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RESEARCH ARTICLE

Analysis of hand kinematics reveals inter-individual differences in intertemporal decision dynamics

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Abstract During intertemporal decisions, the preference for smaller, sooner reward over larger-delayed rewards (temporal discounting, TD) exhibits substantial inter-subject variability; however, it is currently unclear what are the mechanisms underlying this apparently idiosyncratic behavior. To answer this question, here we recorded and analyzed mouse movement kinematics during intertemporal choices in a large sample of participants ($N = 86$). Results revealed a specific pattern of decision dynamics associated with the selection of "immediate" versus "delayed" response alternatives, which well discriminated between a "discounter" versus a "farsighted" behavior—thus representing a reliable behavioral marker of TD preferences. By fitting the Drift Diffusion Model to the data, we showed that differences between discounter and farsighted subjects could be explained in terms of different model parameterizations, corresponding to the use of different choice mechanisms in the two groups. While farsighted subjects were biased toward the "delayed" option, discounter subjects were not correspondingly biased toward the "immediate" option. Rather, as shown by the dynamics of evidence accumulation over time, their behavior was characterized by high choice uncertainty.

Keywords Choice behavior · Decision making · Mathematical models

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Introduction

When people are required to choose between rewards available at different time points, the perceived value of future options typically declines as a function of the delay. This phenomenon, known as *temporal discounting* (TD), has been widely studied using intertemporal choice tasks, in which subjects are required to choose between a certain amount of money which is immediately available and a larger one but available after a variable time interval (McClure et al. 2004; Chabris et al. 2007; Berns et al. 2007; Kable and Glimcher 2007; Figner et al. 2010; van den Bos and McClure 2013). By fitting response distribution with a hyperbolic function, a discount rate (k) is estimated, which reflects the decay of subjective value of monetary rewards with time. Importantly, given its pervasiveness in daily life choices and its relevance for adaptive behavior, temporal discounting has been studied in a very broad range of research fields including economics, psychology and neuroscience. These studies have shed light on specific characteristics of the discounting behavior such the mathematical description of the discounting function (i.e., exponential vs. hyperbolic functions) (e.g., Green and Myerson 1996; Laibson 1997) or the neural bases of the representation of subjective value (single system vs. dual systems hypothesis) (e.g., McClure et al. 2004; Kable and Glimcher 2007).

However, the mechanisms underlying the dynamics of the intertemporal choice process are still largely unknown.

The importance of studying the dynamics of choice is becoming increasingly apparent in the decision-making literature, since decisions are never reached instantaneously and choices—including intertemporal choices—are intrinsically dynamic processes. The dynamic nature of decision processes has been well described within the class of sequential sampling models, such as the Drift Diffusion Model (DDM) (Ratcliff and Rouder 1998). These models assume that a decision derives from a noisy process in which information is collected and accumulated at different rates (v) from a starting point (z) toward one of two response boundaries (a, 0) and that a response is initiated when the decision criterion reaches one of the two boundaries (Ratcliff and McKoon 2008). Notably, even though the DDM has been typically applied to perceptual and memory decisions, a recent work by Summerfield and colleagues (Summerfield and Tsetsos 2012) has shown that the DDM can also be applied to describe economic decisions and that these different classes of decisions share a substantial analogy in the key processing components. In particular, whereas perceptual versus economic decisions fundamentally diverge in the source of information of the evaluation/categorization process (i.e., noisy sensory information from the external environment for perceptual decisions vs. internal information about subjective value for economic decisions), both classes of decision entail a process of uncertainty evaluation and evidence accumulation over time. In the case of perceptual decisions, the accumulated evidence reflects a sensorial (environmental) information, while during economic decisions, including intertemporal choices, the accumulation process is guided by an internal variable reflecting a subjective estimate of the option's value, with no direct dependence on target categories. These considerations suggest that models like the DDM, which were initially developed to study the dynamics of perceptual decisions in terms of evidence accumulation, are also viable candidates to study economic decisions.

Importantly, temporal discounting is not only a dynamic but also an idiosyncratic phenomenon, since it exhibits substantial inter-subject variability. Such variability may reflect critical aspects of behavior, personality, cognitive processing and brain mechanisms that are related to individual differences in reward preferences. Indeed, we have recently shown that variability in subjective preferences during intertemporal choices are paralleled by differences in the intrinsic functional architecture of the brain, as indicated by a significant correlation between TD and functional connectivity within and between critical nodes of the TD neural networks (Calluso et al. 2015). Furthermore, choosing a smaller but immediate reward over a larger but delayed reward (i.e., discounter behavior) has been often described as an "impulsive" behavior (Ainslie 1975; Monterosso and Ainslie 1999) and associated with clinical conditions such pathological gambling and other addiction disorders. However, while in the pathological domain much attention has been paid to personality variables and conditions (i.e., personality traits, impulsivity, anxiety and so on) that may underlie such addictive behavior, in the non-pathological domain the analysis of the relation between discounting and impulsivity has produced controversial results (Mitchell 1999; Reynolds et al. 2006), and the relationship with other state/trait characteristics has rarely been investigated in detail.

Here we investigated the dynamics of the decision process by collecting and analyzing mouse movement kinematics during intertemporal choices. The rationale for this is based on previous studies showing that hand-movement kinematics represent a reliable measure of the dynamics of cognitive processing (Song and Nakayama 2009). Human EEG studies, for example, have shown that visual discrimination processes involve early activations of motor areas, which are presumably used to continuously guide hand-movement responses over time (Freeman et al. 2011b). In addition, a series of monkey studies have shown that the position of the hand and the velocity of the movements are strongly linked to ongoing changes in the firing rate of motor cortical neurons (Paninski et al. 2004), thus suggesting that the dynamics of action is coextensive with the dynamics of perception and cognition, that they continuously change and interact in real time, and that a fast sampling of hand movements could provide a real-time readout of internal cognitive processing (Freeman et al. 2011a). Furthermore, while self-reported measures of behavior are potentially affected by subjective biases (Reynolds et al. 2006), the recording of mouse movement kinematics provides a very specific set of quantitative parameters (e.g., mouse trajectory curvature during the choice) that represent an implicit measure of behavior and that may thus uncover particular aspects of behavior beyond those manifested at the declarative, subjective level. These parameters, which are based on the analyses of the response trajectories during the choice process, permit to capture and reveal the ongoing dynamics of cognitive processing related to higher-level phenomena such as, among others, perceptual and lexical decisions, memory tasks, and various economic choices (Spivey 2007; Freeman et al. 2011b; Dshemuchadse et al. 2012; Barca and Pezzulo 2012; Quinton et al. 2013; Sullivan et al. 2014; Barca and Pezzulo 2015).

As noted above, we additionally examined the relationship between implicit and declarative, self-reported measures of decision behavior by collecting a series of questionnaires on impulsivity, state/trait anxiety, depression and pathological gambling and by testing the correlations

between the scores on these questionnaires and discount rates. Importantly, our research questions were examined on a sample of $n = 86$ healthy subjects with a very broad age range (20–60), which not only served the aim of extending our study conclusions to a large and homogenous sample of subjects, but also that of providing a usable healthy reference for future studies on clinical populations.

