qu, & Kesek, 2010). Previous studies showed that the FRN indicates the motivational significance of negative events in these specific EF tasks (e.g., Gehring & Willoughby, 2002; Yeung, Holroyd, & Cohen, 2005).

A common feature of these tasks is decision uncertainty, which implies that none of the response options is considered more advantageous than the other, since no sufficient information is available about outcome probabilities (Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004). The concepts of decision uncertainty and EFs are related in a specific respect: During task-solving, the presence of uncertainty might increase the need for monitoring performance and adjusting ongoing behavior that are also subprocesses of the EFs (Mushtaq et al., 2011). These subprocesses can be investigated through the FRN in decision making tasks (Walsh & Anderson, 2012).

Among tasks investigating the underlying factors of risky decision making and real-world risk-taking, the Balloon Analogue Risk Task (BART) is one of the most widely used (Lejuez et al., 2002). In this gambling task, participants pump a balloon and each pump is

associated with either a reward or a balloon pop with unknown probability. After each successful pump, participants could either stop and collect the accumulated reward, or continue with a balloon pump. If the balloon pops, the accumulated reward is lost. The probability of a balloon pop increases with each successive pump, but the regularity that determines balloon pops is unbeknown to participants (Lejuez et al., 2002).

It has been shown that FRN can be elicited by negative events in the BART (Euser, van Meel, Snelleman, & Franken, 2011; Fein & Chang, 2008). Some theoretical and empirical frameworks have been delineated that might contribute to clarifying the impact of EFs on FRN in the BART. Figure 1 depicts how these perspectives influence each relevant step of decision making, and Table 1 summarizes the basic premises and consequences of each perspective. Hereafter, we summarize these frameworks and accordingly formulate the main assumptions.

The decision situation in the BART provides information about possible gains and losses and about the outcome of decisions associated with the previous balloon (for more specific details, see section Method). For instance, if the participant saw that the last balloon popped after gaining 15 points (5 pumps), he/she would consider the initiation of a further pump after 10 points (4 pumps) a risky decision in the actual context. In addition, the decision situation might remind the individual to other similar gambling conditions. Therefore, expectations about possible consequences of the subsequent decision could be formed on the basis of previous experience, the known or putative probabilities of different outcomes, the number of remaining trials, and the total amount of reward gained until a certain time point. These pieces of specific information and general problem solving strategies are retrieved from long-term memory, which is monitored by the EFs. Then EFs also control the use of this information in selecting an appropriate decision strategy, which could be influenced by unconscious signals, namely the somatic markers (Bechara, Damasio, Tranel, & Damasio,

2005). Finally, each decision yields different types of feedback that violates or confirms previous expectations and later acts as a somatic marker (see also the original approach of Brand et al., 2006, p. 1272).

In regard to the decision strategy, there are at least two ways for adaptive response modification (Nemeth, Janacsek, Polner, & Kovacs, 2013). First, model-based learning could guide individuals' choices through testing different hypotheses about the structure of the current task. This strategy is suggested to be partly related to executive control processes. Second, the structure of the task could be learned in a hypothesis-free way with less reliance on models (Daw, Niv, & Dayan, 2005; Janacsek, Fiser, & Nemeth, 2012). A previous study compared low and high EF participants in a probabilistic sequence learning paradigm and found striking differences between the two groups (Nemeth et al., 2013). While in the normal alert state high EF participants showed decreased performance as compared to low EF participants, the high EF group's sequence learning was enhanced in the hypnotic state. The latter result was interpreted as the attenuating effect of hypnosis on frontal lobe functions (Gruzelier, 2006).

Similarly, some previous evidence suggests that optimal performance on the BART might not require superior EFs. The study of Fecteau et al. (2007) using transcranial direct current stimulation showed that enhanced bilateral activation of the dorsolateral prefrontal cortex yielded a more conservative and risk-averse response style (i.e., lower number of pumps). Likewise, a recent fMRI study showed that cognitive control networks were more active before safe choices (on trials preceding the accumulation of reward) than before risky choices (on trials preceding a further pump), which suggests the essential role of control processes in risk avoidance (Helfinstein et al., 2014).

The probabilistic structure of the BART also affects decision strategies. Gambling tasks based on uncertain decisions differ in what extent they involve decisions under risk

(when the outcome probabilities are known) or ambiguity (when the occurrence of a specific outcome is unknown) (Bechara et al., 2005). According to the notion of Brand et al. (2006), decision making under risk depends more on the EFs than decision making under ambiguity. The BART involves decisions under ambiguity (Fecteau et al., 2007), since the safe choice (collect the accumulated reward) is obvious to participants, but the exact probability of the outcomes associated with the risky choice (successive pump) remains largely unclear during the entire task. Therefore, the BART performance might be less related to EFs (Campbell, Samartgis, & Crowe, 2013; Fecteau et al., 2007). At the same time, the use of somatic markers or heuristics towards certain responses could be essential in gaining experience with the structure of the task.

We propose that these frameworks predict how individual differences in EFs modulate behavioral performance and FRN/P3 on the BART (see Table 1). Participants with high EFs might use a model-based strategy when choosing between response options. This could involve the forming of outcome expectations on the basis of internal models. Since the FRN reflects salience prediction errors (Talmi et al., 2013), the violation of outcome expectations might elicit a larger FRN than when no conscious expectations have been formed. At the same time, enhanced cognitive control (EFs) and conscious performance monitoring per se could yield larger FRN (Mushtaq et al., 2011). According to previous results (Fecteau et al., 2007; Helfinstein et al., 2014), individuals with high EFs would show decreased risk-taking at the behavioral level, which eventuates the accumulation of reward instead of initiating a further pump. This contradicts, however, that ambiguous decisions might not depend on the EFs (Brand et al., 2006). The BART could be solved by following response preferences based on somatic markers (Bechara et al., 2005; Brand et al., 2006), as well, which would more likely characterize participants with low EFs.

Consequently, in the present study, we assumed that participants with high EFs would solve the BART with a different underlying strategy. We expected larger FRN amplitude in the high EF than in the low EF group reflecting enhanced feedback processing. However, we assumed not to find between-group difference in the behavioral performance, since EFs seem to be less involved in decisions under ambiguity (Brand et al., 2006).

