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# Improving innovative decision-making: Training-induced changes in fronto-parietal networks

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ABSTRACT

*Innovative decision-making* entails the balance of exploitative and explorative choices, and has been linked to the efficiency of executive functioning, including working-memory and attentional skills, associated with fronto-parietal networks. Based on the notion that such skills can be improved by cognitive training, we assessed whether a cognitive training enhancing basic executive skills might also improve the ability to manage the exploration-exploitation trade-off and its financial consequences, and whether any improvement in training-related performance would be reflected in neurostructural changes within fronto-parietal networks. Eighteen subjects participated in a baseline assessment, a training period and a follow-up measurement, while a matched group of 18 subjects did not undertake the training program. A subgroup of subjects underwent a multimodal MRI study to explore training-related changes in grey-matter volume and white-matter microstructure. After training, increased efficiency of *innovative* decision-making, related to the improvement of executive control skills, reflected neurostructural changes involving the right fronto-polar cortex and left superior longitudinal fasciculus. The quality of innovative decision-making can be improved by *ad-hoc* cognitive training procedures focused on executive skills, promoting neurostructural changes in fronto-parietal networks. The manifold implications involve both managerial and rehabilitative settings concerned with the quality of choices in normal and pathological conditions, respectively.

## 1. Introduction

Innovation is the driving force for the development of, and adaptation to, complex and dynamic environments, including human organizations (Woodman, Sawyer, & Griffin, 1993). Whereas at the organizational level innovation results from the optimal balance between known options and novel opportunities (March, 1991), in single individuals the cognitive processes underlying innovation involve value-based decision-making and action selection mechanisms (Rangel, Camerer, & Montague, 2008). Previous studies have associated *innovative* decision-making to flexible behavior that involves managing the trade-off between exploratory and exploitative choices (Boorman, Behrens, Woolrich, & Rushworth, 2009; Daw, O'Doherty, Dayan, Dolan, & Seymour, 2006; Laureiro-Martínez, Brusoni, & Zollo, 2010; Laureiro-Martínez et al., 2013; Laureiro Martínez, Brusoni, Canessa, & Zollo, 2015).

Several studies in the cognitive and management sciences have addressed the exploration-exploitation trade-off with tasks in which subjects make repeated choices among a set of options resulting in variable payoffs over time (Boorman et al., 2009; Daw et al., 2006;

*Abbreviations:* MRI, magnetic resonance imaging; TG, training group; CG, control group; CRT, cognitive reflection test; DTI, diffusion tensor imaging; TBSS, tract-based spatial statistics; FA, fractional anisotropy

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March, 1991; Posen & Levinthal, 2012; Steyvers, Lee, & Wagenmakers, 2009). In such tasks, the balance between exploitative and exploratory choices is associated with the activity of bilateral cortical-subcortical networks involving, respectively, the mesocorticolimbic dopaminergic system, driving reward-related processes (e.g., Tobler, O'Doherty, Dolan, & Schultz, 2006), and the locus coeruleus ascending pathway, modulating attentional control (Aston-Jones & Cohen, 2005). Recent studies indicate that the ability to adaptively manage these competing behaviors depends on the effectiveness of executive abilities such as working memory, attention and inhibition control, with executive performance reflecting in improved financial performance (Laureiro-Martínez, Stefano, Nicola & Maurizio, 2015) and shorter response times (Laureiro-Martínez et al., 2013). Notably, such a relationship seems to reflect a common neural basis to executive functioning (e.g., Fassbender et al., 2004) and explorative choice (Daw et al., 2006; Laureiro-Martínez et al., 2013), which are both associated with the activity of bilateral fronto-parietal networks.

Although the effects of cognitive training are debated (Jaeggi et al., 2011; Jaeggi, Buschkuehl, Shah, & Jonides, 2014), recent evidence suggests that training-related performance changes reflect in brain functional and/or structural modifications (e.g., Colom et al., 2016a; Dahlin, Neely, Larsson, Backman, & Nyberg, 2008; Thompson, Waskom, & Gabrieli, 2016).

On this basis, we predicted that: (1) a training program aiming to enhance the efficiency of working memory, attention and inhibition control would also improve the ability to balance the exploration-exploitation trade-off, and (2) that such improvement would reflect neurostructural changes within specific nodes of the fronto-parietal networks underlying executive functioning.

Therefore, our primary goal was to assess the effect of a 4-week cognitive training involving working memory and attention control on the quality of innovative decision-making. We operationalized the latter as the performance in a strategic innovation decision-making task (Christensen & Shih, 2008), i.e. a ecologically valid computer-based simulation developed to measure the individual-level ability to balance exploratory and exploitative choices within a virtual environment, mimicking the complexity and dynamism of daily-life tasks.

Secondly, we explored whether possible behavioral and/or cognitive effects of this training program would be reflected in neurostructural changes in both grey- and white-matter metrics within the fronto-parietal networks in charge of executive functioning and explorative choice. In particular, based on previous evidence we predicted that the cognitive effects of training would reflect in structural changes involving the superior longitudinal fasciculus (Thiebaut de Schotten, Dell'Acqua, Valabregue, & Catani, 2012) and its target projection, i.e. the frontopolar cortex, associated with the optimal balance between exploitative and explorative choices (Laureiro-Martínez et al., 2013).

## 2. Materials and methods

### 2.1. Subjects

A group of 40 healthy volunteers (25 males and 15 females; age range = 21–25) attending a Master Degree in Economics at Bocconi University (Milan, Italy) took part in the present study. They were recruited via in-person speaking and flyers. Exclusion criteria were left-handedness (Oldfield, 1971), past or current history of neurological and/or psychiatric conditions, substance abuse, and regular consumption of any medication interfering with cognitive functioning. After pre-training measurement, subjects were randomly assigned to a *training group* (TG; 13 males and 7 females) and a *control group* (CG; 12 males and 8 females). Two subjects per group (10%), including 1 male and 1 female in the TG, and 2 males in the CG, dropped-out during the first training week (the 2 TG subjects never started the training program), mainly due to time constraints and the overall commitment required. The final group, completing the whole experimental protocol, included 36 subjects (TG: 12 males and 6 females; CG: 10 males and 8 females). TG and CG subjects were matched for age and gender, and at baseline they did not differ significantly neither in measures of depression (Beck Depression Inventory) and anxiety (State-Trait Anxiety Inventory), nor in psychological and dispositional dimensions possibly influencing their performances and/or their overall commitment to the study (i.e., cognitive flexibility, self-efficacy, goal orientation aptitude) (see Table 1 for data about demographics and control measures).