In our analysis, we investigated the response pattern in both the whole sample of subjects and in two sub-groups representative of a "discounter" (i.e., individuals who prefer small-immediate over larger-delayed rewards) versus "farsighted" (i.e., individuals who are more inclined to wait for larger rewards) behavior. Furthermore, to better characterize the nature of the intertemporal choice process, we fitted the Drift Diffusion Model (DDM) to behavioral data. The DDM variables particularly relevant for the present context were the drift rate (i.e., the average rate of accumulation and integration of evidence for a certain decision) and the starting point or origin of the decision process. Since in our paradigm the choice options were clearly presented as written text at the beginning of each trial, the drift rate parameter was exclusively based on the internal estimate of the options value with no source of perceptual uncertainty, while the latter parameter, when biased toward one of the two alternatives, likely resulted in an a priori bias and a facilitated selection of the corresponding response option. We complemented the DDM fitting with an original analysis of the dynamics of the intertemporal decision by using a computational model that simultaneously considers reaction times (like the DDM) and mouse trajectories (e.g., mouse curvature during the choice). The model (Lepora and Pezzulo 2015) permits to estimate individualized parameters (e.g., a bias toward one of the choice alternatives) from the subjects' mouse trajectories, thus revealing different choice patterns in subjects with different discount rates. This model-based analysis of the data allowed us to unveil the specific aspects of the decision process that were likely responsible of the behavioral differences between discounter and farsighted subjects.

Methods

Subjects

The present study is based on a total sample of eighty-six right-handed healthy subjects (33 males, mean age = 36.21 years, SD = 11.06, range 20–60 years). All participants provided written informed consent before the beginning of the experiment, which was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki. Each subject completed a comprehensive assessment of impulsivity, anxiety, depression and pathological gambling (as an exclusion criterion), and a behavioral session of an intertemporal choice task. Eleven subjects (6 males, mean age = 41.27 years, SD = 8.59, range 25–56 years) were excluded from data analysis for the following reasons: in three subjects the scores in the South Oaks Gambling Screen (SOGS) exceeded the cut-off (and could potentially suffer of a pathological gambling problem), while the remaining eight subjects showed no choice variability in the intertemporal task (they gave only "now" or "later" responses in all the 420 trials of the task) which precluded the estimation of the indifference points and diffusion model fit. The final sample included seventy-five subjects (29 males, mean age = 35.24 years, SD = 11.61, range 20–60 years).

Assessment of impulsivity, anxiety, depression and pathological gambling

Impulsivity was assessed through the Italian adult version of the Barratt Impulsiveness Scale (BIS-11) (Patton et al. 1995; Fossati et al. 2001). The BIS-11 is a gold-standard questionnaire for the assessment of impulsivity that evaluates three specific dimensions: attentional impulsiveness (AI) involving task-focus, intrusive thoughts, and racing thoughts; motor impulsiveness (MI), involving the tendency to act on the spur of the moment and consistency of lifestyle; and non-planning impulsiveness (N-PI), involving careful thinking and planning and enjoyment of challenging mental tasks.

Anxiety was tested through the Italian version of the State/Trait Anxiety Inventory (STAI) (Spielberger et al. 1970) that indicates the intensity of feelings of anxiety and distinguishes between state anxiety, i.e., a temporary condition experienced in specific situations, and trait anxiety, i.e., a general tendency to perceive situations as threatening.

Finally, the presence of depression and pathological gambling was assessed through the Italian versions of the Hamilton Depression Rating Scale (HDRS) (Hamilton 1960; Kobak et al. 1999) and the South Oaks Gambling Screen (SOGS) (Lesieur and Blume 1987), respectively. As exclusion criteria we used a standard cut-off score of 15 for the HDRS (Kobak et al. 1999) and a standard cut-off of 5 for the SOGS (Lesieur and Blume 1987).

All questionnaires were administered in electronic version through the implementation in SuperLab 4.0.7b (Haxby et al. 1993; Abboud et al. 2006).

Intertemporal choice task

Participants were asked to make a series of intertemporal choices between two different amounts of money, one immediately available and the other offered at different time delays. Based on previous intertemporal choice

studies reporting no differences between hypothetical and real (involving actual monetary gain) choices (Johnson and Bickel 2002; Madden et al. 2003, 2004; Lagorio and Madden 2005), we adopted a paradigm in which all choices were hypothetical and rewards not cumulative across trials. On this basis, subjects were clearly instructed to provide hypothetical decisions and to consider each trial as independent from the others. The immediate option was a fixed amount of 10€, while the future choices were parametrically manipulated across seven amounts (15€, 25€, 30€, 40€, 45€, 55€ and 60€) and six delay periods (7, 15, 30, 60, 90 and 180 days) for a total of 42 possible choice contingencies. A total of 420 trials, including 10 repetitions per condition, were pseudo-randomly distributed across three experimental blocks. Visual presentation of choice alternatives and response recording was performed using the Mouse Tracker software (Freeman and Ambady 2010) which allows the recording of the mouse movement kinematics associated with the choice at a sampling rate of 70 Hz. Choices options were presented on a 17" LCD computer monitor (1285 × 1039 pixels) with a 60 hertz refresh rate at a viewing distance of ~60 cm.

An instruction screen was presented at the beginning of the experiment and was followed by five training trials, which were used to warm-up/familiarize subjects with the task and were identical to those from the main experiment. The immediate ("now") and delayed ("later") options were presented as written text on a black box (297 × 140 pixels) at the top left and top right of the computer screen, respectively, and remained on the screen for the entire duration of the block. To control that the results were not affected by the position of the response buttons, a sub-group of subjects ($N = 25$) performed a counterbalanced version of the task in which the position of "now" and "later" buttons was reversed (i.e., "later" positioned at the top left and "now" at the top right of the screen).

Participants were instructed to press the "start" button (129 × 72 pixels) positioned at the central bottom of the screen to visualize the choice options and then to express their preference by clicking on the corresponding button (Fig. 1). The "now" and "later" buttons were positioned at the same distance (1114 pixels) from the "start" button to ensure proper recording of the mouse trajectories. Participants were explicitly instructed to begin their movements early and were warned with a pop-out window after slow trials (>2000 ms).

Discount rate estimation

Using subjects' observed behavior and the well-known hyperbolic function as a model to describe the decline of subjective value with increasing time delays (Mazur 1987; Laibson 1997), we estimated a subject-specific parameter,

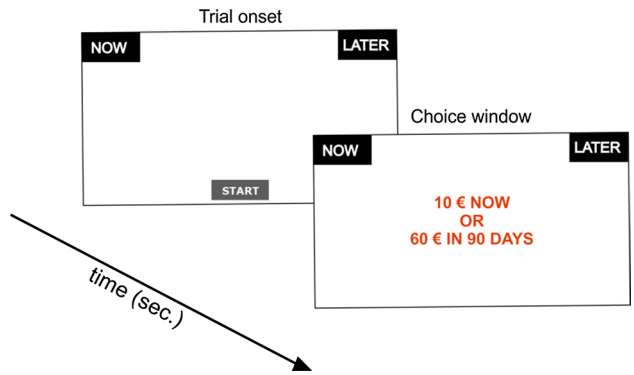

Fig. 1 Behavioral paradigm. On each trial, the subjects were instructed to press the "start" button positioned at the central bottom of the screen to visualize the choice options and to express their preference by clicking on the corresponding button ("now" versus "later")

named discount rate (or k parameter), expressing the steepness of the discounting function and the rate of decline in the value of rewards.

As a first step, we estimated the fraction of times the subjects chose the future amount over the immediate amount as a function of the objective value of the delayed reward. We then fit the data to a logistic function to calculate the indifference points (ip), defined as the amount for each delay at which the subject would chose the immediate and delayed rewards with equal frequency. We subsequently estimated the subjective value (SV) for each time delay using the following equation:

$$\mathrm{SV} = \frac{10}{\mathrm{ip}}$$

where 10 was the amount of money immediately available. This procedure ensured that the subjective value was normalized to the immediate amount of money. We finally estimated the subject-specific k parameter by fitting the subjective value points obtained for each time delay (D) to the hyperbolic function described by the following equation:

$$\mathrm{SV} = \frac{1}{(1 + kD)}$$

The k parameters were then normalized using the natural-log transformation and a Kolmogorov–Smirnov normality test was used to control that the resulting distribution was normally distributed ($p > 0.05$).