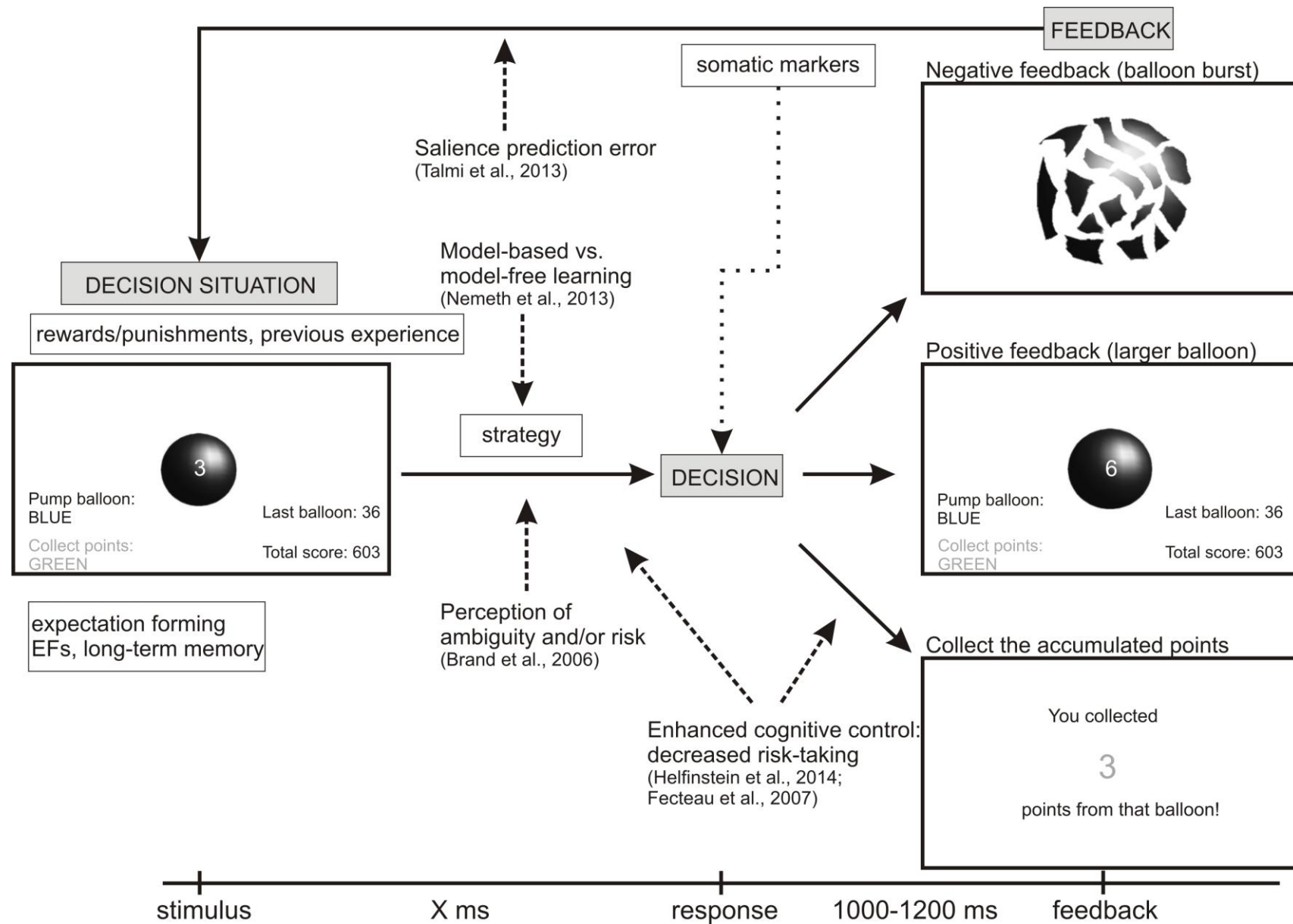


Fig. 1. Schematic illustration of the trial structure in the BART and the steps of decision making. A screen with five objects was displayed; at each new balloon, a zero was presented in the middle of the sphere. “Total score” depicted the points in the permanent bank, “Last balloon” depicted the points collected from the previous balloon. Participants could choose to collect the accumulated points from the actual balloon, which ended the trial, or they could choose to pump the balloon further. As a consequence of a pump, a negative feedback (balloon burst) or a positive feedback (larger balloon with more points inside) could have appeared. Negative feedback also ended the trial and a new balloon was presented.

Dashed arrows indicate the steps of decision making on the basis of previous theoretical or empirical frameworks. Grey-shaded boxes present the main steps of decision making, while transparent boxes present the involved processes and background mechanisms. The dotted line depicts the direct path through the limbic loop between somatic markers and the decision per se. This illustration is an adapted and amended version of figures published by Brand et al. (2006, p. 1273) and by Fein and Chang (2008, p. 144). For more details, see text and Table 1.

Table 1. Summary of relevant theoretical and empirical frameworks.

Framework	Premises	Predictions/Consequences
Model-based vs. model-free learning (Nemeth et al., 2013)	<p>Model-based learning involves testing hypotheses about the structure of the task.</p> <p>Internal models could be established about the distribution of balloon bursts.</p> <p>Model-based learning, at least in part, depends on higher cognitive control processes (i.e., higher EFs).</p> <p>Model-free learning is more effective than model-based learning in ambiguous decision making situations.</p>	<p>Higher EFs are associated with model-based learning.</p> <p>Constant updating of working memory in case of model-based learning.</p> <p>Lower total score (less effective task-solving) in case of model-based learning.</p>
Perception of ambiguity and/or risk (Brand et al., 2006)	<p>Decision making under risk is more dependent upon EFs than decision making under ambiguity.</p> <p>The BART involves decision making under ambiguity: The explicit risk (outcome probability) of a given pump is unknown.</p>	<p>The level of EFs and BART behavioral performance are independent.</p>
Salience prediction error (Talmi et al., 2013)	<p>The FRN reflects prediction errors associated with motivational salience.</p> <p>Balloon bursts are salient events.</p> <p>Balloon bursts are more salient for those who expect balloon increase.</p>	<p>Balloon bursts as salient events elicit larger FRN.</p> <p>The FRN is larger for those who expect balloon increase.</p>
Enhanced cognitive control (Fecteau et al., 2007; Helfinstein et al., 2014)	<p>Activation of the prefrontal cortex decreases risk-taking.</p> <p>Greater activation can be found in the extensive networks of cognitive control before safe choices on the BART.</p>	<p>More risk-averse response style (less pumps) in the high EF group.</p> <p>Larger FRN and P3 amplitude for balloon bursts in the high EF group.</p>

Method

Participants

Table 2 summarizes the descriptive characteristics of the sample. Thirty-nine undergraduate students took part in the experiment. Altogether seven of them were excluded by reason of excessive artifacts or not having sufficient number of negative-feedback locked epochs (see section EEG Recording and Analysis). Thirty-two young adults remained in the final sample. They were assigned to two groups according to their performance on tasks measuring EFs (see sections Neuropsychological Measures and Data Analysis). All participants had normal or corrected-to-normal vision, reported normal hearing, and provided informed consent to the procedures as approved by the Institutional Review Board of Eötvös Loránd University, Hungary. Participants received course credit for taking part in the ERP experiment.

