Apathy in Older Adults is Associated with a Selective Over-Weighting of Effort in Everyday Decisions

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Abstract

Apathy, characterized by diminished motivation and reduced goal-directed behavior, is prevalent in normal aging. Recent evidence suggests that it may result from biases in the evaluation of costs and benefits during decision making. However, most research has focused on simple decisions involving the trade-off between motor or cognitive effort and monetary reward. Meanwhile, it is possible that the disrupted real-life decisions of people with apathy reflect biases affecting many other dimensions of value. Additionally, the extent to which mood symptoms that frequently co-occur with apathy also contribute to biases in decision making is unclear. To address these gaps, we developed a novel online task completed by 158 older adults who first rated everyday activities (e.g., watching TV, going to the park) across 19 value attributes (e.g., enjoyment, social obligation), and then made a series of choices between random pairs of the different activities. A factor analysis of attribute ratings identified three latent factors representing reward, effort, and obligation, which strongly predicted choices and choice response times. Apathy was selectively associated with an *over*weighting of effort-related attributes in models controlling for impulsivity, depression, or anhedonia; it did not affect the weighting of reward or obligation-related attributes. Interestingly, impulsivity, which was positively correlated with apathy, was associated with an *under*weighting of effort. Hierarchical drift diffusion modelling supported these findings, showing that apathy and impulsivity modulated the influence of effort on the rate of evidence accumulation in opposite directions. Overall, these results suggest that decisions about everyday activities rely on the integration of a wide range of value attributes and that apathy is selectively associated with an overweighting of the effort dimension of value, driving choices away from activities that require greater effort.

Deciding which activities to engage in throughout our day requires an evaluation of the different attributes of those activities. Apathy, defined as a reduction in goal-directed behaviour and motivation, typically manifests as reduced engagement in everyday activities, such as a decreased tendency to go out with friends or to get things done without reminders (Clarke et al., 2010; Marin, 1991; Starkstein et al., 1995; Steffens et al., 2022; Valles et al., 2023). It is a common and often debilitating symptom of several neurological (e.g., Parkinson's disease, frontotemporal dementia) and psychiatric (e.g., schizophrenia) conditions where it can be severe enough to interfere with the completion of basic everyday activities (Bortolon et al., 2018; den Brok et al., 2015; Leroi et al., 2011; Musa Salech et al., 2022). However, it is also common in healthy older adults, occurring in about 11-20% of the population, and it is associated with functional decline and disability (Ayers et al., 2017; Clarke et al., 2010; Groeneweg-Koolhoven et al., 2014; Harrison et al., 2023). Despite the prevalence of apathy and the significant impact it can have on the quality of life of patients and healthy adults alike, the cognitive mechanisms underlying the pattern of maladaptive decisions characteristic of apathy remain largely unknown.

One promising avenue to examine decision making and apathy has been to design, in the lab, more constrained decisions than those that take place in everyday life by examining how individuals engage with the two-dimensional trade-off between experimentally manipulated costs (e.g., mental or physical effort) and benefits (e.g., monetary reward) when making decisions. This line of research suggests that apathy reflects underlying biases in the evaluation of costs and benefits that determine the subjective value of different actions (Bonnelle et al., 2015; Le Bouc et al., 2023; Le Heron, Apps, et al., 2018; Muhammed et al., 2016). It is unknown, however, whether these observations would hold true when applied to the more typical decisions that people make about engaging in everyday activities, where the costs and benefits presumably extend beyond monetary rewards and effort exertion costs to other dimensions of value including social and emotional outcomes. Bridging the gap between the study of decision behaviour in highly controlled task environments and the study of more naturalistic decisions has important implications for identifying the cognitive mechanisms underlying the maladaptive behaviour that results in the real-world manifestations of apathy.