Kinematics analysis

Using the mouse tracker software, we recorded the x and y coordinates of the mouse trajectories associated with the participants' choices. Because each choice tended to have different length and, as a consequence, a different number of x–y coordinate pairs, we conducted a normalized time

analysis. To permit averaging and comparison across multiple trials with different numbers of coordinate pairs, trajectories were resampled to a given number of time steps ($n = 101$) using a linear interpolation.

The normalized trajectories were then used to compute two parameters: the Maximum Deviation (MD) and the Area Under the Curve (AUC). For both measures, we first computed an idealized response trajectory (a straight line between each trajectory's start and endpoints). The MD of a trajectory was then calculated as the largest perpendicular deviation between the actual trajectory and its idealized trajectory out of all time steps. The AUC of a trajectory was instead calculated as the geometric area between the actual trajectory and the idealized trajectory. Thus, while AUC and MD reflect different measures of overall attraction toward the unselected alternative (Freeman and Ambady 2010), they both provide an index of spatial attraction toward the concurrent, not-selected alternative (i.e., overall higher values of MD and AUC indicated a high spatial attraction by the unselected alternative during the trajectory toward the selected choice option) and prior studies have shown no change in the results if they are interchangeably used (Freeman et al. 2008). More importantly, both parameters provide critical information about decision uncertainty (Freeman and Ambady 2010).

AUC and MD parameters were normalized using a z-score normalization before statistical analysis (see Freeman and Ambady 2010).

Statistics

We first compared response distribution, reaction times (in mouse tracker paradigms, the reaction time is the time between the click of the start button and the selection of the chosen response, that is the time for movement execution), and MD and AUC parameters associated with immediate versus delayed choices in the entire sample using paired *t* tests and the relationship between discount rates and both the state/trait variables (impulsivity, anxiety, depression and SOGS scores) and the demographic characteristics (age and years of education) by performing Pearson's correlations between the questionnaires scores and the *k* parameter.

In order to control that the kinematics results were not affected by the position of the response buttons, we conducted a series of 2×2 repeated measures ANOVA with task (classic vs. counterbalanced) and response (now vs. later) as factors on both the MD and AUC parameters. Moreover, to ensure that the results were not affected by the different number of participants involved in the two versions of the task (classic = 50, counterbalanced = 25), we conducted the same analysis on a comparable group of subjects (25 for each version of the task).

We then divided the total sample of participants in two groups based on their k parameter (median split): one group (discounter, $N = 37$) included the subjects whose discount rate was higher than the median log-transformed *k* value, while the other group (farsighted, $N = 37$) included the subjects with a k parameter lower than the median. To ensure the validity of this group split, we compared the discount rates by a two-sample *t* test. In addition, to control that the results of the group comparisons where exclusively explained by inter-subject variability in intertemporal choice behavior, we conducted a series of two-sample *t* tests comparing the two groups of subjects both in terms of general characteristics, such age and years of education, and in terms of impulsivity and anxiety scores.

We compared the two groups on the percentage of immediate versus delayed choices, reaction times and MD and the AUC estimates by conducting a series of mixed 2×2 repeated measures ANOVAs with group (discounter vs. farsighted) as between-subjects factor and response type (now vs. later) as within-subjects factor. Finally, because we were interested in understanding whether mouse movement kinematics could actually represent a behavioral marker of individual differences in choice preferences, we performed Pearson's correlations between MD and AUC values associated with "now" and "later" choices and discount rates over the entire sample. We also used the MATLAB robust fit function (Holland and Welsch 1977; O'Leary 1990) to compute robust multilinear regression tests in which the log-transformed *k* parameter was treated as dependent variable and the MD and AUC parameters associated with the "now" and "later" choice options as regressors.

Control analyses: difficulty effect

To test whether our kinematics findings were modulated by choice difficulty, and particularly whether the effect of choice difficulty interacted with response type (compared to the immediate option, which remained fixed across trials, the future option required a trial-by-trial computation of the reward/delay trade-off likely resulting in a higher computational load) and group (discounter vs. farsighted subjects), we included choice difficulty as factor in the ANOVAs. Subjects' choices were divided in easy versus hard based on the distance from individual's indifference points (ip). As the mean increment of our amount set was 7.5€, for each time delay, trials whose amount fall in the range of ip ± 7.5 were considered "near" to the indifference point, while those out of this range were considered "far" from the indifference point.

The effect of choices difficulty on MD and AUC parameters was then analyzed through a series of repeated measures ANOVAs with response type (now vs. later), choice difficulty (hard vs. easy) and group (discounters vs. farsighted) as factors.

Fitting the Drift Diffusion Model (DDM) to data

To test possible modulations of the parameters of the diffusion decision model by inter-group or inter-subject variability in intertemporal choice preferences, we fitted the Drift Diffusion Model (Ratcliff and McKoon 2008) to behavioral data (reaction times and choice distribution) using the MATLAB Diffusion Model Analysis Toolbox [DMAT (Vandekerckhove and Tuerlinckx 2007, 2008)].

We hypothesized that the most relevant DDM parameters for intertemporal decisions were the starting point and drift rate and the best fit model was identified by comparing different parameterizations with various combinations of free and fixed parameters (Philiastides et al. 2011; Sestieri et al. 2014): (1) a model in which all parameters were fixed; (2) a model in which only the starting point was free to vary across conditions (the other were fixed); (3) a model in which only the drift rate freely varied across conditions; (4) a model in which both starting point and the drift rate were free to vary; (5) a model in which all parameters were allowed to freely vary across conditions.

The analysis of the best fit model was carried out by evaluating the best fit able to account for within-group variability, and this procedure was performed in both discounter and farsighted groups.

The goodness of fit and model selection was performed using the Bayesian Information Criterion (BIC) to account for model complexity.

Finally, based on the results of the model parameterization analysis, significant variations of the drift rate and starting point across groups were assessed by two-sample *t* tests on the parameters estimates.

Comparison with Embodied Choice model

To evaluate the consistency between the results of the DDM fit and the pattern of mouse movement kinematics in the two groups, the results of the DDM analysis were compared with a model of Embodied Choice (Lepora and Pezzulo 2015): an extension of the DDM that also models motor response (here, mouse movement) by assuming that it is part of the decision-making process.

A key assumption of the model is that action can be initiated from the start of the decision process (rather than after its completion) and that action dynamic essentially reflects choice uncertainty. Specifically, to formalize tasks using continuous measure of performance (like the Mouse Tracker), the Embodied Choice model supplements the DDM with an "action focus": a point toward which the agent moves the mouse based on the current state of the decision process and the current mouse position. Intuitively, if choice uncertainty is high, the subject movements are "attracted" by both response buttons, and so they will be directed to an action focus that lies between the two (e.g., halfway if uncertainty is maximal). If, instead, the subject is almost sure about his/her choice, the action focus will be (close to) one of the two buttons. A more detailed description of the methods used to calculate the action focus and to model the overall decision process is provided in the "Appendix" and in Lepora and Pezzulo (2015). The action focus changes during the decision as an effect of the subject's changing belief on the desired choice, based on accumulated evidence as in the DDM. Modeling the (moving) action focus permits the Embodied Choice model to reproduce mouse trajectories, including changes of mind that can arise when the subject movements initially target one of the buttons and then the other button.

The Embodied Choice model was initialized with the parameters taken from the fit to the DDM model (Sect. "Fitting the Drift Diffusion Model (DDM) to data"), supplemented with tuning the decision bound b to reproduce the observed trajectory behavior. The aim of this comparison was to assess whether the DDM parameters could explain and reproduce the participants' trajectories in addition to their reaction times.