Table 2. Descriptive data of demographic variables, rating scales, EF performance, and basic behavioral measures of the BART in low EF and high EF groups.

	Low EF (<i>n</i> = 16) <i>M</i> (<i>SD</i>)	High EF (<i>n</i> = 16) <i>M</i> (<i>SD</i>)	<i>t</i> / χ^2 / <i>Z</i>
Age [years]	21.1 (1.4)	21.4 (1.7)	n.s.
Male / Female ^a	1 / 15	3 / 13	n.s.
Left / Right handed ^a	3 / 13	2 / 14	n.s.
BIS TS	59.6 (11.2)	63.9 (10.2)	n.s.
BSSS TS	17.3 (4.8)	16.1 (5.5)	n.s.
STAI-T	40.6 (10.3)	34.8 (10.6)	n.s.
BDI TS ^b	11.6 (3.1)	10.3(1.4)	n.s.
Verbal Fluency [correct items]	97.4 (11.8)	120.8 (15.6)	-4.78***
Listening span level ^b	2.8 (0.3)	3.7 (0.9)	-2.61**
Go/No-Go [discriminability]	0.22 (0.16)	0.42 (0.27)	-2.48*
EF index [z-score]	-0.54 (0.21)	0.54 (0.45)	-8.60***
Mean adjusted pumps	8.8 (1.7)	8.5 (1.6)	n.s.
Number of balloon bursts ^b	38.8 (10.2)	40.2 (10.4)	n.s.
Mean score before bursts	24.49 (7.96)	23.40 (7.76)	n.s.
Total score	2258.3 (354.7)	2065.1 (395.5)	n.s.

Note. ^a = in case of cells with an expected count less than five, exact significance tests were selected for Pearson's chi-square. ^b = in case of violating the assumption of normality, Mann-Whitney *U* tests were performed. BIS TS = Barratt Impulsiveness Scale total score; BSSS TS = Brief Sensation Seeking Scale total score; STAI-T = T-Anxiety score; BDI TS = Beck Depression Inventory short version total score.

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

Balloon Analogue Risk Task (BART) Implementation

Figure 1 illustrates the modified version of the BART (Lejuez et al., 2002) that was originally designed by Fein and Chang (2008). The general structure and appearance of the task was the same as described by Fein and Chang (2008, p. 143), but some modifications were implemented to optimize the paradigm for ERP analysis. Participants were asked to pump a balloon (increase its size and value) by pressing one of the response keys on a Cedrus RB-530 response pad (Cedrus Corporation, San Pedro, CA).

The probability of the balloon popping and the score to be lost if the balloon popped increased with each successive pump. There were two possible outcomes for each balloon pump: (1) the balloon inflated incrementally and the score presented inside the balloon increased (positive feedback), (2) the balloon popped and the score shown inside was lost (negative feedback). The pop stimulus was a silent balloon burst, which preserved the features of a medium-sized balloon picture (no text was presented). Upon balloon presentation, participants could end the actual trial and collect the score from the balloon (temporary bank) instead of choosing to pump the balloon again.

The task consisted of 90 balloons to increase the probability of obtaining sufficient number of negative feedback-locked epochs for averaging. The maximum breaking point was 20 pumps for each balloon; after the 20th pump, the balloon popped inevitably. Pops resulting from the first and second pumps of the balloon were disabled. The probability of the balloon popping after the third pump was 1/18, after the fourth pump was 1/17, and so on, until the 20th pump, where the probability of balloon pop was 1/1. This design produced an experimental session lasting no longer than about 25-30 minutes. We increased the rewards by one point at each pump: The first pump added 1 point to the temporary bank, the second added 2 points, the third 3 points, and so on.

After a balloon appeared on the screen, participants had unlimited time for each pump to initiate or to collect the accumulated reward. A random delay of 1000-1200 ms was inserted between each possible response and feedback stimulus. The negative feedback stimulus and the screen which indicated that participants transferred the accumulated scores to the permanent bank were displayed for 3000 ms. The new empty balloon appeared 10 ms after these events.

The major behavioral measures for the BART were the mean adjusted number of pumps across balloons (mean number of pumps on balloons that did not explode; for this

convention, see Lejuez et al., 2002), the number of balloon bursts, the mean score before bursts, and the total score at the end of the experiment.

Participants were instructed to collect as many points as possible. With regard to the reward scheme, each of them was told that if they exceeded the mean of total scores gained by those participants playing the BART before them, they would receive an extra course credit. After completing the task, they were informed about the prior criterion and whether they have attained it or not.

Neuropsychological Measures

EFs were measured with different neuropsychological tasks: Participants performed a Verbal Fluency Task, a Listening Span Task, and a Go/No-Go Task. With the selection of these tasks, we intended to tap the three main subprocesses of EFs: shifting, updating/working memory, and inhibition (Miyake et al., 2000).

Verbal Fluency Task

Three subtasks were administered as part of the Verbal Fluency Task (Lezak, Howieson, & Loring, 2004; Mitrushina, Boone, Razani, & D'Elia, 2005; for the Hungarian version, see Tánczos, Janacsek, & Németh, 2014a; Tánczos, Janacsek, & Németh, 2014b). First, participants were required to say words that begin with a specified phoneme (K, T, and S, respectively; phonemic fluency). Second, they were asked to recite animals and then fruit items (semantic fluency). Finally, participants had to alternate between producing items from two categories: “clothes” and “musical instruments” (category switching). Participants were given 60 seconds to generate as many different words as possible in each subtask. The total number of correct items was used as an outcome variable.