**Table 1**
Demographic and control variables of the whole sample.

| | TG (n = 18) | CG (n = 18) | p-value |
|---|---|---|---|
| Age | 22.58 ( ± 0.98) | 22.64 ( ± 1.09) | 0.847 |
| Gender (m:f) | 12:6 | 10:8 | 0.729 |
| Mood (BDI) | 6.33 ( ± 3.93) | 8.14 ( ± 6.65) | 0.293 |
| Anxiety (STAI) | State: 36.39 ( ± 6.80) | State: 36.38 ( ± 9.10) | State: 0.821 |
| | Trait: 38.00 ( ± 8.12) | Trait: 41.52 ( ± 6.82) | Trait: 0.084 |
| Cognitive flexibility (CFS) | 52.83 ( ± 7.60) | 56.56 ( ± 6.10) | 0.114 |
| Self-efficacy (GSES) | 30.61 ( ± 2.93) | 30.72 ( ± 4.11) | 0.920 |
| Goal orientation (AGOS) | 53.38 ( ± 7.73) | 53.83 ( ± 9.55) | 0.880 |

TG = Training Group; CG = Control Group; BDI = Beck Depression Inventory; STAI = State-Trait Anxiety Inventory; CFS = Cognitive Flexibility Scale; GSES = General Self-Efficacy Scale; AGOS = Academic Goal Orientation Scale.

Subjects were informed that those completing the study would be rewarded on the basis of their performance in the strategic innovation decision-making task (cumulative payoff), cognitive reflection test (CRT) (Frederick, 2005) and N-Back task (Kirchner, 1958) (see below). Subjects gave their written informed consent to the experimental procedure, which was approved by the local Ethics Committee.

### 2.2. Experimental procedure

The experimental procedure included three main stages: (i) pre-training measurement, to establish a baseline level of behavioral, cognitive and neurostructural variables; (ii) a 4-week training program focused on executive ability (i.e., working memory, attention and inhibition control) for the training group, or an equivalent waiting period for the control group; and (iii) a post-training measurement, to evaluate the effect of the training program (vs. no training) on the different variables collected.

A "passive" waiting period may not represent an optimal control for placebo effects in the cognitive training group (see Au, Buschkuehl, Duncan, & Jaeggi, 2016; Klingberg, 2010). The choice was motivated by several reasons. In the first place, the selection of any "active" control procedure would be prone to concerns regarding the cognitive processes which could, or could not, be controlled for. In addition, previous works in the same research area highlighted that there are no significant differences between active and passive control groups (Chooi and Thompson, 2012; Colom et al., 2013). In the awareness of the pros and cons of either approach, we thus opted for the simplest procedure, which has been pursued in previous reference papers in this field (e.g. Colom et al., 2016b; Dahlin et al., 2008).

#### 2.2.1. Pre- and post-training measurements

We collected pre- and post-training behavioral and cognitive variables at the Bocconi Experimental Laboratory for the Social Sciences (BELSS). Each testing session, lasting about 2 h, included different tasks preceded by specific instructions.

We assessed innovative decision-making skills via an on-line managerial simulation task focused on strategic innovation (*Back Bay Battery: Strategic Innovation Simulation*) (Christensen & Shih, 2008), aimed to measure the individual ability to balance explorative and exploitative choices in realistic complex and dynamic environments. During the decision-making task, subjects played the role of a business unit manager over eight simulated years, with the main goal to manage available resources between sustaining the existing business and investing in a new, but potentially disruptive, technology. In each of the eight rounds of play, the subjects must process several sources of information, which require to effectively key in on the most critical pieces of data for diagnosis, strategy development, and decision-making, while meeting both short-term and long-term performance requirements for the business. To achieve high performance, the subject needs to balance financial goals against the need to innovate, capitalize on new product/market opportunities, and guard against disruptive technologies. The subject must take into account resource requirements, product performance, investment timing, and end-market opportunities for a new technology in the context of nebulous market information and constraining financial performance criteria. While the performance evolution may not precisely track the real-world case, the plethora of indicators used helps to give subject a flavour of the nature of daily-life management situations (see supplementary material for further details). Subjects played two rounds of the same task for about 90 min. They were informed that the purpose of the first round was to familiarize themselves with the task, while only the payoff from the second round would be taken into account. The main study outcome was the cumulative payoff obtained at the end of the second round. This measure has been used in a previous study (Laureiro-Martinez, 2014), as it represents a proxy of the overall efficiency of innovative decision-making (Christensen & Shih, 2008).

We additionally collected measures related to different facets of executive control and flexibility, such as working memory, inhibition control and attention skills. Importantly, none of these measures were used in the training program. In particular, we assessed working memory with a verbal version of the *N-Back task* (Kirchner, 1958), requiring subjects to report whether a stimulus in a sequence (upper and lower case letters) has been presented *n* times before the current one or not (with *n* being either 2 or 3 in different experimental conditions, i.e. 2-back or 3-back respectively). Subjects had to press the right arrow on the keyboard to indicate a target stimulus, i.e. one that occurred *n* times before the present one, and the left arrow otherwise. Subjects completed three familiarization runs before starting the real task. The main outcome variables were individual performance in the N-Back task in terms of (1) accuracy and (2) response times, separately for 2-back and 3-back conditions.

Subjects were also tested on the *Cognitive Reflection Test* (CRT) (Frederick, 2005). The latter allows to measure inhibition control, i.e. the ability to suppress a spontaneous and prepotent, yet wrong, answer prompted immediately as a result of a fast and automatic process, in favor of a reflective and deliberative right answer driven by a slower and conscious process. A classical example is *"In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?"*. While the prepotent but incorrect answer is "24 days", the correct solution, which requires conscious effort and reflection, is "47 days". The test included 10 problems with no intuitive correct solutions. We considered (1) the final score (i.e., total number of right answers) and (2) the time required to complete the entire test (i.e., all the problems) as outcomes of individual performance.