Results

Relationship between discount rate and individual differences

The Hamilton Depression Rating Scale indicated no pathological scores for all participants, while the South Oaks Gambling Screen revealed three subjects with an individual score exceeding the pathological cut-off. As reported above, these subjects were excluded from all the analysis because of a potential gambling problem (see Table 1 for a comprehensive report of mean scores and standard deviations).

As indicated in Table 2, no significant correlation (Pearson's) was observed between discount rate (k parameters) and the evaluated dimensions of impulsivity (BIS 11), state/trait anxiety (STAI), depression (HDRS) and pathological gambling (SOGS) as well as between discount rate and general characteristics (age and years of education) of the sample population.

Intertemporal choice behavior

As indicated by the absence of significant effects in the ANOVAs on the classic versus counterbalanced version of the intertemporal choice task, kinematics measures of discounting were not affected by the spatial position of the response buttons (main effect of task, MD: $F_{1,\,48} = 0.82$,

Table 1 Mean scores and standard deviations of the Barratt Impulsiveness Scale 11 (BIS-11), State/Trait Anxiety Inventory (STAI), Hamilton Depression Rating Scale (HDRS) and South Oaks Gambling Scale (SOGS)

BIS-11	
Attentional impulsivity	15.72 ± 3.12
Motor impulsivity	19.11 ± 3.59
Non-planning impulsivity	23.80 ± 4.54
Total score	58.61 ± 8.98
STAI	
State	49.48 ± 3.50
Trait	42.44 ± 10.74
HDRS	
Psychic	1.16 ± 1.56
Somatic	2.76 ± 1.53
Total score	3.98 ± 2.27
SOGS	
Total score	0.54 ± 0.65

Table 2 Correlations between Barratt Impulsiveness Scale 11 (BIS-11), State/Trait Anxiety Inventory (STAI), Hamilton Depression Rating Scale (HDRS) and South Oaks Gambling Scale (SOGS) individual scores and discount rate parameter (k)

	Discount rates (k)	
BIS-11		
Attentional	$r = 0.09$	$p = 0.43$
Motor	$r = -0.08$	$p = 0.46$
Non-planning	$r = -0.04$	$p = 0.74$
Total score	$r = -0.02$	$p = 0.87$
STAI		
State	$r = -0.17$	$p = 0.13$
Trait	$r = 0.15$	$p = 0.16$
HDRS		
Psychic	$r = -0.07$	$p = 0.54$
Somatic	$r = -0.07$	$p = 0.55$
Total	$r = -0.08$	$p = 0.53$
SOGS	$r = -0.07$	$p = 0.56$
General characteristics		
Age	$r = 0.09$	$p = 0.42$
Years of education	$r = -0.22$	$p = 0.06$

$p > 0.05$, AUC: $F_{1,\,48} = 1.20$, $p > 0.05$; response by task interaction, MD: $F_{1,\,48} = 1.39$, $p > 0.05$, AUC: $F_{1,\,48} = 1.46$, $p > 0.05$) and the same (null) result was obtained when comparing an equal number of participants ($N = 25$) on the two versions of the task (no significant main effect of task: MD: $F_{1,\,48} = 0.14$, $p = 0.71$, AUC: $F_{1,\,48} = 0.29$, $p = 0.59$, no significant task by response type interaction: MD: $F_{1,\,48} = 34$, $p = 0.56$, AUC: $F_{1,\,48} = 30$, $p = 0.59$), thus suggesting that our results were not affected by the different number of participants involved in the classic versus counterbalanced version of the task. We observed instead a substantial variability in the log-transformed k parameters of our sample (mean $k = -1.28 \pm 0.66$). To characterize the participants' differences in intertemporal choice behavior, we computed the median value of the log-transformed k parameters and used this measure to divide the entire group in two representative samples of discounter and farsighted subjects. A two-sample t test showed a statistically significant difference between the k values of discounter and farsighted subjects ($t = 10.85$, $p < 0.01$, CI (95 %) 0.84; 1.22) which confirmed the reliability of such division. Notably, no statistically significant difference was observed between the two groups in terms of general characteristics (age, years of education) or impulsivity, anxiety, depression and gambling scores.

Figure 2a shows the mean discounting function for the entire sample ($n = 75$, green line) and for the two groups of discounter (red line) and farsighted (cyan line) subjects (to ease interpretation, Fig. 2b shows the k mean values of the two subgroups instead of the log-transformed k values).

At the level of the entire sample of subjects, we observed that the future larger amount was selected with higher frequency than the immediate one and was associated with faster reaction times (percentage of "later" > "now" choices, $t = -3.06$, $p < 0.01$, CI (95 %) 0.06, 0.28; reaction times for "later" < "now" choices, $t = 1.98$, $p < 0.5$, CI (95 %) −308.51, 0.92; Fig. 3a, b).

The inspection of the behavior in the two groups of discounter and farsighted subjects, however, suggested that whereas the farsighted show a pattern of results consistent with those obtained in the whole sample, discounter subjects deviated from this trend. This was confirmed by a statistically significant interaction of response type (now, later) by group (discounter, farsighted) conducted both on the percentage of responses ($F_{1,\,72} = 23.66$, $p < 0.01$, e.s. = 0.96) and on the reaction times ($F_{1,\,72} = 7.63$, $p < 0.01$, e.s. = 0.71). As explained by post hoc tests (Newman–Keuls), while discounter subjects showed a comparable response percentage and reaction times for the two options, farsighted subjects showed a higher percentage and faster reaction times for "later" compared to "now" responses ($p < 0.01$) (Fig. 3c, d). As a result of this interaction, the percentage of "later" choices was higher in farsighted than discounter ($p < 0.01$), while the percentage of "now" responses was higher in discounter compared to farsighted ($p < 0.01$) (Fig. 3c).

Kinematics of intertemporal choice

We studied in deeper detail the intertemporal choice dynamics by analyzing the parameters associated with the kinematics of mouse movements during decisions.

As a first step, we compared the MD and AUC parameters associated with the "now" and "later" choices in

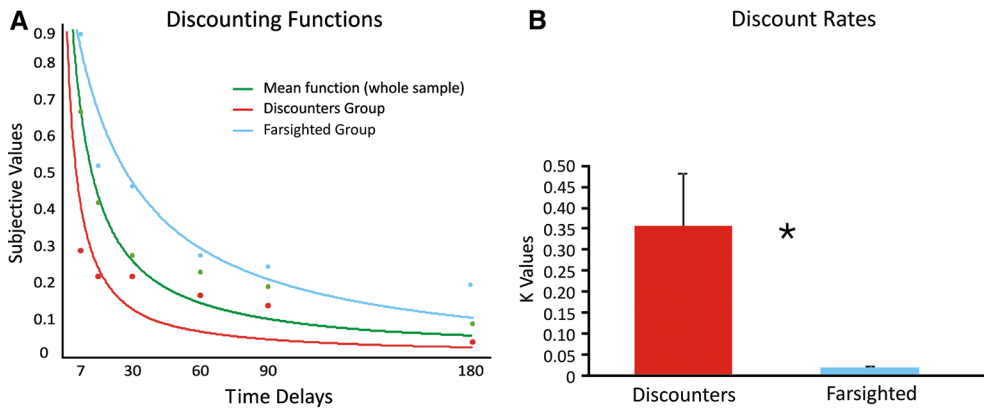

Fig. 2 Mean discounting functions of the entire sample ($n = 75$, *green line*), the discounter group (*red line*) and the farsighted group (*cyan line*) (**a**). Comparison between discounter and farsighted discount rates (mean k values) (**b**) (color figure online)