Listening Span Task

In this verbal working memory task (Daneman & Blennerhassett, 1984; Hungarian version: Janacsek, Tánczos, Mészáros, & Németh, 2009) participants listened to blocks of sentences read by the experimenter. Each block consisted of two to eight short sentences, and three different block sequences were used (each consisted of 7 blocks). To ensure the comprehension of sentences, participants had to give true/false responses following each sentence. After all sentences have been presented in the given block, participants were asked to recall the last word of each sentence. The actual sequence terminated when participants failed to recall the last words in the correct order. Then the experimenter started the next sequence from the first block. The mean level (i.e., number of words) at which a participant was correct in every sequence was taken as a measure of listening span.

Go/No-Go Task

Participants performed a two-tone Go/No-Go Task (adapted from Gaál, Csuhaj, & Molnár, 2007) in order to measure response inhibition and selective attention. A series of tones were presented binaurally via headphones (250 stimuli with 50 ms duration each; ISI: 500 ms). The sequence of No-Go trials (tones of 1000 Hz; .8 probability) was interrupted by Go trials (tones of 1030 Hz; .2 probability) according to a pseudorandom order. Participants were instructed to press a target button as accurately and rapidly as possible at the occurrence of the high frequency tone, but to withhold a response for the low frequency tone. A discriminability index (see Hershey et al., 2010) was calculated as hit rate (proportion of correct Go trials) minus false alarm rate (proportion of incorrect No-Go trials) to indicate the level of performance.

Procedure

Before coming to the laboratory, participants filled out four questionnaires online. The Barratt Impulsiveness Scale (BIS-11; Patton, Stanford, & Barratt, 1995; translated to Hungarian by Anna Székely, Zsolt Demetrovics, and Sándor Rózsa; see also Varga et al., 2012), the Brief Sensation Seeking Scale (BSSS; Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002; Hungarian version: Urbán, 2010), the Beck Depression Inventory short version (BDI; Beck, Ward, Mendelson, Mock, & Erbaugh, 1961; Hungarian short version: Rózsa, Szádóczy, & Füredi, 2001), and the State-Trait Anxiety Inventory (Hungarian version: Sipos & Sipos, 1983; STAI; Spielberger, Gorsuch, & Lushene, 1970) were administered to assess impulsivity, sensation seeking, depression, and anxiety, respectively. This pre-testing phase aimed to control the confounding effects of personality traits on the measured ERPs (Cohen, Wilmes, & Vijver, 2011; Mushtaq et al., 2011; Onoda et al., 2010).

The session at the laboratory begun with EEG data collection while performing the BART. Neuropsychological testing followed the removal of the electrode net. The whole procedure lasted about 80 minutes. The BART and the Go/No-Go Task were written in Presentation software (v. 16.3; Neurobehavioral Systems).

EEG Recording and Analysis

EEG activity was recorded by using the Electrical Geodesics system (GES 300; Electrical Geodesics, Inc., Eugene, OR) with a 128-channel Geodesic Sensor Net. We used Cz as a reference, and a sampling rate of 500 Hz was applied with a 70 Hz online low-pass filter.

Before starting any offline analysis, spline interpolation of bad electrodes was performed if necessary. During pre-processing, the data were first band-pass filtered offline between 0.3 – 30 Hz (48 dB/oct), and notch filtered at 50 Hz. Eye-movement artifacts and

heartbeats were corrected with independent component analysis (ICA; Delorme, Sejnowski, & Makeig, 2007). After, EEG data were re-referenced to the mean activity of all electrodes. Epochs extended from -100 to 1000 ms relative to the presentation of negative (balloon burst) or positive (the balloon and score increased) feedback stimuli, and were baseline corrected based on the mean activity from -100 to 0 ms. We applied an automatic artifact rejection algorithm implemented in Brain Vision Analyzer software (Brain Products GmbH, Munich, Germany) that was based on four criteria: The maximum gradient allowed for an epoch was 50 $\mu\text{V}/\text{ms}$, we rejected those segments where the activity exceeded $\pm 100 \mu\text{V}$, the lowest activity allowed was 0.5 μV , and the maximum absolute difference between the minimum and maximum voltages in an epoch was 200 μV . This was necessary for removing the artifacts still contaminating the data after ICA correction. A minimum of 19 artifact-free epochs were required in the negative feedback condition in order for a participant's data to be included. Of those participants whose data remained in the analysis, the mean number of kept segments in the negative feedback condition was 33.2 ($SD = 10.9$; range: 19 – 65).

Epochs locked to negative and positive feedback stimuli were averaged separately; then, difference waves were created by subtracting the positive feedback-locked waveform from the negative feedback-locked waveform (see also Fein & Chang, 2008). A grand average ERP waveform was calculated for the difference waves to determine the latency range of each component: FRN and P3. An automatic peak detection algorithm was used for quantifying ERP component peaks at three frontocentral electrodes: E11 (closest to the Fz position), E6 (closest to the FCz position), and Cz. These electrodes were used in previous BART studies (Euser et al., 2011; Fein & Chang, 2008) and also showed maximum amplitudes in the present study. FRN was determined as the most negative peak within the time interval of 200 – 300 ms. P3 was measured as the most positive point between 300 – 600 ms. Individual waveforms

were visually inspected to ensure that the algorithm identified the local maxima in the given time interval.

Data Analysis

Standardized values (z -scores) were calculated for the main outcome variables of each EF task (see section Neuropsychological Measures) in the final sample. Afterwards, an EF index was created as the arithmetic mean of the three z -transformed variables. Participants were assigned to low EF (equal or below -0.24) or high EF (above -0.23) groups based on a median split on the EF index.

FRN and P3 amplitudes and latencies from difference waves were entered into two-way mixed ANOVAs with Group (low EF, high EF) as a between-subjects factor, and Electrode (Fz, FCz, Cz) as a within-subjects factor. The Greenhouse-Geisser epsilon (ϵ) correction (Greenhouse & Geisser, 1959) was used when necessary. Original df values and corrected p values are reported together with partial eta squares (η_p^2) as the measure of effect size. To control for Type I error, we used Tukey HSD tests for pair-wise comparisons. For correlational analysis, FRN and P3 amplitudes were used from the difference waves. EEG and behavioral data were analyzed with Brain Vision Analyzer software, STATISTICA 11, and IBM SPSS Statistics 19.

Results

Sample Characteristics and Behavioral Results

Table 2 demonstrates the between-group differences in demographic variables, rating scale measures, EF performance, and behavioral measures of the BART. There was no significant difference in any rating scale measures or BART outcome variables (mean

adjusted number of pumps, number of balloon bursts, mean score in the balloon before bursts, total score) between participants with low EFs and high EFs (all p s > .1).