### 2.2.2. Training program

The subjects belonging to the TG participated in a 4-week training program aiming to improve the efficiency of key executive functions supporting innovative decision-making (Laureiro-Martínez et al., 2013). After the pre-training session we instructed them about the planning and management of their training sessions, and provided them with the training software, developed *ad-hoc* and pre-tested on a pilot study with 15 subjects for the present study. The software required Internet connection to run, and at the end of each session a log file was automatically forwarded to the lab mailbox.

The training software included two alternating blocks of exercises, focused on working-memory, attention and inhibition control (see details below). The training schedule consisted of 30-minute sessions, 4 times per week (16 sessions overall). To motivate subjects and ensure their commitment throughout the training period, we provided them with a feedback after each trial (correct/incorrect/missed response) and task (% of accuracy), so that the difficulty of exercises could be automatically increased based on their increase in performance, i.e. when 80% accuracy had been reached.

The working-memory block comprised two updating tasks, i.e. the *Numbers* and the *Keep-track* tasks (Dahlin et al., 2008). The Numbers task entails the serial presentation of 1-digit numbers, randomly extracted from a pool of four items (1, 2, 3, 4). Items are grouped into different sequences (i.e., task trials), with length varying from 4 to 15 items, depending on task difficulty. Specifically, the Numbers task included three levels of difficulty. Each level included 10 trials, with sequences having a different length range: namely, levels 1, 2 and 3 entailed a random presentation of 10 sequences of 4 to 7, 6 to 11 and 7 to 15 items (i.e., 1-digit numbers). Subjects, who were not aware in advance of the length of single sequences, are asked to recall (via the keyboard) the four last presented items at the end of each sequence. The Keep-track task included sequences of 15 words belonging to different semantic categories displayed at the bottom of the screen for the entire trial duration. Subjects are instructed to mentally keep track of the category of every item in the presented sequence. At the end of the trial, they have to report the last presented item for each category by typing their responses on the keyboard. The Keep-track task included seven difficulty levels reflecting the number of semantic categories involved (3 to 6, from the easiest to the hardest level) (Fig. S2).

The attention control block comprised the *Stroop task* (Stroop, 1935) and a *visual search task* (Wei, Müller, Pollmann, & Zhou, 2011). The Stroop task consisted in the presentation of color words written in the color they designate (*congruent trials*) or in a different color (*incongruent trials*). In each trial, subjects have to press the keyboard button associated with the color designated by the stimulus. This task entailed nine difficulty levels, each one including 100 trials, reflecting the combination of (a) the number of response options (2–4) and (b) time pressure, inversely related to the amount of time available to respond (low: 2000 ms, medium: 1000 ms, high: 500 ms) (Fig. S3). The visual search task consisted in the presentation of a pattern of *n* items (distractors) in which a target stimulus may be present or not. Before each trial, the target was presented at the center of the screen. There were three different conditions differing in terms of the features shared by target and distractors (shape and orientation, color and orientation). Subjects are asked to respond to the presence/absence of the target via the keyboard. Also in this case there were nine difficulty levels, each one including 40 trials, resulting from the combination of the number of distractors (8, 12, or 18) and time pressure (low: 2000 ms, medium: 1000 ms, high: 500 ms) (Fig. S4).

We used the maximum level reached in each task as a proxy to analyse single subjects' training results and plot the leaning curves (see Fig. 1). In particular, we analysed the overall improvement relative to single training tasks with non-parametric tests (Friedman test). Additionally, post-hoc analyses (Wilcoxon test with Bonferroni correction) revealed the timepoint (i.e., session number) at which subjects reached the most difficult level and stabilized their performances.

## 2.3. MRI data acquisition and analysis

All subjects were invited to participate in an fMRI study entailing pre- and post-training scanning sessions. Based on individual willingness and standard MRI exclusion criteria (i.e., presence of claustrophobia, brain trauma, ferromagnetic implants, pacemaker, or inability to lie still), a subgroup of 26 subjects ($n_{TG} = 15$; $n_{CG} = 11$) underwent two multimodal MRI sessions, at the baseline stage and immediately after the end of the training period. We performed MRI scans using a 3 Tesla Philips Achieva scanner (Philips Medical Systems,

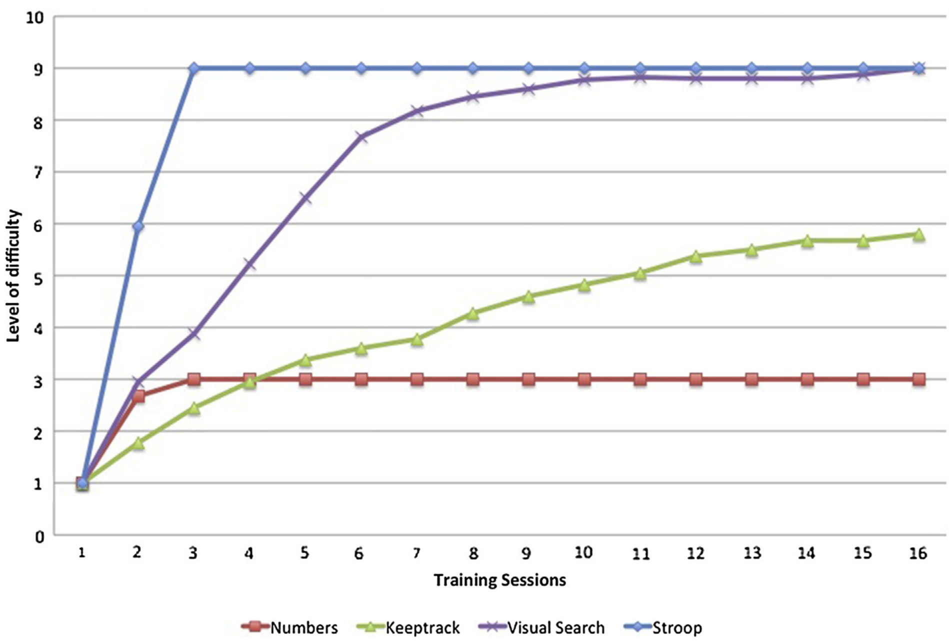


**Fig. 1.** Training performances and learning curves. The figure shows the average performance for each training task (red line: Numbers task; green line: Keep-track task; purple line: Visual Search task; blue line: Stroop task) at each timepoint (session number). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Best, NL) with an 8-channel head coil (SENSE reduction factor = 2). The MRI protocol included a high resolution T1-weighted anatomical scan (150 slices, TR = 600 ms, TE = 20 ms, slice thickness = 1 mm, in-plane resolution = 1 mm × 1 mm), and a DTI sequence (50 slices; TR = 13021 ms; TE = 50 ms; voxel size = 1.8 × 1.8 × 2.3 $mm^3$; diffusion gradients along 35 non-collinear directions, 2b-values = 0–1000 $sec/mm^2$).