Most accounts of value-based decision making in neuroeconomic theory maintain that a series of computational processes (i.e., option generation, value computation, option selection, action initiation, and feedback processing) must be carried out by an individual when initiating goal-directed behaviour (Rangel et al., 2008). Among these, the process of value computation, which is thought to be supported by dopamine signalling (Berke, 2018; Schelp et al., 2017; Soutschek et al., 2022), has been of particular interest as a possible locus of dysfunction in apathy. This is due to the high prevalence of apathy in diseases that involve aberrant dopamine signalling, such as schizophrenia and Parkinson's disease (Bortolon et al., 2018; Chong & Husain, 2016; Sierra et al., 2015), suggesting the possibility that abnormal or reduced dopamine signaling might be one mechanism underlying apathy. Consistent with this, several studies conducted across a range of populations with a variety of pathologies have shown that individuals with apathy have decreased sensitivity to the anticipated benefits of an action and/or increased aversiveness to the effort required of those actions, both of which are processes that have been linked to dopamine function (Apps et al., 2015; Basten et al., 2010; Croxson et al., 2009; Le Heron, Apps, et al., 2018; Le Heron et al., 2019; Le Heron, Manohar, et al., 2018; Le Heron, Plant, et al., 2018; Saleh et al., 2021). This same pattern is also observed in healthy adults for whom apathy, even at subclinical levels, is associated with an unwillingness to exert effort when the amount of available reward is small (Bonnelle et al., 2015). Taken together, these studies suggest that biased integration of value-related information during decision making could represent a mechanism underlying apathy.

Although the advances made by linking apathy to aberrant valuation during decision- making are promising, it remains unclear whether the behaviour observed during decisions where only the reward and effort dimensions of value are being considered generalizes to the more complex and presumably multidimensional valuation process that people engage in when choosing how to fill their days. For instance, a decision between going to the movies vs. staying home to do the dishes likely requires the evaluation and integration of a wide range of value attributes, beyond the physical effort and immediate secondary rewards (e.g., financial) derived from actions. Indeed, the clinical scales typically used to diagnose apathy include items that measure the importance placed on a wide range of value dimensions that can influence everyday decisions, such as social factors (e.g., "I care deeply about what others think of me"), cognitive factors (e.g., "I make decisions firmly and without hesitation"), or more intrinsically rewarding factors such as novelty ("Do you like visiting places you've never been to before") (Ang et al., 2017; Marin, 1991; Sockeel et al., 2006). Important advances in understanding disorders like anorexia nervosa and addiction, which also involve maladaptive decision-making, have come from considering illness-specific decisions and value attributes relevant to the pathologic behaviours (Biernacki et al., 2022; Foerde et al., 2015, 2022; Konova et al., 2019). For instance, studying food choices in individuals with anorexia nervosa has revealed biases in the valuation and relative weighting of food-specific value dimensions (e.g., healthiness) and has demonstrated that maladaptive eating behaviours cannot simply be explained by more generalized deficits in decision-making (Foerde et al., 2015). Establishing a more complete understanding of apathy might similarly require laboratory tasks that allow for the investigation of a wider range of value attributes relevant to everyday decisions.

The objectives of this study were threefold. First, we aimed to develop a new task paradigm which sought to examine more ecologically valid decisions about engaging in everyday activities (e.g., watching TV, going to the park). We administered this task to a large online sample of healthy older adults. In the task, participants first rated typical everyday activities on a wide range of value attributes that could contribute to a cost-benefit evaluation. We included value attributes conceptually related to the typical operationalization of reward and effort in laboratory tasks (e.g., degree of physical or mental effort required of an activity), in addition to attributes related to other facets of the reward and effort domains (e.g., positive anticipation of an activity, degree of planning required of an activity), as well as attributes related to other dimensions of valuation (e.g., perceived obligation, social connection). Second, in the decision-making phase of the task during which participants made a series of choices between the different activities, we aimed to quantify the independent contribution of these previously rated value attributes towards decisions to engage in the everyday activities. Third, we aimed to determine if apathy, measured using the Apathy Motivation Index (Ang et al., 2017), influenced the valuation process by biasing the relative weights placed on the different value attributes. Additionally, we explored the influence of apathy alongside that of other mood symptoms affecting motivation – namely impulsivity and depression – in order to investigate the potential mechanistic overlap between them, as suggested by past research (Dalley et al., 2011; Husain & Roiser, 2018; Lanctôt et al., 2023; Petitet et al., 2021, 2022). We predicted that apathy would be associated with overweighting of attributes related to effort and underweighting of attributes related to reward during choices between everyday activities.