ERP Results

Grand average ERP waveforms split by feedback type and difference waves for each group are presented in Figure 2. The amplitude distribution of FRN and P3 components (from the difference waves) for each group is presented in Figure 3. The FRN was present on the difference waves at each electrode for both groups, and the FRN amplitude was largest at electrode Cz. After presenting negative feedback stimuli, the FRN was followed by a large P3 component. In contrast, positive feedback stimuli evoked a positive potential in the FRN latency window, and the subsequent P3 was absent.

A 2 (Group) * 3 (Electrode) ANOVA was performed on FRN peak amplitude. The main effect of Group was significant, $F(1, 30) = 7.36, p < .05, \eta_p^2 = .20$, and also the main effect of Electrode was significant, $F(2, 60) = 9.87, \varepsilon = .590, p < .001, \eta_p^2 = .25$. The FRN peak amplitude was larger (more negative) in the high EF group than in the low EF group (-6.31 μ V vs. -3.52 μ V). The same 2 * 3 ANOVA was performed on FRN peak latency. The main effect of Group was marginally significant, $F(1, 30) = 4.03, p = .054, \eta_p^2 = .12$, while the main effect of Electrode was significant, $F(2, 60) = 36.65, \varepsilon = .743, p < .001, \eta_p^2 = .55$. The FRN latency was slightly delayed in the high EF group compared to the low EF group (254 ms vs. 247 ms).

A 2 (Group) * 3 (Electrode) ANOVA was performed on P3 peak amplitude. The main effect of Electrode was significant, $F(2, 60) = 65.94, \varepsilon = .753, p < .001, \eta_p^2 = .69$, and the Electrode * Group interaction was also significant, $F(2, 60) = 7.30, \varepsilon = .753, p < .01, \eta_p^2 = .20$. Pair-wise tests revealed that the P3 amplitude was enhanced in the high EF group compared to the low EF group, but only at electrode Cz (21.92 μ V vs. 16.47 μ V, $p < .05$). The

same 2 * 3 ANOVA was performed on P3 peak latency. The main effect of Group was significant, $F(1, 30) = 4.27, p < .05, \eta_p^2 = .12$, indicating that the P3 was delayed in the high EF group compared to the low EF group (363 ms vs. 349 ms). The main effect of Electrode was significant, as well, $F(2, 60) = 4.92, \epsilon = .727, p < .05, \eta_p^2 = .14$.

Correlations were also run between ERP measures (FRN/P3 amplitude and latency) and EF index on the entire sample to check whether the results hold with a continuous approach. Results obtained from these analyses are in line with the ANOVA results (see Appendix).

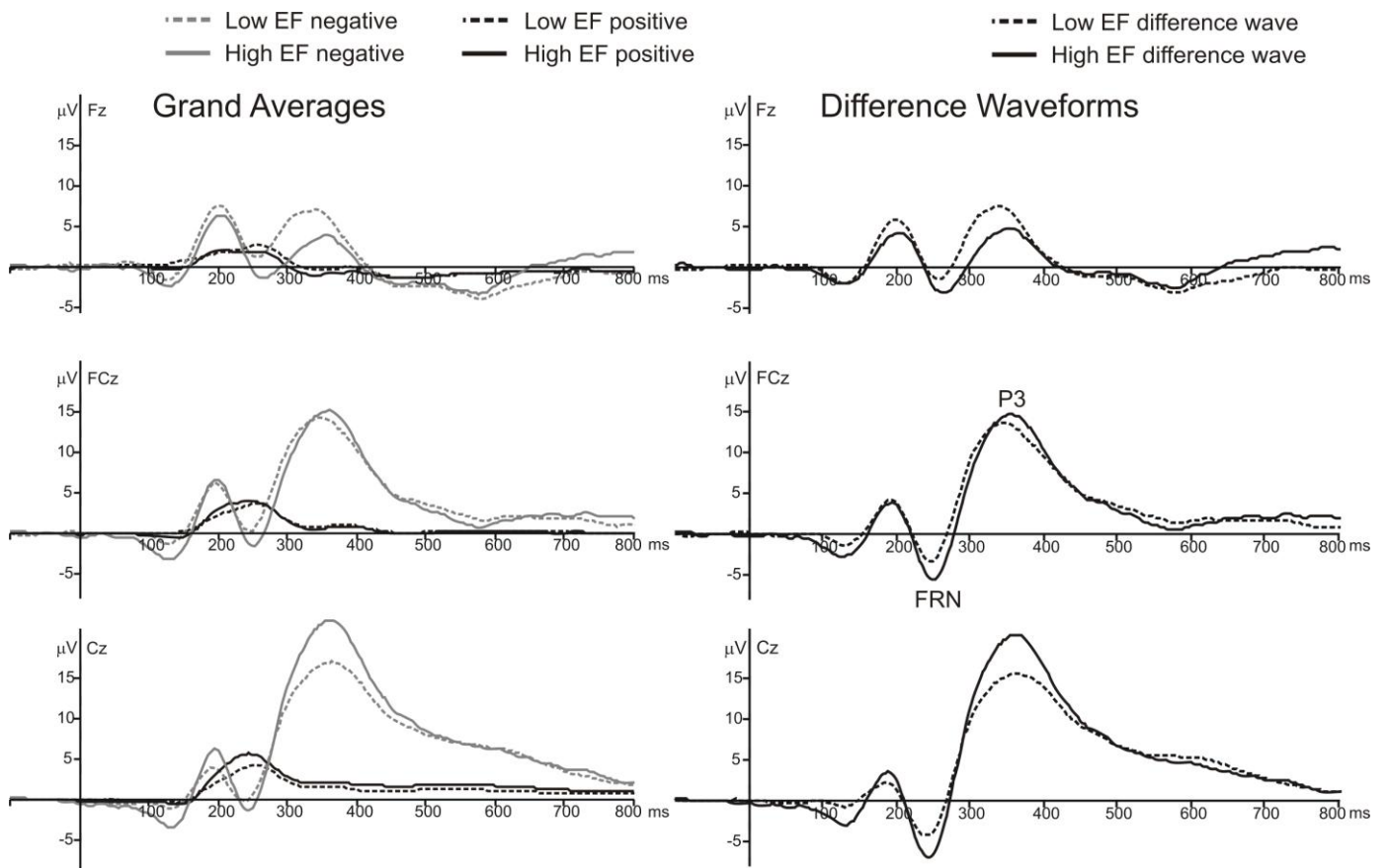


Fig. 2. Grand average ERP waveforms (left panel) after the onset of negative (grey) and positive (black) feedback split by group and electrode position. Difference waves (right panel) were calculated by subtracting the positive feedback-locked waveform from the negative feedback-locked waveform. Please note, positivity is plotted upwards.