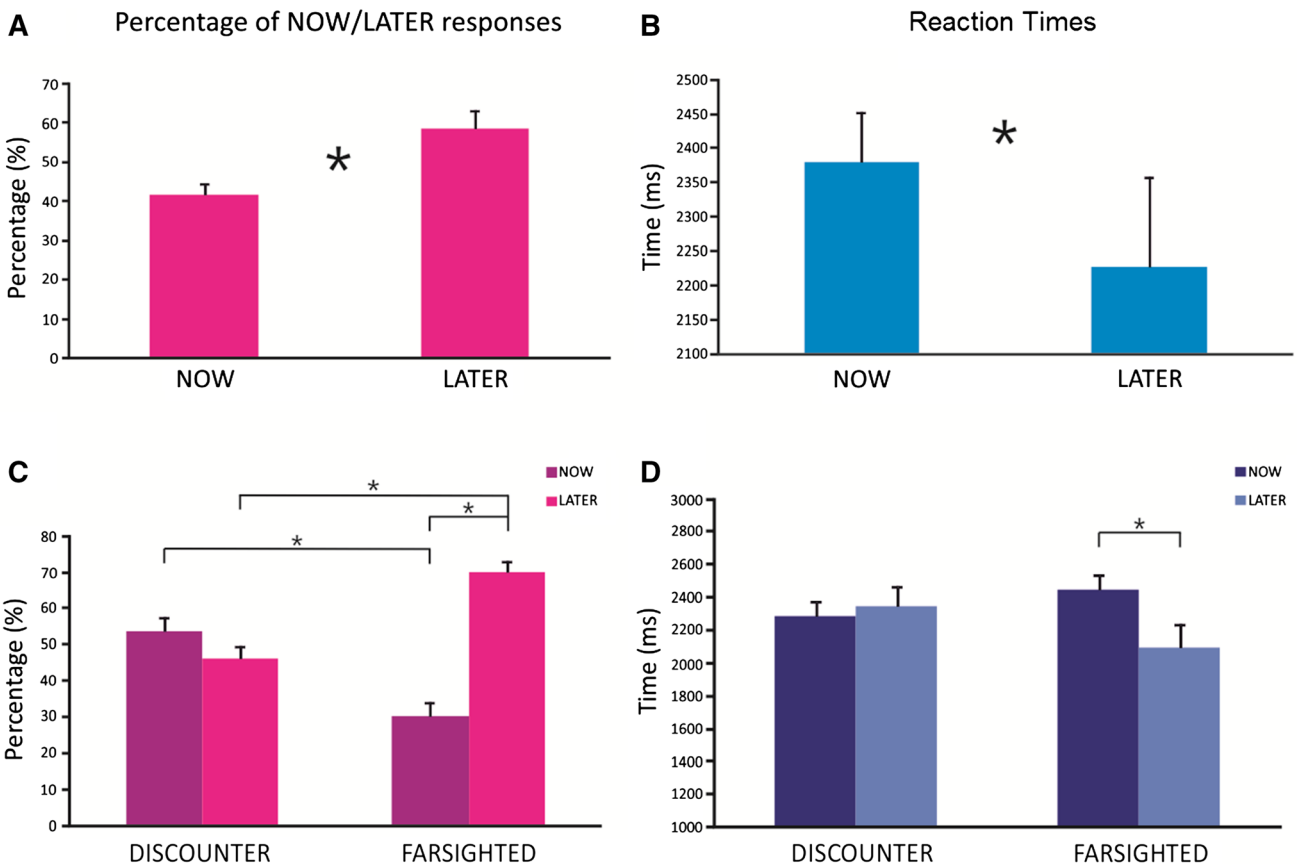

Fig. 3 Results of the paired t tests conducted on the percentage of now/later responses (**a**) and reaction times (**b**). Results of the 2 × 2 (group by response type) repeated measures AVOVAs conducted on percentage of now/later responses (**c**) and reaction times (**d**)

the entire group. As illustrated by the mean trajectories associated with the selection of the two response alternatives shown in Fig. 4a, the selection of the immediate outcome was associated with a greater spatial attraction toward the future outcome than vice versa. Statistically this was confirmed by a significant or marginally significant difference between the MD and AUC values associated with the two choices (MD, $t = 2.16$, $p < 0.05$, CI (95 %) −0.03, −0.76; AUC, $t = 1.78$, $p > 0.05$, CI (95 %) −0.04, −0.71, Fig. 5a, b).

We next examined the kinematic patterns in the two groups of subjects and performed a series of 2 × 2 repeated measures ANOVAs with group (discounter vs. farsighted) and response type (now vs. later) as factors. The pattern of trajectories showed by the farsighted group appeared similar to the pattern observed in the entire sample, i.e., greater spatial attraction by the delayed option during the selection of the immediate one (Fig. 4b). By contrast, the discounter group showed a different pattern, characterized by high spatial attraction by the unselected response during the selection of both alternatives

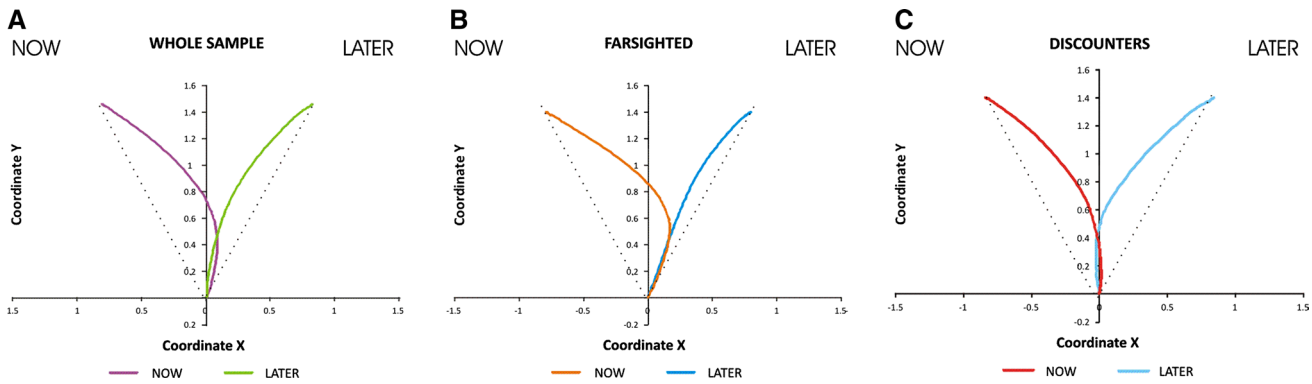

Fig. 4 Mean trajectories associated with "now" and "later" responses in the entire sample (**a**), in the farsighted group (**b**) and in the discounter group (**c**). The *continuous lines* indicate the mean trajectories, while the *dotted lines* indicate the average ± standard deviation of each trajectory