### 2.3.1. VBM data pre-processing and statistical analysis

We performed the preprocessing of T1-weighted images with the VBM8 toolbox (http://dbm.neuro.uni-jena.de/vbm/), an extension of the SPM8 software (http://www.fil.ion.ucl.ac.uk/spm/) running on MATLAB v7.4 (Mathworks, Inc., Sherborn, MA). The preprocessing of longitudinal VBM data included (a) the coregistration of the two images of each subject, and the creation of their average; (b) a further realignment of both images to such average image, followed by their bias-correction for field-intensity inhomogeneities; (c) the segmentation and spatial normalization of the average image; (d) warping of both pre- and post-training bias-corrected images based on the resulting normalization parameters; (e) final realignment of the resulting normalized segmentations; (f) smoothing of the normalized and realigned GM maps with an 8-mm Full-Width-Half-Maximum (FWHM) Gaussian-kernel. We assessed the effect of training using a repeated-measures ANOVA (i.e., Full Factorial model in SPM8) with *time* and *group* as within- and between-subject factors, respectively. We tested an interaction between time and group using a statistical threshold of $p < 0.05$ FWE-corrected at the cluster level. We localized the brain regions showing significant effects using the cytoarchitectonical-mapping implemented in the SPM Anatomy Toolbox v 2.0 (Eickhoff et al., 2005). Then, we extracted mean GM volume from significant clusters to carry our *off-line* correlation analyses between changes in grey matter volume and behavioral variables of innovative decision-making.

### 2.3.2. DTI data pre-processing and statistical analysis

Preprocessing and analysis of DTI data were performed using the FMRIB Software Library (FSL) tools (http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/). Single-subject datasets were first corrected for eddy current distortions and motion artifacts by applying a full affine (linear) alignment of each volume to non-diffusion weighted images. Corrected datasets were then skull-stripped and finally, as a results of the fitting of the diffusion tensor model at each voxel, maps of main DTI metrics were generated. We performed whole-brain analyses on fractional-anisotropy (FA) images of pre- and post-training sessions with Tract-Based Spatial Statistics (TBSS), following the procedure described by Smith and colleagues (Smith et al., 2006). FA reflects the coherence of the directionality of water diffusion, and can be considered a proxy of white matter structure and integrity (Basser, 1995; Douaud et al., 2011) providing information about connectivity and neuroplasticity. For this reason, this DTI metric has been widely used in studies assessing the effects of training (e.g. Engvig et al., 2012; Mackey, Whitaker, & Bunge, 2012; Salminen, Mårtensson, Schubert, & Kühn, 2016; Scholz, Klein, Behrens, & Johansen-Berg, 2009).

To explore possible training-induced changes in white-matter microstructure, we subtracted the pre-training FA image from the post-training one for each subject. We then created a 4D dataset containing the *post-minus-pre* FA images of all subjects. Then, based both on a priori hypotheses and VBM results, in these images we assessed group effects (i.e. TG vs. CG) along the bilateral superior longitudinal fasciculus (JHU White matter Tractography Atlas) (Hua et al., 2008). We performed a voxelwise group comparison with FSL *randomise*, by setting 10.000 random permutations per contrast. We employed the Threshold-Free Cluster Enhancement method (Smith & Nichols, 2009) and set the significance threshold at $p < 0.05$ corrected for multiple comparisons across voxels. For graphical purposes, we smoothed the maps of corrected results with a Gaussian Kernel of 3 mm via the *tbss_fill* script. Finally, we extracted mean FA values from significant clusters to perform *off-line* correlation analyses between changes in Superior Longitudinal Fasciculus microstructure and behavioral variables of innovative decision-making.

## 3. Results

### 3.1. Behavioral results

#### 3.1.1. Cognitive training and learning curves

83% of subjects (15/18) in the TG completed all the sessions (16 sessions, 8 h training program) within the training period. The remaining 3 subjects failed to reach the required number of sessions, due either to personal reasons (e.g., exam preparation, health reasons) or failure of Internet connection. We decided to include them in subsequent analyses as they completed more than 60% of the training program (see Table 2), took part in the post-training measurement, and

**Table 2**
Subjects' commitment to the training program.

| TG subjects (n = 18) | Number of sessions completed |
|---|---|
| 15 | 16/16 (100%) |
| 1 | 15/16 (94%) |
| 1 | 11/16 (69%) |
| 1 | 10/16 (62.5%) |

**Table 3**
Training results.

| Training Task | Number of subjects achieving the most difficult level | Friedman test |
|---|---|---|
| Numbers | 18 (100%) | $\chi^2 = 124.36$, $p < 0.01$ |
| Keep-track | 7 (39%) | $\chi^2 = 92.63$, $p < 0.01$ |
| Visual Search | 18 (100%) | $\chi^2 = 97.96$, $p < 0.01$ |
| Stroop | 18 (100%) | $\chi^2 = 98.57$, $p < 0.01$ |

successfully achieved the most difficult levels in 3 out of 4 tasks included in the cognitive training (i.e., Numbers, Stroop and Visual Search tasks). One of these subjects, who completed 15 out of 16 training sessions, also achieved the most difficult level in the Keep-track task, which resulted the hardest task of the training program (see below).