Methods

Participants

158 healthy older adults between the ages of 60 and 90 (96 female, mean ± SD age: 65.4 ± 5.3) were recruited online using Prolific (www.prolific.co). A target sample size of 150 before was selected prior to recruitment to provide 80% power to detect a unique effect corresponding to a partial

correlation of $r \geq 0.25$ for an individual predictor in multivariable linear regression. Given the use of verbal stimuli, only participants whose first language was English were eligible to participate in the study. Exclusion criteria included self-reported diagnosis of mild cognitive impairment, dementia, autism spectrum disorder, and a mental illness that is uncontrolled or has a significant impact on daily life as indicated by participants' online profiles. All participants provided informed consent electronically and were compensated for their time at a rate of £7.25 (12 $CAD) per hour. This study was approved by the Neurosciences panel of the McGill University Health Centre's Research Ethics Board. Demographic characteristics are presented in **Table 1**.

General Study Procedures and Neuropsychiatric Measures

The study consisted of three different sections: a demographic and socioeconomic questionnaire, a value-based decision-making task, and four neuropsychiatric questionnaires. Participants could take breaks between sections of the protocol but not in the middle of a section. The average time between the start and the end of participation was 62.4 minutes (range: 35.8 to 109.4 minutes). Neuropsychiatric questionnaires included (1) Apathy Motivation Index (AMI), an 18-item questionnaire assessing emotional, behavioural, and social apathy and with total score ranging from 0 to 4 (Ang et al., 2017); (2) the Barratt Impulsiveness Scale-11 (BIS-11), a 30-item questionnaire assessing attentional, motor, and non-planning impulsiveness where total scores range from 30 to 120 (Patton et al., 1995); (3) the Geriatric Depression Scale Short Form (GDS-S), a 15-item questionnaire where total scores range from 0 to 15 (Sheikh & Yesavage, 1986); and (4) the Snaith Hamilton Pleasure Scale (SHAPS), a 14-item questionnaire assessing the domains of social interaction, food and drink, sensory experience, and interest/pastimes where total scores range from 0 to 14 (Snaith et al., 1995). 3 of the 158 total participants were missing data on neuropsychiatric measures and were removed from all choice phase-related analyses. Additionally, because of the very low variability and narrow range in scores on the SHAPS (i.e., 151 out of 155 participants had a score less than 3, the cut-off for normal hedonic tone), the SHAPS was removed from all further analyses. **Supplementary Figure 1** shows the distribution of responses on the four questionnaires.

Table 1

Demographics and mood characteristics of participants

Characteristic	***n = 158***
Age	65.4 (5.3)
Sex (female/male)	96/62
Education, years	14.5 (3.5)
Apathy Motivation Index (AMI) *Range: 0-4*	1.44 (0.44)
Barratt Impulsiveness Scale (BIS) *Range: 30-120*	57.79 (9.24)
Geriatric Depression Scale *Range: 0-15*	3.51 (3.61)
Snaith-Hamilton Pleasure Scale *Range: 0-14*	0.54 (1.34)

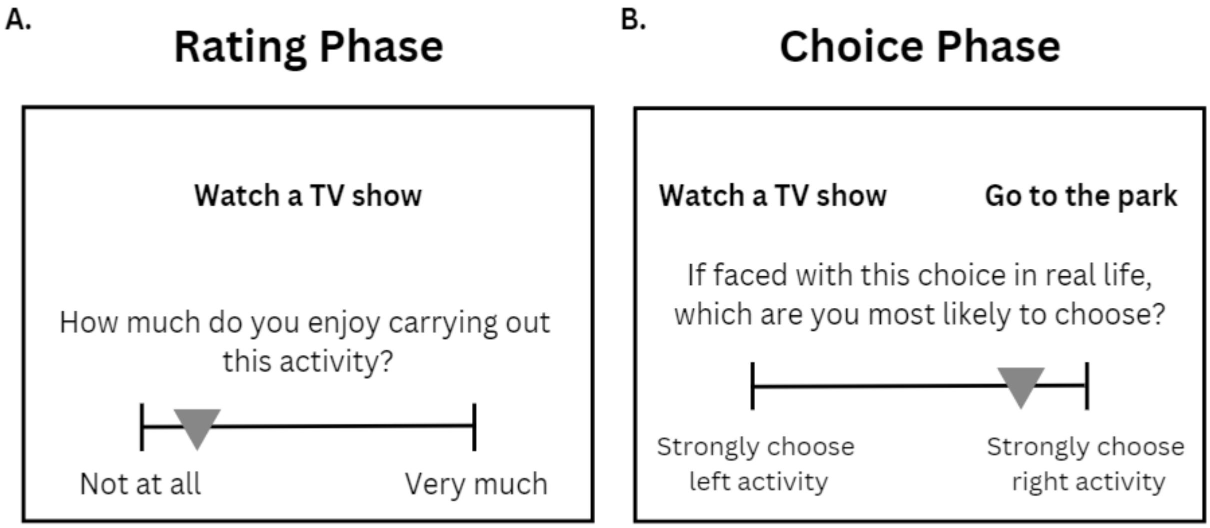
Note. Values represent mean (SD).