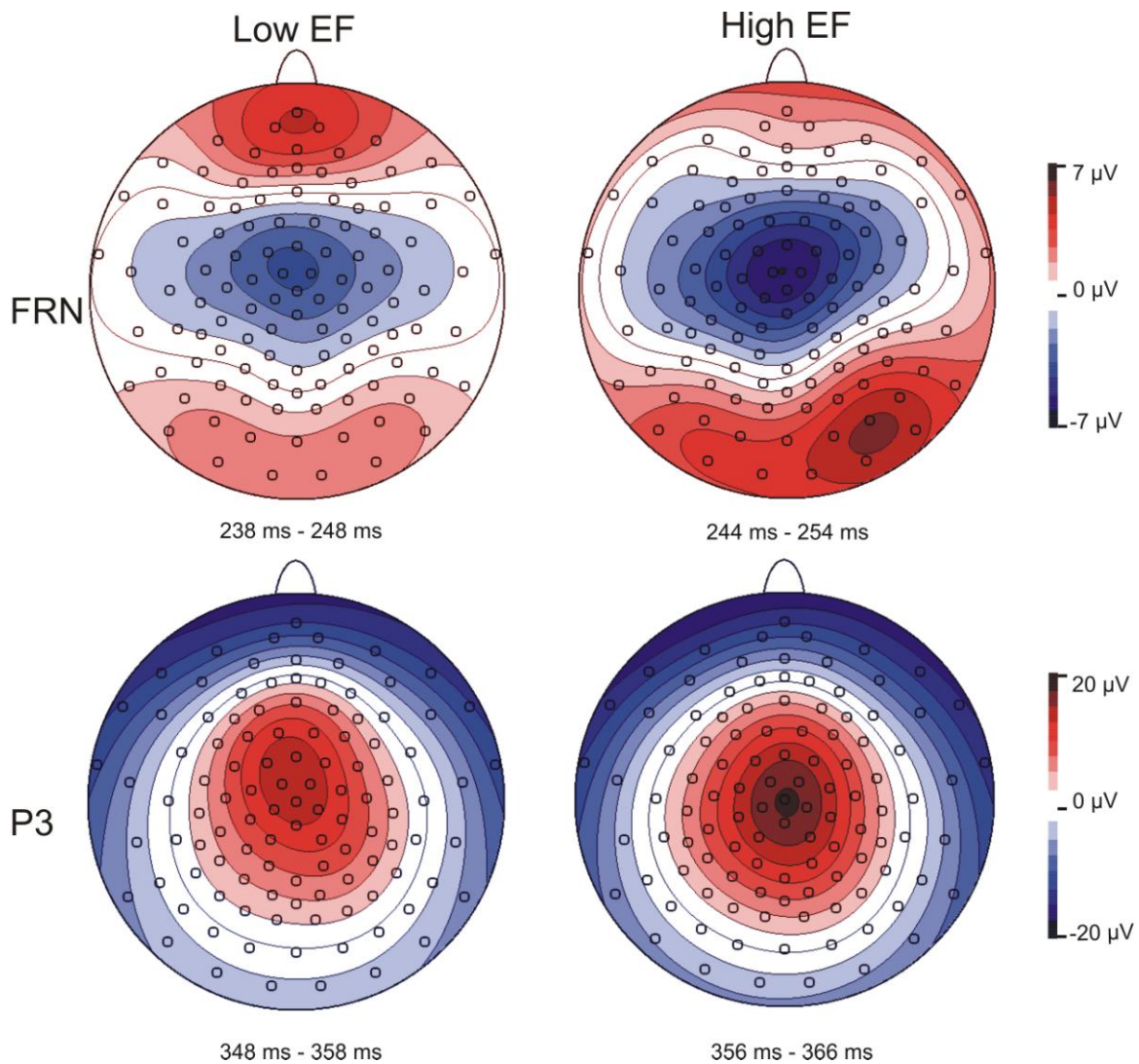


Fig. 3. The scalp topography (amplitude distribution) of FRN and P3 components at the time of their maximum amplitude split by group.

Correlations Between ERP Measures

The FRN amplitude is plotted against P3 amplitude for the entire sample at each electrode separately in Figure 4. Significant correlations were found at electrode FCz and Cz: Larger (more negative) FRN amplitude was associated with larger P3 amplitude. At the same time, we did not find significant correlation between FRN and P3 amplitude at electrode Fz.

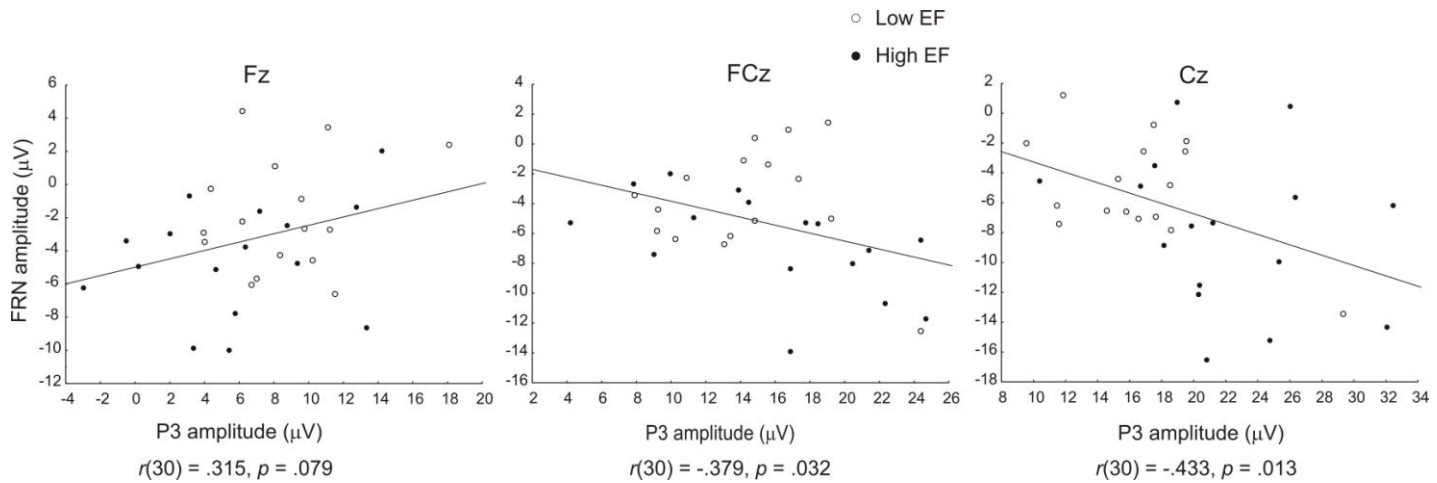


Fig. 4. Scatter plots illustrating the association between FRN and P3 amplitude at each electrode. Pearson correlations calculated for the entire sample are presented below each figure. In order to be consistent with Fig. 2, in the amplitude scale of FRN, positivity is plotted upwards.