Overall, Friedman tests highlighted a significant improvement in all tasks and subjects after training (Table 3, Fig. 1). In particular, the Numbers and Stroop tasks resulted the easiest ones, showing the steepest curves and a stabilization of performance at the most difficult level of the task between Session 2 and Session 3 (Wilcoxon test – Numbers task: $z = -2.12$, $p = 0.03$, effect size (d) = 1.15; Stroop task: $z = -3.68$, $p < 0.01$, effect size (d) = 3.49). The learning curve of Visual Search performance reflected an intermediate difficulty and, on average, the Wilcoxon test highlighted a stabilization of performance at Session 6 ($z = -2.25$, $p = 0.02$, effect size (d) = 1.25). Indeed, most subjects reached the most difficult level between Session 5 and Session 10. Only one out of 18 subjects achieved the most difficult level in the last session. Finally, as mentioned above, the Keep-track task was the hardest one, showing the largest variability both in terms of the maximum difficulty level achieved, and of the individual stabilization of performance. Indeed, only 7 subjects reached the hardest level of the task, showing different patterns of stabilization of performance (see Table S1 for a description of subjects' performance in the training).

#### 3.1.2. Strategic innovation decision-making task

We assessed the effects of training on innovative decision-making using a two-way repeated-measures ANOVA with *group* (i.e., TG and CG) and *timepoint* (i.e., pre- and post-training) as independent variables, and the cumulative payoff obtained in the strategic innovation decision-making task as dependent variable. This analysis revealed an overall improvement of the cumulative payoff after training in both TG and CG groups [main effect of time: $F(1,34) = 18.58$, $p < 0.01$, effect size (d) = 1.48]. While we found only a trend toward significance in the interaction between group and timepoint [time * treatment: $F(1,34) = 3.43$, $p = 0.07$, effect size (d) = 0.63], post-hoc group comparisons (Bonferroni corrected) revealed that the effect of time was significant in the TG ($p < 0.01$), but not in the CG ($p = 0.18$).

A further, complementary, analysis was motivated by the high variability of cumulative payoffs resulting from the strategic innovation decision-making task (see Table 4, section A). We categorized both the pre- and post-training cumulative payoffs of both TG and CG into quintiles, calculated on the basis of pre-training ones (Table 4, section B). As a result, we obtained two new ordinal variables, in which cumulative payoffs were grouped into five categories reflecting the quality of pre- and post-training performances (i.e., very low, low, medium, high, very high). Then, we carried out non-parametric Friedman tests on these variables to detect, in both TG and CG, time-dependent differences in the quality of innovative decision-making. Only in TG subjects ($p < 0.01$), and not in CG ones ($p = 0.13$), this analysis highlighted a significant difference in the cumulative payoff between pre- and post-training sessions.

#### 3.1.3. Inhibition control and working-memory

We used two-way repeated-measures ANOVAs also to analyze training effects on the executive skills underpinning the ability to optimize the trade-off between explorative and exploitative behavior.

We found no significant main effect of group or timepoint on the global score at the CRT, with accuracy being about 70% in both groups and timepoints. We observed, however, a time × treatment interaction effect on CRT completion time [$F(1,34) = 4.23$, $p < 0.05$, effect size (d) = 0.71], showing a larger decrease of completion time from the pre-training to the post-training timepoint in the TG compared with CG.

When performing the same analysis on working-memory variables (2-back and 3-back global score and response times) we found a significant main effect of timepoint regardless of group [$F(1,34) = 4.52$, $p = 0.04$, effect size (d) = 0.73], as well as a time by group interaction on the 3-back global score [$F(1,34) = 4.87$, $p = 0.03$, effect size (d) = 0.76]: compared with CG, the TG group showed a larger increase in 3-back performance from the pre-training to the post-training timepoint.

#### 3.1.4. Regression analysis

To investigate the relationship between the significant improvement of executive functioning skills (working memory, attention and inhibition control) and the ability to balance exploration and exploitation in dynamic and complex contexts, we performed a multiple regression analysis including TG subjects. We used the *post-minus-pre* residuals of cumulative payoff at the strategic innovation decision-making task as dependent variable, and the *post-minus-pre* residuals of CRT completion time and 3-back global score as independent variables. We found that the enhancement of 3-back and CRT performances (in terms of global score and completion time respectively) accounted for 42% of the total variance of the improvement observed in the strategic innovation performances [adjusted $R^2 = 0.42$, $F(2,15) = 7.19$, $p < 0.01$, effect size ($f^2$) = 0.72].

### 3.2. Neurostructural results

The demographic and individual characteristics of the MRI subsample mirror those reported for the whole sample, including the lack of significant difference in control measures between TG and CG subgroups (Table 5). Moreover, a multiple regression on the 15 subjects in the training subgroup confirmed that the improvement in executive abilities accounts for the increased performance in innovative decision-making [adjusted $R^2 = 0.47$, $F(2,12) = 7.309$, $p < 0.01$, effect size ($f^2$) = 0.85].

The results of longitudinal VBM highlighted a significant interaction between group and timepoint ($p < 0.01$, FWE-corrected). Compared with the control group, the training group showed a larger increase of grey matter volume in a portion of the right frontopolar cortex involving the middle orbital gyrus (x = 36, y = 45, z = −11) (Fig. 2).

Tract-Based Spatial Statistics on post-minus-pre FA images highlighted, in TG vs. CG, a significant increase of fractional anisotropy after training in a cluster along the left superior longitudinal fasciculus (cluster size: 73 voxels; cluster maxima coordinates: 32, −29, 26; $p < 0.05$, FWE-corrected) (Fig. 3). In addition, in the TG group the FA values extracted from this cluster are positively related to the increase in the cumulative payoff in the strategic innovation task ($r = 0.56$, $p = 0.03$, effect size (d) = 1.35) (Fig. S5).