Everyday Choice Task

The development of the Everyday Choice Task was modelled after the widely used Food Choice Task (Hare et al., 2009). The Everyday Choice Task is a value-based decision making task that is divided into two phases: (1) a rating phase, in which participants rate everyday activities along multiple attributes of value, (e.g., enjoyment, physical effort required) and (2) a choice phase, in which participants are presented with a random pairing of two activities and are asked to indicate which one they would most likely engage in if given the choice in real life (**Figure 1**).

Figure 1

Everyday Choice Task



Note. A) Rating phase: participants were presented a random subset of 26 out of 81 everyday activities and rated each activity along all 19 value attributes. B) Choice phase: activity pairs were presented and participants chose which activity they would most likely do in real life. The maximum time to respond was 15000 ms for both phases.

Everyday Activities and Value Attribute Stimulus Sets

To develop a list of common everyday activities, we referenced a normative study in which 40 older adults (20 males and 20 females) recorded all their daily activities for seven days (Rosen et al., 2003). We also used the World Health Organization's International Classification of Functioning, Disability, and Health (ICF) to ensure that we included everyday activities representing the different domains of activity as laid out in the ICF, including learning, communication, mobility, self-care, domestic life, relationships, and community life. Finally, we included activities that represented various forms of rest, which were not represented in the above resources. We then conducted a series of small pilot studies (total n = 67) focused on obtaining qualitative feedback from participants to select the most relevant activities for daily life. From this, we developed the final set of 81 everyday activities, which included 76 activities representing an active state (e.g., Go to the park) and 5 activities representing a less active state (e.g., Rest, Do nothing in particular). See **Supplementary Table 1** for the full list of activities.

We developed the list of value attributes by first starting with an expansion of the two value dimensions most commonly examined in relation to apathy in laboratory-based tasks, namely reward (typically operationalized as monetary reward) and effort (typically operationalized as either physical effort or cognitive effort). To better characterize the possible influence of reward-related attributes on choices, we included questions about the anticipation of an activity's outcome, enjoyment of the activity itself, the utility of the activity, and a question about negative feelings elicited by the activity. To similarly expand the range of effort-related value attributes that contribute to everyday decisions, we included questions about the subjective difficulty in initiating an activity, the planning involved, and the level of skill, in addition to questions about the amount of physical and mental effort required of an activity. We also included questions related to the perceived sense of obligation to complete an activity, and of uncertainty about its outcome. Finally, because the everyday activity stimulus set necessarily included activities that differed on extrinsic characteristics that could also influence the overall valuation of an activity, we included questions about five 'external' value attributes: time cost, monetary cost, frequency of engaging in an activity, the extent to which an activity was part of one's routine, and the extent to which age or health conditions might interfere with the ability to carry out an activity. Because they were not of primary interest for their relationship to apathy, these attributes were included in the regression models predicting choice as nuisance variables. In total, there were 19 value attribute questions (see **Table 2** for the full list of attributes).

Table 2

Full List of All Value Attributes Included in the Everyday Choice Task

Question	***Attribute name***
How much does this activity help you feel closer or connected to others?	socialConnection
How certain are you about how the activity will turn out?	certainOutcome
How much do you look forward to the outcome of this activity?	lookForwardToOutcome
How mentally effortful does this activity feel to you?	mentalEffort
How physically effortful does this activity feel to you?	physicalEffort
How hard is it to get started on this activity?	difficultyInitiation
How much do you have to plan for this activity?	planning
How much do you feel you should do this activity?	shouldSelf
How much do your loved ones think you should do this activity?	shouldOthers
How negative do you feel when doing this activity?	negFeeling
How much is this activity good for you?	goodForYou
How much do you enjoy carrying out this activity?	enjoyProcess
How good are you at this activity?	goodAtIt
To what extent is this activity part of your routine?	routine
How much time does it usually take to do this activity?	timeCost
How much money does it take to do this activity?	moneyCost
How often do you carry out this activity?	frequency
How much does your age interfere with your ability to complete this activity?	ageInterfering
How much does your health condition affect your ability to complete this activity?	healthInterfering