Discussion

The present study explored the neuro-cognitive correlates of uncertain decision making by comparing feedback processing during the BART between adults of low EF and high EF. We found no between-group differences in any of the behavioral measures of the BART. On the contrary, the FRN, time-locked to the negative feedback presented, was enhanced and delayed in the high EF group compared to the low EF group. To a lesser extent, the P3 following the FRN was also found to be larger and delayed in the high EF group. We observed moderate correlations between the amplitude of FRN and P3 for the entire sample.

Interpretation of ERP Findings

According to the theoretical framework of model-based vs. model-free learning (see Table 1), executive control processes and hypothesis-driven strategies seem to be less useful in tasks with implicit rules and decisions under ambiguity (Filoteo, Lauritzen, & Maddox,

2010; Frank, O'Reilly, & Curran, 2006; Fu & Anderson, 2008), such as the BART. This framework predicted that high EF participants would follow a model-based strategy.

However, decision making under ambiguity does not necessarily require high EF performance (Brand et al., 2006); and therefore, participants with high EFs might not take advantage of their superior EFs. In a broader sense, the BART might also involve some decisions under risk. In the current study, the risky nature of the task was presented to participants via task instructions. They were aware of the increasing amount of reward for each successive pump, and also of the fact that pumping the balloon too large, it would have popped. However, no explicit information was provided regarding the optimal number of balloon pumps, or the equation that determined the probability of balloon popping on a given pump. Therefore, participants could not recall an exact problem solving strategy in order to evaluate how many pumps are appropriate for the optimal final outcome: Although the probability of a balloon burst increased as a function of balloon size, a particular balloon burst could have happened after any pump. Accordingly, the probability of a balloon increase or balloon burst could have been evaluated only by trial and error learning, and participants could have made decisions under a quite good approximation of risk only in the later trials (Fecteau et al., 2007).

Given this ambiguity in the BART, in our interpretation, larger FRN in the high EF than in the low EF participants may represent the different task-solving strategies of the two groups. High EF participants could have worked up internal models on the basis of their experiences gathered during early trials of the task. Leaning on their enhanced control processes, high EF individuals might have solved the task by testing outcome expectations derived from these models. However, the level of ambiguity in the BART precludes an explicit access to the task structure (Fecteau et al., 2007; Lejuez et al., 2002). Therefore, in case of using a model-based strategy, several outcomes could have represented prediction errors associated with motivational salience (Talmi et al., 2013). This suggests that the

internal model developed did not meet the outcome, and as a result, the violated expectations might have induced a larger FRN. This argument is in line with the current P3 results, since the P3 was also larger and delayed in the high EF group. Again, a model-based strategy requires constant updating of working memory during the task, while a hypothesis-free solution does not necessarily involve this. The P3 amplitude also reflects the amount of information transmitted to working memory (Polich & Kok, 1995); therefore, an enhanced P3 might furthermore indicate a model-based strategy used by the high EF group.

When outcome probabilities are largely unpredictable, the enhanced processing of actual outcomes and their integration to previous reinforcement history might also denote a strategy to fulfill task goals (Mushtaq et al., 2011). This strategy yielding larger FRN and P3 amplitudes could be a consequence of enhanced cognitive control per se. Therefore, we cannot rule out the possibility of this more parsimonious interpretation of the observed group differences in ERPs.

However, evidence for altered feedback processing in different task-solving strategies under ambiguous decision making was observed previously in the weather prediction task (Rustemeier, Schwabe, & Bellebaum, 2013). In this probabilistic classification learning task, the FRN amplitude did not differ between participants using a declarative and a nondeclarative strategy. At the same time, the feedback P3 reflecting conscious cognitive processes was larger in the declarative learners' group. Those participants who followed a nondeclarative strategy showed more success in learning (more correct responses) than those who followed the declarative strategy. Even though the high EF group in our study did not show weaker performance at the behavioral level, we think that their model-based strategy is similar in some degree to the declarative strategy identified in the study of Rustemeier et al. (2013). It is important to note, however, that the classification of learning strategies in the weather prediction task and the EF group assignment in the present study is rather different.

In addition, the specific details of putative internal models and explicit strategies are unknown in our study. Nevertheless, more evidence should be accumulated to elucidate whether processes of implicit (procedural) learning are sufficient to adjust performance in uncertain conditions or higher-order executive control processes are needed (Mushtaq et al., 2011).

According to the correlational results, FRN and P3 might indicate similar and/or related processes in BART performance. Generally, in performance monitoring tasks, an early frontocentral negativity is usually followed by a sharp frontocentral positivity and by a later parietal positivity (Ullsperger, Fischer, Nigbur, & Endrass, 2014). The early complex might signal the need for implementing cognitive control. Specifically, an enhanced neural response to motivationally salient events (i.e., balloon bursts) could orient attention to relevant information about task-performance and increase subsequent adaptation if needed (Ullsperger et al., 2014). This mechanism is probably present both in the low EF and high EF groups, regardless of the exact strategy used.

Oversensitivity to Negative Events

Altered sensitivity to negative outcomes could be a manifestation of the model-based strategy suggested to be used by the high EF group. Either an enhancement or an attenuation of the FRN amplitude has been observed in regard to various neurological and psychiatric syndromes indicating maladaptive feedback processing (Onoda et al., 2010; Talmi et al., 2013). Therefore, increased FRN could reflect an increased sensitivity to losses or negative outcomes. The FRN signals the motivational impact of feedback for task performance, as well (Yeung et al., 2005). As a consequence, individuals with high EFs might have considered balloon bursts as more significant negative events than those with low EFs, since these outcomes might have violated their internal models. In addition, they might have felt that each negative feedback weakened their total performance. Euser et al. (2013) found reduced P3

amplitudes for both negative and positive feedback in the BART among high-risk adolescents with a parental history of substance use disorders compared to normal risk controls. In their interpretation, this might have reflected a weaker processing of feedback and suggested a hyposensitivity to future consequences. Accordingly, we presume that the increased P3 amplitude in the high EF group might show an enhanced attention to further process salient events of motivational importance.