**Table 4**
TG and CG performances in the strategic innovation decision-making task.

| A | | CG | | TG | |
|---|---|---|---|---|---|
| | | Mean (sd) | Range | Mean (sd) | Range |
| Pre-training cumulative payoffs | | 10.81 ( ± 122.53) | −394.5:174.67 | 74.06 ( ± 139.74) | −338.11:279.92 |
| Post-training cumulative payoffs | | 116.89 ( ± 227.22) | −530.54:450.43 | 222.18 ( ± 156.21) | −67.64:460.09 |
| B | | Count | % | Count | % |
| Pre-training cumulative payoffs (quintiles) | Very low performance | 5 | 27.8% | 3 | 16.7% |
| | Low performance | 4 | 22.2% | 3 | 16.7% |
| | Medium performance | 4 | 22.2% | 3 | 16.7% |
| | High performance | 2 | 11.1% | 5 | 27.8% |
| | Very high performance | 3 | 16.7% | 4 | 22.2% |
| | Total | 18 | 100% | 18 | 100% |
| Post-training cumulative payoffs (quintiles) | Very low performance | 5 | 27.8% | 2 | 11.1% |
| | Low performance | 0 | 0.0% | 1 | 5.6% |
| | Medium performance | 3 | 16.7% | 0 | 0.0% |
| | High performance | 1 | 5.6% | 1 | 5.6% |
| | Very high performance | 9 | 50.0% | 14 | 77.8% |
| | Total | 18 | 100% | 18 | 100% |

TG = Training Group; CG = Control Gro.

**Table 5**
Demographic and control variables of the DTI sub-sample.

| | TG (n = 15) | CG (n = 11) | p-value |
|---|---|---|---|
| Age | 22.43 ( ± 0.91) | 22.60 ( ± 1.02) | 0.66 |
| Gender (m:f) | 10:5 | 7:4 | 0.22 |
| Mood (BDI) | 6.6 ( ± 3.91) | 8.62 ( ± 6.15) | 0.24 |
| Anxiety (STAI) | State: 36.93 ( ± 7.30) | State: 37.87 ( ± 8.86) | State: 0.77 |
| | Trait: 37.08 ( ± 10.79) | Trait: 41.62 ( ± 7.31) | Trait: 0.13 |
| Cognitive flexibility (CFS) | 52.00 ( ± 8.02) | 54.73 ( ± 5.64) | 0.34 |
| Self-efficacy (GSES) | 30.02 ( ± 2.91) | 30.82 ( ± 3.49) | 0.63 |
| Goal orientation (AGOS) | 53.47 ( ± 88.11) | 54.64 ( ± 10.35) | 0.75 |

TG = Training Group; CG = Control Group; BDI = Beck Depression Inventory; STAI = State-Trait Anxiety Inventory; CFS = Cognitive Flexibility Scale; GSES = General Self-Efficacy Scale; AGOS = Academic Goal Orientation Scale.

## 4. Discussion

We used behavioral and neural metrics to investigate whether neurostructural changes underpinning a training-induced enhancement of executive performance additionally reflect in improved performance in innovative decision-making.

We first provide evidence of *near-transfer effects*, i.e. that training working-memory, attention and inhibition control improves performance in untrained tasks related to these abilities, such as the N-back and cognitive reflection test (Buschkuehl et al., 2008; Dahlin et al., 2008; Holmes, Gathercole, & Dunning, 2009, 2010; Li et al., 2008). In addition, we show that such improvement also results in higher ability to balance exploratory and exploitative choices in a realistic dynamic decision-making environment. Besides confirming the relationship between executive skills and flexible behavior (Laureiro-Martínez et al., 2013, 2015), our results thus suggest a far-transfer effect from executive enhancement to a more complex cognitive domain such as innovative decision-making.

Far-transfer effects, i.e. the transfer of gains achieved by a training program focused on a specific skill to untrained tasks requiring higher-order cognitive skills, have been extensively investigated (Jaeggi et al., 2014; Barnett & Ceci, 2002). Although their reliability is controversial (Jaeggi et al., 2014; Harrison et al., 2013; Shipstead, Redick, & Engle, 2012; Spierer, Chavan, & Manuel, 2013), several studies reported that training working memory can also improve individual performance on complex cognitive abilities such as fluid intelligence (Au et al., 2015; Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Jaeggi et al., 2011), reading (Chein & Morrison, 2010; García-Madruga et al., 2013; Loosli, Buschkuehl, Perrig, & Jaeggi, 2012), mathematical skills (Witt, 2011), visual short-term memory (Schwarb, Nail, & Schumacher, 2015), as well as executive (Klingberg, Forssberg, & Westerberg, 2002, 2005; Salminen, Strobach, & Schubert, 2012; Thorell, Lindqvist, Nutley, Bohlin, & Klingberg, 2009), attentional (Choi et al., 2012) and affective control (Schweizer, Hampshire, & Dalgleish, 2011). Far-transfer effects have been also reported in association with training inhibition control via a stop signal task (Spierer et al., 2013), which seems to modulate a variety of complex behaviors including risky decision-making (Verbruggen, Adams, & Chambers, 2012), alcohol consumption (Houben, Wiers, & Jansen, 2011) and food intake (Houben et al., 2011; Houben & Jansen, 2011; Veling, Aarts, & Papies, 2011). Overall, transfer effects seem to occur when the trained and the untrained tasks involve the same processing components, underpinned by a common neural basis (Dahlin et al., 2008).

In the case of executive control, a common activation pattern across different cognitive demands has been associated with the so-called Multiple-Demand (MD) system, including fronto-lateral, fronto-mesial and parietal regions (Duncan, 2010; Müller, Langner, Cieslik, Rottschy, & Eickhoff, 2014). These regions are jointly recruited by lower-level sub-processes supporting working memory, attention and inhibition control, which ultimately shape higher-level processes related to executive functioning (Duncan, 2010). Therefore, the effects of cognitive training on the quality of innovative decision-making may reflect improved functional and/or anatomical connectivity within this network.

In line with this hypothesis, we observed that the training of basic skills supporting executive control promotes neurostructural changes involving both white- and grey-matter metrics of specific fronto-parietal structures.