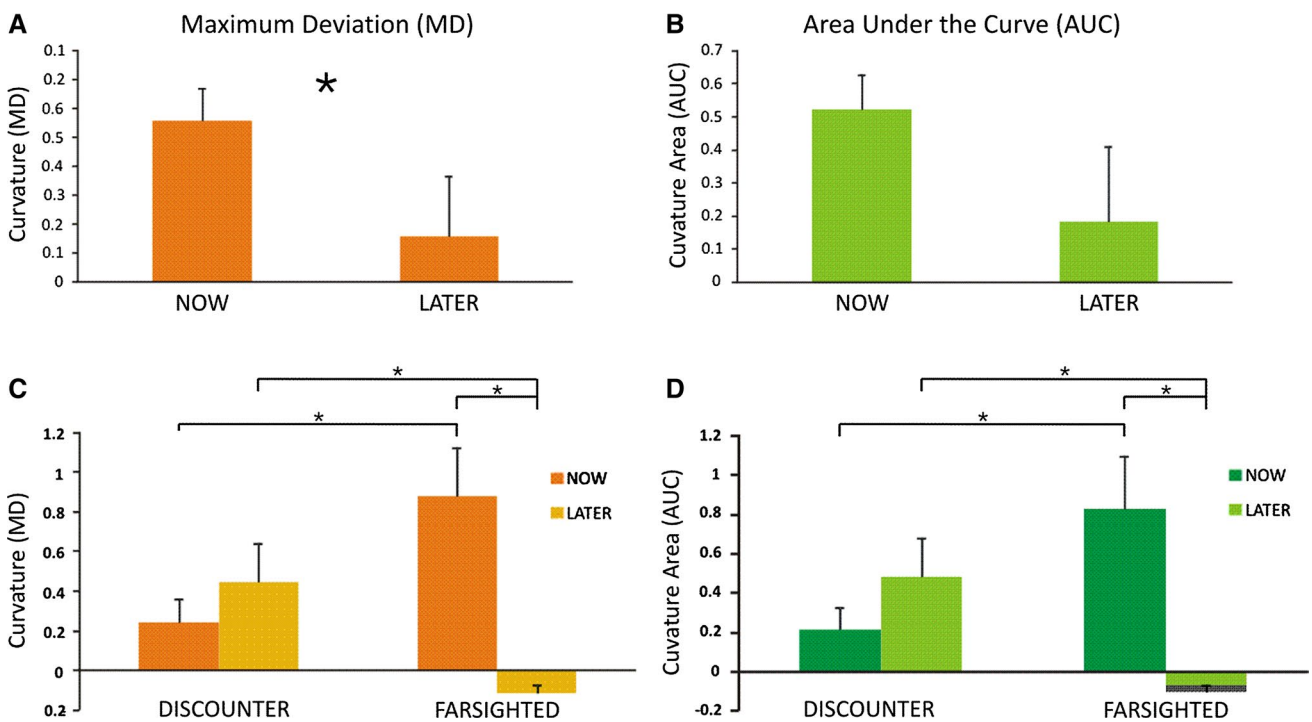

Fig. 5 Results of the paired *t* tests conducted on Maximum Deviation (MD) (**a**) and Area Under the Curve (AUC) (**b**), to compare the "now" to "later" choice options in the entire sample. Results of the 2 × 2 repeated measures ANOVA with response type and group as factors conducted on MD (**c**) and AUC (**d**)

(Fig. 4c). This observation was statistically confirmed by a significant group by response type interaction on both MD ($F_{1,72} = 11.83$, $p < 0.01$, e.s. = 0.92) and AUC ($F_{1,72} = 11.32$, $p < 0.01$, e.s. = 0.91) (Fig. 5c, d), with a significant difference between the two choices in farsighted ($p < 0.01$; MD and AUC: now > later) but not in discounter subjects ($p > 0.05$; MD and AUC). As shown in Fig. 5c, d, this brought to a significantly higher attraction toward the "later" option when choosing the "now" one in farsighted compared to discounter ($p < 0.05$; MD and AUC: now in farsighted > now in discounter), and a significantly higher attraction toward the immediate option when choosing the "later" one in the discounter compared to the farsighted group ($p < 0.05$; MD and AUC: later in discounter > later in farsighted) (Figs. 4 and 5).

Finally, we tested the predictive relationship between mouse kinematics and intertemporal choice behavior by computing Pearson's correlations between the kinematic parameters associated with the two choices and discount rate. To control the reliability of the correlation results, we also computed robust multilinear regression tests in which

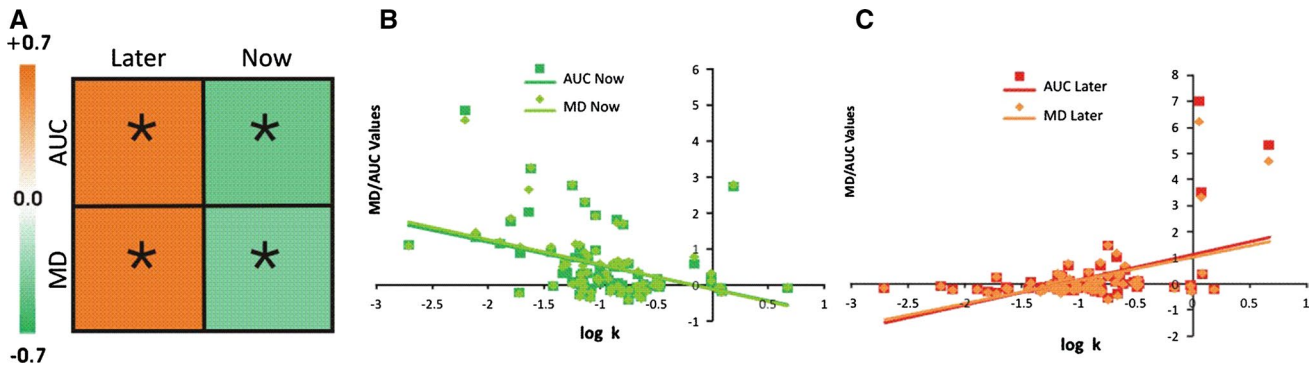

Fig. 6 Kinematics-behavior Person's correlation matrices: relationship between discounting rate and mouse movement kinematics (MD and AUC) in "now" and "later" choices conducted on the entire sample (**a**), within the farsighted group (**b**) and within the discounter group (**c**). *Orange color* indicates positive correlations, *green color* indicates negative correlations, and *white color* indicates non-significant correlations. All significant correlations are marked by an *asterisk* ($p < 0.001$) (color figure online)

the discount rate was treated as dependent variables and the MD and AUC parameters as regressors.

The results of the Pearson's correlations (Fig. 6a) showed a negative correlation between the kinematics parameters associated with the selection of the immediate reward ("now" choices) and discount rate (Fig. 6a, b; MD: $r = -0.47$, $p < 0.01$; AUC: $r = -0.46$, $p < 0.01$). Such a negative correlation indicated that the spatial attraction toward the competing option (i.e., later) increased with the decrease in discount rate. In other words, subjects with a smaller k (i.e., farsighted subjects) show higher values of MD and AUC when selecting the immediate amount. Conversely, the kinematics parameters associated with the selection of future reward ("later" choices) showed a positive correlation with the k parameter (Fig. 6a–c; MD: $r = 0.51$, $p < 0.01$; AUC: $r = 0.50$, $p < 0.01$) indicating that the spatial attraction toward the "now" option increased with increasing k values (i.e., discounter subjects). This pattern of results was also confirmed by a robust multilinear regression on MD (now: $\beta = -0.38$, $p < 0.01$; later: $\beta = 0.33$, $p < 0.01$) and AUC values (now: $\beta = -0.38$, $p < 0.01$; later: $\beta = 0.31$, $p < 0.01$).

Difficulty effect

The results of a 2 × 2 ANOVA on MD and AUC with response type and choice difficulty as factors indicated a main effect of response (now > later; MD: $F_{1, 74} = 9.41$, $p < 0.05$; AUC: $F_{1, 74} = 6.53$, $p > 0.05$), a main effect of difficulty (hard > easy; MD: $F_{1, 74} = 13.69$, $p < 0.01$; AUC: $F_{1, 74} = 9.64$, $p < 0.01$) but no interaction between difficulty and response type. These results indicated that kinematic behavior was significantly modulated by choice difficulty, but also that this effect was not specific for the two responses. An analogous result was obtained when including the group (discounters vs. farsighted) as factor in the ANOVAs [main effect of response (now > later; MD: $F_{1, 74} = 20.15$, $p < 0.01$; AUC: $F_{1, 74} = 18.07$, $p < 0.01$), main effect of difficulty (hard > easy; MD: $F_{1, 74} = 7.16$, $p < 0.01$; AUC: $F_{1, 74} = 3.73$, $p > 0.05$), significant response by group interaction (MD: $F_{1, 74} = 4.87$, $p < 0.01$; AUC: $F_{1, 74} = 4.45$, $p < 0.05$), no significant interaction between response or group and difficulty], thus confirming that choice difficulty exerted an overall effect on kinematic behavior but that it did not differentiate between response type or group.