Interpretation of Behavioral Findings

We assumed that we would not find between-group differences in the BART behavioral performance, since the task involves mainly decisions under ambiguity (Campbell et al., 2013; Fecteau et al., 2007), and according to the notion of Brand et al. (2006), these decisions depend on the individual level of EFs in a lesser degree. The observed null-finding is in line with the hypothesis that EFs and behavioral performance on the BART are independent from one another.

At the same time, the present behavioral findings do not support previous evidence (Fecteau et al., 2007; Helfinstein et al., 2014) suggesting that higher EFs are related to a risk-averse response style (more cautious responses). The decreased behavioral performance of high EF participants presumed according to the model-based strategy should have been manifested in lower total score, but we did not find significant difference in this outcome variable. However, as we investigated the BART performance of a nonclinical adult sample, it is not obligatory to obtain group differences at the behavioral level, since EFs have been considered to be intact in these individuals (cf. Campbell et al., 2013).

Clinical Implications

As mentioned in the Introduction, impaired decision making is a common cognitive characteristic of several psychiatric syndromes such as ADHD, depression, or substance abuse (Onoda et al., 2010). The high co-morbidity rate between these disorders may mirror the contribution of a general psychopathology factor (Caspi et al., 2013; Lahey et al., 2012). General psychopathology is associated with weaker cognitive control or EFs (Caspi et al., 2013). However, it is controversial how atypical EFs influence feedback processing in clinical syndromes, even though these mechanisms jointly contribute to adaptive decision making.

As an important syndrome of enormous clinical and economical impact, alcoholism is associated with impulse control problems in risk-taking, and it is thought to be caused by the impairment of EFs (Campbell et al., 2013; Fein & Chang, 2008). It was previously shown in a BART experiment on treatment-naïve alcoholic participants that behavioral outcome of the task did not correlate with the FRN amplitude (Fein & Chang, 2008). However, a negative association was shown between FRN and the family history density of alcoholism. This indicated an attenuated sensitivity to negative feedback in participants with an inherited risk for developing alcoholism. Alterations in frontostriatal circuits and in EFs have been considered as potential root causes of this attenuation (Fein & Chang, 2008). Nevertheless, without behavioral measurements of EFs, the association between EFs and the FRN remained unclear in this study.

Another behavioral study found that chronic alcohol users made less optimal decisions in the BART than their healthy counterparts (Campbell et al., 2013). The authors suggested that this was caused by EF impairments in the clinical group. However, as it was also presented in that study, chronic alcohol use could lead to performance attenuation in a broad range of cognitive functions, which could not entirely confirm their proposed explanation.

Our results could indirectly contribute to the investigation of alcoholism by demonstrating the relevance of EFs in feedback processing with healthy young adults. Since modulation of the FRN has been proposed as a potential biomarker in psychopathology, a clearer understanding of the functional significance of this component and the different neural/cognitive systems supporting decision making is essential for further studies (Talmi et al., 2013).

Limitations and Further Aspects

Some issues merit consideration when interpreting the current results. Labeling the two groups as “low EF” and “high EF” was somewhat arbitrary, and it could only be understood as compared to the median of the actual EF index of our sample. Without normative scores for each EF task, we cannot be certain of the performance range (i.e., normal EFs or high EFs) to which the whole sample could have been assigned.

We selected the EF tasks on the basis of the three-factor model of Miyake et al. (2000) that has appeared to be robust using complex EF tasks, as well (Lehto, Juujärvi, Kooistra, & Pulkkinen, 2003). It is probable that Verbal Fluency Task and Listening Span Task might also tap verbal skills as much as EF subprocesses (see also the task impurity problem: Burgess, 1997). However, conducting this study with mostly female undergraduate students might assure that the observed differences between low and high EF groups stem from differences in the underlying EF subprocesses. In addition, BART performance does not involve a verbal component; thus, it is unlikely that ERP results are related to verbal skills. At the same time, the present results should be replicated by defining low EF and high EF groups on the basis of simpler EF task performance.

We assume that the low EF group could have chosen between response options following somatic markers instead of conscious strategies. However, in order to directly prove

this assumption, autonomic responses (e.g., skin conductance measures, heart rate variability) should be investigated in future studies.

Finally, it should be further tested whether impaired EFs in a broader sense might deteriorate BART performance at the behavioral level (cf. Campbell et al., 2013). In terms of individual differences in EF dimension, the investigation of treatment effects, the effect of fatigue, or transcranial magnetic stimulation are worth considering in order to confirm and replicate the present results both at the behavioral and neural levels.

Conclusion

The different steps of decision making could be influenced by multiple factors, for instance, the number of available response options, the information about related outcome probabilities, individual differences in cognitive state, performance, and personality traits, the required effort and time available for a given choice, and the presence of other participants. Among these variables, this study focused on how individual differences in EF performance modulate feedback processing during decision making, which has not been clarified so far.

In sum, the present results emphasize the general role of cognitive control amongst the hidden factors of risky decision making by providing evidence for the EF level modulating FRN and P3 components. We found that individuals with high EFs might have followed a model-based strategy in task-solving, and we also propose that superior EFs might not be needed in optimal BART performance. The presented method is useful to shed light on the underlying strategies in decision making as shown by the dissociation between findings at the behavioral and brain level. These results could have clinical implications since altered FRN has been interpreted as a risk indicator in psychopathology.

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Appendix. Correlation coefficients between ERP measures and EF index.

	EF index	
	<i>r</i>	<i>r_s</i>
FRN(A)_Fz	-.376*	-.367*
FRN(A)_FCz	-.391*	-.370*
FRN(A)_Cz	-.378*	-.318+
FRN(lat)_Fz	.176	.189
FRN(lat)_FCz	.286	.366*
FRN(lat)_Cz	.180	.227
P3(A)_Fz	-.265	-.266
P3(A)_FCz	.040	.049
P3(A)_Cz	.392*	.488**
P3(lat)_Fz	.268	.362*
P3(lat)_FCz	.333+	.463**
P3(lat)_Cz	-.111	-.053

Note. A = amplitude; lat = latency; *r_s* = Spearman's rank correlation coefficient.

N = 32

+ $p < .1$; * $p < .05$; ** $p < .01$