Concerning the former aspect, we found a significant increase in diffusion orientation coherence (FA index) within the left superior longitudinal fasciculus with training. The superior longitudinal fasciculus is a long-range bidirectional bundle connecting frontal and parietal regions (Thiebaut de Schotten et al., 2012; Hecht et al., 2015), involved in several functions ranging from eye movements and visuospatial processing to sensory-motor integration and working-memory (Thiebaut de Schotten et al., 2012). In particular, and in line with the present findings, the *left* superior longitudinal fasciculus has been associated to verbal working-memory (Peters et al., 2012) and attention (Urger et al., 2014). The increase of diffusion coherence within the left superior longitudinal fasciculus with training may thus reflect enhanced

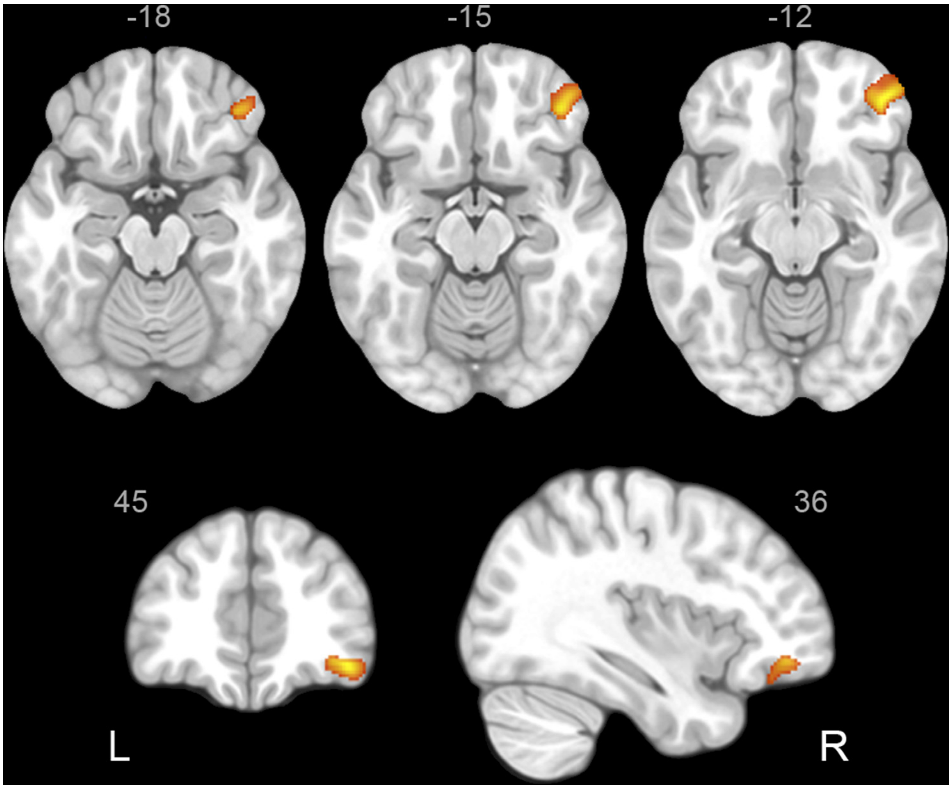


**Fig. 2.** VBM whole-brain group * timepoint interaction. Whole-brain results from longitudinal VBM highlighting a significant increase ($p < 0.05$, FWE-corrected) in grey matter volume in the right frontopolar cortex from the pre-training to the post-training timepoint in the training group (TG) compared with the control group (CG). The statistical map is superimposed on the MNI T1 template.

information processing underlying executive control, in turn driving an improvement in decisional skills. The latter hypothesis is supported by the positive correlation between the increase of diffusion coherence along the superior longitudinal fasciculus and the quality of innovative decision-making in the training group. Importantly, a recent study has highlighted that training working-memory for four weeks alters white-matters microstructural metrics (mean diffusivity) in key nodes of the mesocorticolimbic dopaminergic system (Takeuchi et al., 2015). Also this neural system, traditionally associated with reward experience and anticipation (e.g., Schultz, Dayan, & Montague, 1997), is involved in the exploration–exploitation trade-off, in which it supports value-based exploitative choices by tracking the value of the current option (Boorman et al., 2009; Kolling, Behrens, Mars, & Rushworth, 2012). Therefore, further microstructural changes along the mesocorticolimbic pathway may underpin the cognitive and behavioral effects of our cognitive training. Future studies may address this issue, by assessing joint experience-dependent structural changes in both the dopaminergic ascending pathway and fronto-parietal circuitry.

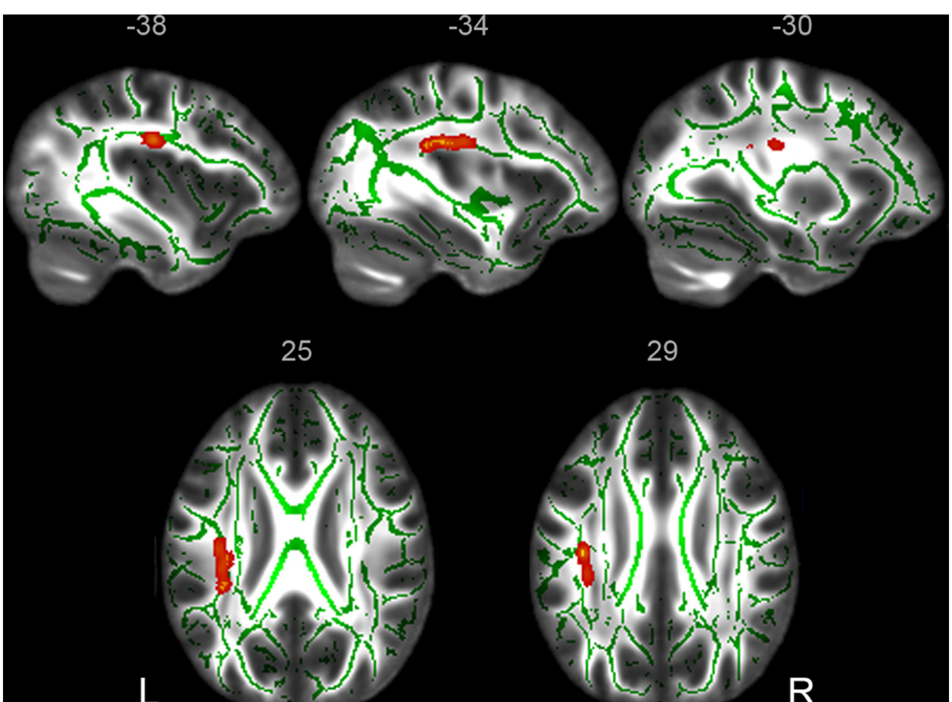


**Fig. 3.** TBSS whole-brain comparison between TG and CG. TBSS whole-brain comparison of post-minus-pre FA images showing a significant fractional anisotropy (FA) increase ($p < 0.05$ FWE-corrected) along the left superior longitudinal fasciculus in training group (TG) compared with the control group (CG). The statistical map (red-yellow) and mean FA skeleton (green) are superimposed on FMRIB standard-space FA template.