DDM fit

This step of the analysis investigated whether the individual differences in discounting behavior were reflected in the modulation of specific parameters of the DDM, namely the starting point (z) and/or the drift rate (v). A within-group analysis was performed in both discounter and farsighted subjects in order to identify the model's parameter able to account for inter-subject variability within each group.

Our underlying hypothesis was that differences between discounter and farsighted choice behavior could be explained by different parameterizations of the DDM. This hypothesis was suggested by the between-group differences obtained in the main kinematics analysis (see Figs. 4, 5). Specifically, in discounter subjects all the trajectories, i.e., both the selection of the immediate and future option, appeared to be curved, as if their behavior reflected a process of evidence accumulation, which suggested a selective modulation of the drift rate (v). Conversely, in the farsighted group only trajectories associated with the immediate choice appeared to reflect a process of evidence accumulation, whereas the trajectories associated with the future choice appeared straight as if their selection was a default choice, thus suggesting a modulation of both the drift rate and the starting point.

Table 3 The five model parameterization of the within-group analysis

No.	Model parameterization	Bayesian information criterion (BIC)	
		Within discounter	Within farsighted
1	No (all parameters are fixed)	28,147.76	22,622.93
2	*z*	25,945.82	20,173.22
3	*v*	**23,338.05**	19,975.05
4	*z*, *v*	25,242.35	**19,637.56**
5	All (*v*, *a*, Ter, *n*, st, *z*, sz)	24,168.30	21,421.58

Bayesian Information Criterion was used to identify the best fitting model

Bold values indicate the best model for each group analysis

v: drift rate, Ter: non-decision time, *a*: boundary, *z*: starting point, *n*: variance in drift rate, st: variance in non-decision time, sz: variance in starting point

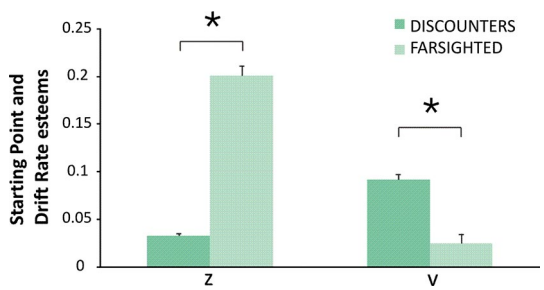

Fig. 7 Results of the two-sample *t* test conducted on both the starting point (*z*) and drift rate (*v*) estimates

As reported in Table 3, our hypothesis was statistically confirmed by the BIC values estimates. The best fitting model within the discounter group was the one in which only the drift rate was free to vary, whereas the best fitting model within the farsighted group was the one in which both the starting point and the drift rate freely varied.

Furthermore, a significant variation of the drift rate and starting point across groups was assessed by two-sample *t* tests conducted on the parameter estimates. These results showed that the drift rate was significantly higher in discounter than farsighted subjects ($t = 6.11$, $p < 0.01$), while the starting point was significantly higher in farsighted compared to discounter subjects ($t = -15.61$, $p < 0.01$) (Fig. 7).

Comparison with Embodied Choice model

The last step of the analysis investigated whether the observed variation in the parameters of the DDM, which have been related to the observed pattern of discounting behavior, were consistent with the pattern of mouse movement kinematics in the two groups. A model of Embodied Choice in which action performance is considered as part of the decision-making process (Lepora and Pezzulo 2015) was used to model the trajectories using the starting point (*z*) and/or the drift rate (*v*) estimated in the discounter and the farsighted group. In this model, the DDM was supplemented with movement kinematics by defining a focal point situated between the two targets whose position depends on the accumulated evidence toward either target and a dynamic trajectory with preparation and changes of mind was produced. The main research aim here was to test whether, by endowing the Embodied Choice model with the parameters extracted by the DDM for the two (discounter and farsighted) groups, it was possible to re-produce the mouse trajectories observed in the two groups. Specifically, using the Embodied Choice model we tested whether the higher starting point (*z*) observed in the farsighted versus discounters group through data fitting of the DDM was associated with mouse movements that were initially attracted toward the "later" alternative as well as whether the higher drift rate (*v*) observed in the discounters versus farsighted group was associated with mouse movements trajectories that were spatially interposed between the two choice alternatives and characterized by several changes of mind. Of note, we did not use the Embodied Choice model to fit the data of individual subjects as this analysis was already computed using the DDM. Rather, based on the parameters extracted from the DDM, we created two "virtual subjects": one representative of the discounter and one representative of the farsighted group, and we used the Embodied Choice model to *simulate* their mouse trajectories in order to assess whether they were qualitatively consistent with the (average) kinematic patterns observed in the two groups.

The results of the Embodied Choice modeling analysis showed that the simulated trajectories were qualitatively consistent with those empirically observed in the two groups (Fig. 8) thus indicating that the kinematic features of the intertemporal choice behavior described above (Sect. 3.3) nicely followed from the DDM supplemented with the Embodied Choice model.

Discussion

Intertemporal choice is a complex behavior requiring the collection and computation of many different sources of information to evaluate the subjective value of each alternative, the imagination and anticipation of the future outcome consumption, and finally the maintenance of the planned behavior until a decision and its consequences are accomplished (Berns et al. 2007; Peters and Büchel 2011). Given that intertemporal choices are dynamic, they can be better understood by analyzing how they unfold in time rather than just focusing on the decision outcome.

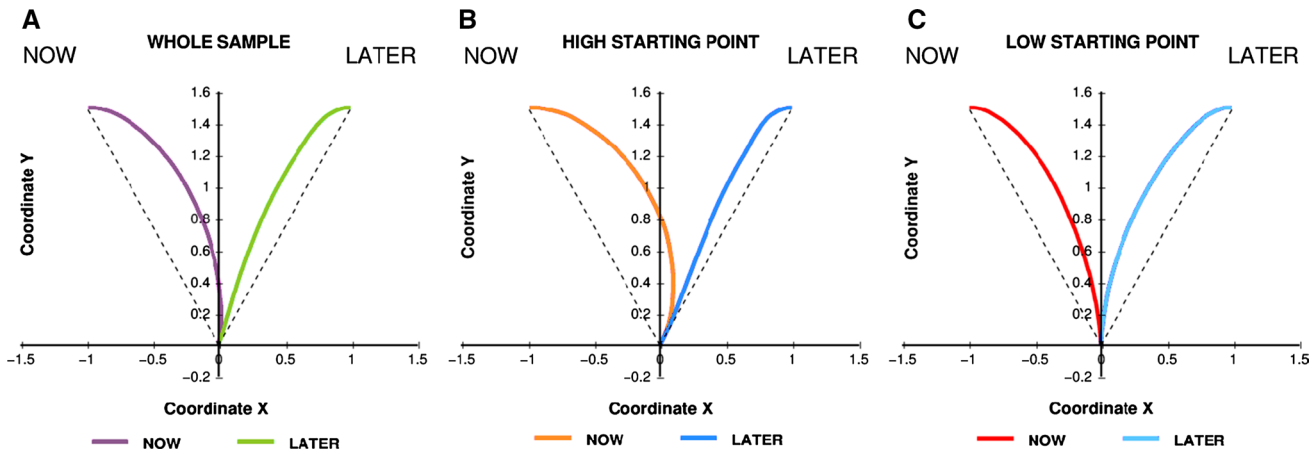

Fig. 8 Embodied choice model of the mean trajectories associated with "now" and "later" responses in the entire sample (**a**), in the far-sighted group (**b**) and in the discounter group (**c**). Other details are the same as Fig. 4. The parameters used for the model are extracted from the DDM fit, except for the value of the decision bound (which was not constrained by the DDM fit) that was set to a value of $b = 0.1$ in order to have a profile and mean response time compatible with the experimental data (see Lepora and Pezzulo 2015 for further details)