Rating Phase

In the first phase of the task, participants rated each activity with respect to each of the 19 value attributes. The order of the presentation of the activities and the attribute questions were randomized. Participants indicated their rating using a mouse cursor on a continuous slider, where the ends were labelled as “Not at all” and “Very much” (**Figure 1A**). The left-right assignment of the labels was counterbalanced across participants (but kept consistent within participant), such that “Not at all” could be presented either on the left or right end. The location of the cursor was reset to the middle at the beginning of every new rating trial and participants had 15 seconds to provide a rating, following which there was a reminder to submit a rating before moving to the next trial. To reduce the duration of this phase and the burden of testing, each participant rated only a subset of 26 out of the 81 activities. These 26 activities were chosen pseudo-randomly: all participants rated the five less active activities and additionally rated a random subset of 21 out of the 76 more active activities, resulting in a total of 494 ratings (26 activities x 19 attributes) per participant.

Choice Phase

The choice phase immediately followed the rating phase. On each trial, participants were shown a pair of previously rated activities and had to choose one of the two activities following the prompt “If faced with this choice in real life, which activity are you most likely to choose?” To indicate their choice, they used a cursor on a continuous slider where the slider ends indicated “Strongly choose the left activity” and “Strongly choose the right activity” on either side (**Figure 1B**). The total number of choice trials was 26. Activity pairs were created pseudo-randomly to ensure that no pairs were repeated, and that each activity appeared exactly twice.

Statistical Analysis

All analyses of the rating and choice data were completed using R version 4.1.2. Rating trials with response times (RTs) slower than 15s (maximum allotted time) or faster than 0.3s were discarded from both the rating and choice phases, resulting in the removal of 0.2% of choice trials and 1% of rating trials. Since participants only rated a subset of 26 activities out of the full list of 81, the total number of participants per activity was calculated to ensure adequate representation of each activity in the dataset (**Supplementary Table 1**).

Rating Task Analyses

Value attribute ratings were numerically coded from 0 (“Not at all”) to 100 (“Very much”) from the placement of the cursor on the slider. Pearson correlation coefficients were calculated to assess the pairwise association between each of the 19 value attributes by using the averaged attribute ratings across all participants for each activity (i.e., 19 averaged ratings for each of the 81 activities) (see **Figure 2**). Because of the semantic similarity and high positive correlation (R=0.87) between the ratings of attributes assessing frequency (“How often do you typically engage in this activity?”) and routine (“To what extent is this activity part of your routine?”), we removed the frequency attribute from all subsequent analyses, leaving 14 value attributes and 4 external attributes. The averaged attribute ratings were then used to run an exploratory factor analysis (EFA) with a maximum likelihood estimation method implemented by the *factanal* function of the *psych* R package, an approach that was used in a similar dataset of food attributes (Lloyd et al., 2020). The EFA included 14 value attributes in total; excluded were the four external value attributes, which were included as nuisance variables at the later stages of analysis (ageInterfering, healthInterfering, moneyCost, timeCost). The number of factors to retain was determined by the Cattell-Nelson-Gorsuch (CNG) test to be 3, which was carried out using the *nFactors* package (Raîche et al., 2013). An orthogonal rotation (varimax) was applied to find a set of uncorrelated factors that best represent the relationships among the variables and therefore simplify factor interpretability.