The neurostructural effects of training involved also grey-matter properties, namely a significant increase of grey matter volume in the right frontopolar cortex. This brain region is known to play a key role in the coordination of information processing and integration of results between multiple separate cognitive operations required to accomplish supramodal higher-order goals (Koechlin, Basso, Pietrini, Panzer, & Grafman, 1999; Owen, McMillan, Laird, & Bullmore, 2005). In particular, the *right* frontopolar cortex has been associated either with subgoal coordination (Braver & Bongiolatti, 2002) or with resuming an ongoing task following interruption by a subgoal (De Pisapia & Braver, 2008). The increase of grey-matter volume in the right frontopolar cortex thus likely reflects the crucial role played by both these processes on the executive and inhibitory control tasks performed by the training-group. Importantly, however, this brain region is also involved in managing the switch between exploration and exploitation (Boorman et al., 2009; Daw et al., 2006; Laureiro-Martínez et al., 2013), possibly due to its role in action selection based on prior outcomes (Beharelle, Polania, Hare, & Ruff, 2015), particularly when the latter are worse than expected (i.e., negative prediction errors). Indeed, two previous studies have shown that right frontopolar activity reflects individual differences in effective behavioral adaptations based on the relative uncertainty about the expected value of available options (Badre, Doll, Long, & Frank, 2012; Boorman et al., 2009). It is noteworthy that the coordinates reported in these studies (e.g. xyz = 36 56–8 in Badre et al., 2012) largely overlap with the cluster showing grey-matter increase after training in the present study (xyz = 36 45–11). While supporting a triadic relationship between the cognitive, behavioral and neurological effects of training, this evidence raises several opportunities for future research.

A first question regards understanding what aspect of training underpins the observed near- and far-transfer effects. Relevant evidence in this respect comes from two recent studies using the very same executive and decision-making tasks used here. The first shows that executive skills (as measured by a battery of tasks including the N-back and CRT) support performance (i.e. cumulative payoff) in the same strategic innovation decision-making task employed in the present study (Laureiro-Martínez et al., 2013). Crucially, this effect is mediated by the tendency to automatize the decisional process, i.e. routinization, which in turn enhances the ability to manage the trade-off between explorative and exploitative choices. Another study shows that individual differences in the tendency to routinize, as measured by decision-making efficiency (i.e. performance divided by response time), can be linked to heightened activity of the same right frontopolar region reported here (Laureiro-Martínez et al., 2015). Importantly, in this and other related studies (e.g. Boorman et al., 2009; Daw et al., 2006) explorative choices involve an extensive bilateral dorsal network, in which connectivity between frontal and parietal nodes is mediated by the superior longitudinal fasciculus, i.e. the same bundle highlighted by our DTI results.

A second research question concerns the microstructural biological mechanisms underlying the observed neurostructural effects. Different proposals have been made for activity-dependent changes in both grey-matter properties (neurogenesis, synaptogenesis and changes in neuronal morphology) and white-matter metrics (number, diameter and packing density of axons, as well as their trajectories and branching) (Zatorre, Fields, & Johansen-Berg, 2012). While this issue is beyond the scope of the present study, future research based on multimodal neuroimaging, possibly in combination with histological data from animal models (e.g., Lerch et al., 2011), will likely unveil which of these mechanisms underpin the experience-dependent structural changes highlighted by neuroimaging studies.

In conclusion, we extended to the decisional domain the notion that transfer effects require that both the trained and untrained tasks involve common processing components and neural bases (Dahlin et al., 2008), i.e. executive skills underpinned by fronto-parietal networks in the present study.

This study has several limitations that highlight the need of follow-up studies to support the present preliminary evidence. First, we found only a trend, approaching statistical significance, for the interaction between the effects of group (training-control) and timepoint (pre-post assessment) on decision-making performance. On the other hand, only the training group displayed a significant improvement, while no such effect was found in the control group. In this respect, statistical power was limited by the intrinsically high variability of the cumulative payoffs resulting from the strategic innovation decision-making task (see Table 3). Such variability is the side-effect of using as the main study outcome an ecologically valid measure of individual flexibility in choice behavior (i.e. the cumulative payoff on the strategic innovation decision-making task). Such a tool has been developed and used for educational purposes, and no normative data are currently available in literature. For these reasons we created a new variable, based on data distribution, to obtain a qualitative index of innovative decision-making, which confirmed training-related changes in behavioral performance. In addition, statistical power was limited by the small sample size, mainly due to the high commitment required from the subjects. The present work should thus be considered a proof-of-concept study, providing preliminary data on the effectiveness of cognitive training on decision-making performance, and requiring replication and further supporting evidence. The fact that only the training group displayed a significant increase of decision-making performance in this task can nevertheless be considered as positive evidence for transfer-effects of cognitive training on decision-making skills. Most importantly, the significant association between the extent of such effects and the neurostructural changes in white-matter bundles underlying executive functions supports the internal coherence of the reported association among decision-making performance, executive skills and the functionality of fronto-parietal networks underlying both processes.

Our data thus ground in specific neurostructural changes the role played by executive skills in mediating the effects of cognitive training on the quality of innovative decision-making. Besides contributing to unveil the neurocognitive bases of behavioral learning and decision-making, the present evidence may represent a basis for developing training programs aimed at improving choices in settings requiring an optimal balance between exploratory and exploitative choices. Indeed, our findings, within the limitations discussed above, contribute toward the development of an evidence-based discussion about how to assess educational tools that target adults. Enormous resources are spent to train ‘leaders’ in business organizations and political institutions, to enable them to take ‘better’ decisions. However, very little is known about the extent to which such training programs deliver skills that are indeed transferred to the subjects’ professional environment. Assessment methods (as routinely applied in, e.g., business schools) rely mainly, if not exclusively, on the subjects’ own assessment. We would argue that these methods should be complemented with experimental evidence based on the combination of behavioral and neural impacts of specific training processes. This combination will provide a way forward to develop evidence-based improvements of extant educational strategies, with hopefully broader and deeper long-term societal benefits.

## 5. Declarations of interest

None.

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## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bandc.2018.11.004.

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