Here we used a measure of mouse movement kinematics to investigate the dynamics of the motor response during intertemporal decisions and we observed a dissociation in the patterns of temporal evolution associated with the selection of the immediate versus delayed alternative. The selection of the immediate reward was associated with a greater spatial attraction toward the delayed option than vice versa, arguing against the widely held idea that immediate choices are guided by motor impulsiveness (Ainslie 1975; Monterosso and Ainslie 1999). This pattern of results was even more evident when considering the results obtained in the two sub-groups of discounter and farsighted subjects. While in farsighted subjects (like in the entire sample), the selection of the immediate option was associated with greater spatial attraction toward the competing option (i.e., delayed) than vice versa, the discounter subjects were characterized by a different pattern of behavior: they showed an high spatial attraction toward the competing alternative both during the selection of the immediate and the delayed options, indicating that their selection process was characterized by high choice uncertainty independently of the selected option.

This main result was in line with what we observed by fitting the Drift Diffusion Model (DDM) to the behavioral data collected during the task. We hypothesized that the uncertainty observed in economic choices could derive from the variability in internal information about the subjective value of each alternative, as if the participants were "accumulating" internal evidence about the value of each choice option. Similarly, preferences toward a specific choice option could derive from a biased decisional mechanism. These hypotheses were statistically confirmed by the results of the model fitting, which indicated that the best fitting model's parametrization for the discounter group was the one in which only the drift rate was free to vary across subjects. This is in accordance with the observation that, in these subjects, both immediate and future choices were characterized by high choice uncertainty and with the idea that discounter's choices are "constructed over time" (Ratcliff and McKoon 2008)—a process that is possibly reflected in "motor uncertainty" during choice. On the contrary, the best fitting model parameterization in the far-sighted group was the one in which both the drift rate and the starting point were free to vary across subjects and this is consistent with the kinematics results observed in this group. More specifically, while the higher starting point values in farsighted (vs. discounter) subjects suggest that they considered the delayed option as a "default" alternative, the modulation of the drift rate parameter suggested that in this group, as in the discounter group, immediate choices were characterized by high choice uncertainty.

Our computational modeling approach, which incorporates mouse kinematics into the DDM, shed further light on the inter-individual differences in intertemporal choices. The model could indeed correctly reproduce the trajectories of both groups by increasing the "starting point" in the farsighted vs. the discounter group. This computational-based analysis thus supported the hypothesis that farsighted subjects have an initial bias (here described as a high "starting point" in the DDM) to move toward the delayed option, which can be eventually revised during the decision-making process; this revision process, in turn, produces the observed curvature in the mouse movements of farsighted subjects. Although not shown, we additionally found that the model trajectories were less affected by variations of the drift rate and we speculate that the

higher drift rate found in discounters subjects (DDM fitting) could be more evident in the "temporal" (i.e., in reaction time as well as acceleration and velocity, which are not modeled here) than in the "spatial" domain (i.e., in the mouse trajectories).

Taken together, the results of the kinematics analysis, the DDM fit to behavioral data, and the modeling of dynamic trajectories suggest that the preferential selection of the immediate versus delayed outcome in discounter versus farsighted subjects can be explained in terms of different mechanisms by which they construct their decisions over time, which would also correspond to specific kinematics patterns and different parameterizations of the DDM.

The presence of significant correlations between discount rate and kinematics parameters in the two groups of subjects additionally suggests that mouse kinematics can be considered a reliable predictor of intertemporal choice behavior. Indeed, the uncertainty linked to the selection of the delayed reward (i.e., the attraction toward the immediate option) appeared to predict the discount rate in discounter subjects, whereas the uncertainty linked to the selection of the immediate reward (i.e., the attraction toward the delayed option) appeared to predict the discount rate in farsighted subjects.

These findings, and in particular the absence of a straight trajectory toward the immediate alternative in the discounter group, are in line with the lack of a significant correlation between discount rate and impulsivity scores. Many works have tried to assess the role of impulsivity in steep discounting functions often reaching inconsistent results (Kirby et al. 2004; Gianotti et al. 2012). As proposed by Reynolds et al. (2006), this might be associated with the use of different measures and tools which likely result in the assessment of different forms of impulsivity (Reynolds et al. 2006). Indeed, while self-report measures of impulsivity require people to recognize and report their behavior, and this may result in an inaccurate description of the actual behavior, behavioral measures (e.g., intertemporal choice and stop-signal tasks) are operative ways to measure different impulsivity components but are likely influenced by other task-specific factors. More importantly, as outlined by recent models (Berns et al. 2007; Pezzulo and Rigoli 2011; Peters and Büchel 2011), the preference for the immediate option during intertemporal choices could also be explained by other processes, for example, the ability of anticipate the consequences of a decision or the capacity to imagine the future reward consumption.

Finally, because not only impulsivity but also affective factors have long been proposed to play a crucial role in decision making, influencing probability and value computation, especially in clinical populations (Kirby et al. 2004; Paulus and Yu 2012), we also investigated the relationship between discounting rate and other state/trait characteristics such anxiety and depression, but the results yielded no statistically significant correlations.

Conclusions

Our work provides evidence that the kinematics of mouse movement during intertemporal decisions may represent a reliable behavioral marker of temporal discounting behavior, as it reveals specific response patterns during the choice selection process. Moreover, as shown by the positive/negative correlations between spatial attraction indexes and discount rate, and by the different parameterizations of the DDM, mouse kinematics was also able to discriminate between farsighted and discounter subjects. Finally, our results indicate that uncertainty, rather than state/trait personality variables, can be an important determinant of intertemporal choice behavior in healthy subjects—a result that resonates with its ubiquitous role in choice situations (Daw et al. 2005; Pezzulo et al. 2013), and a factor to be considered in future studies on clinical populations.

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Author contribution C. C., A. T., G. P and G. C. designed research; C. C. performed research; C. C., A. T., and N. L. analyzed data; and C. C., A. T., G. P., N. L. and G. C. wrote the paper.

Appendix

This Appendix summarizes the methods used in the Embodied Choice model to calculate the action focus; for further details, see Lepora and Pezzulo (2015). Mathematically, we represent the action focus as a point (x (z), y (z)) that is a function of the accumulated information $z(t)$. At each instance of time, the action is a move (Δx, Δy) from the present location toward the action focus

$$(\Delta x(t), \Delta y(t)) = v\Delta t \frac{(x(z), y(z)_{\text{focus}} - x(t), y(t))}{|(x(z), y(z)_{\text{focus}} - x(t), y(t))|}$$

which for simplicity we assume is at constant speed v taken at discrete time steps of Δt.

In the two-target forced choice task considered here, we consider a preparatory move toward an action focus between the two targets, to approach the most likely target prior to accumulating sufficient information to make a decision. Mathematically, we define the focus as collinear

with the two targets with distance from each in the proportion $|b+z|$: $|b-z|$ for $-b \leq z \leq b$

$$(x(z), y(z))_{\text{focus}} = \begin{cases} (x_1, y_1), & z(t) \geq b \\ \frac{|b-z|}{2b}(x_1, y_1) + \frac{|b+z|}{2b}(x_2, y_2) & -b \leq z(t) \leq b \\ (x_2, y_2) & z(t) \geq -b \end{cases}$$

This range is bounded such that the focus is coincident with a target if the decision bound is passed. Hence, the decision bound no longer defines decision termination directly, but rather the choice follows indirectly from action completion (upon reaching a target).

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