Creating Composite Value Attribute Scores

Using the attributes with highest loadings onto the 3 factors identified in the EFA, we created composite scores that combined the loadings of all value attributes with factor loadings higher than 0.5 for a given factor. We chose 0.5 as the threshold because it is the midpoint of the 0.4-0.6 range of loading thresholds commonly suggested by researchers for practical significance (Hair, 2009; MacCallum et al., 2001; Stevens, 2002). The purpose of creating these composite scores was to obtain operational rating variables that would encompass the multiple related individual value attributes, and to use these, rather than the multiple highly correlated individual attributes, to predict choice in the regression models. To calculate the composite scores, the raw value attribute ratings for each activity during the choice phase were multiplied by the corresponding factor loading of each attribute and summed trial-by-trial. This resulted in three new variables for each activity per participant, which represented the weighted sums of all attribute loadings within a factor. For the analysis of choice data, we created Δvalue_comp scores (i.e., ΔEffort_comp, ΔShould_comp, ΔReward_comp), computed from the difference between the right minus left activities presented in a pair at each choice trial.

Choice Task Analyses

The choice responses were coded from 0 to 100, with 0 representing a strong choice preference for the activity presented on the left and 100 representing a strong choice for the activity on the right. We conducted mixed effects linear regression models on choices and choice RTs, where the differences in value attribute ratings between the two activities presented on screen were used to predict choice behaviour (choice of right-sided activity) and choice RTs. To model choice behaviour, the three Δvalue_comp scores (i.e., ΔEffort_comp, ΔShould_comp, ΔReward_comp) were used as predictors in one mixed-effects linear regression model together while controlling for the four external activity attributes (i.e., right minus left activity differences for moneyCost, timeCost, ageInterfering, healthInterfering). To model choice response times, the absolute values of these Δvalue_comp scores were used as predictors instead since both large positive and large negative differences were expected to have the same effect on RT. All models included random intercepts for subject. Maximally specified models that also included random slopes for all Δvalue_comp scores were initially run but did not converge so models were run with random intercepts only. Prior to running the models, all three Δvalue_comp scores, which were already normally distributed around zero, were standardized by dividing by the standard deviation using the *scale* function in R.

To determine if neuropsychiatric symptoms influenced the weighting of value attributes during everyday decision-making, we repeated the above linear regressions predicting choice behaviour from the three Δvalue_comp scores, but also included the neuropsychiatric questionnaire scores (z-scored) as well as their interactions with each of the Δvalue_comp scores. Models included random intercepts for subject.

Hierarchical Drift Diffusion Modeling (HDDM)

Drift diffusion models (DDMs) have been applied to value-based decisions where participants make choices on the basis of their preference in order to decompose choices and response times into the cognitive mechanisms underlying decision-making (Bakkour et al., 2019; Basten et al., 2010; da Silva Castanheira et al., 2022; Krajbich et al., 2010; Milosavljevic et al., 2010; Yan & Huang-Pollock, 2023). In brief, the DDM assumes that the internal evidence used to make a value-based decision accumulates over time. The goals of fitting a DDM model to the data in our study were twofold. First, we wanted to determine whether the different dimensions of value would have dissociable influences on two key underlying mechanisms of choice behaviour: the drift rate, which represents the process of evidence accumulation – i.e., the amount of evidence at a given time in favour of one decision or another (here: which activity to do) – and/or the decision boundary, which represents the level of evidence required to make a decision and has often been taken to represent response caution. Second, we wanted to determine whether apathy would have a main effect on these underlying decision-making mechanisms (e.g., an overall slowing of drift rate, reflecting reduced evidence accumulation speed, or wider thresholds, reflecting or an overall increased response caution in apathy) or whether it would instead interact with the modulatory effect of value dimensions on these mechanisms.

Because the DDM requires choice data to be represented as a binary variable, the continuous choice responses were dichotomized to either 0 (Choice strength = 1-49 indicating left activity chosen) or 1 (Choice strength = 51-100 indicating right activity chosen) as has been done in other studies (Hernandez et al., 2024; Schneider et al., 2024). Responses with the exact value of 50 (representing complete indifference between the activities) were omitted, resulting in the removal of 3% of choice trials. Before fitting the DDM, we first confirmed that logistic regressions conducted on the new binary choice response produced a pattern of results qualitatively similar to the results obtained from the linear regressions conducted on the continuous choice responses (as described above). Next, we fit a DDM to the choices and response times using the HDDM toolbox on Python (Wiecki et al., 2013). HDDM combines the DDM with a hierarchical Bayesian approach, which estimates parameters at the subject and group levels while enhancing statistical power even with smaller sample sizes. Subject-level parameter estimates are assumed to be random variables drawn from a parent distribution defined by the group-level estimates.

Model Selection. The HDDM models included boundary (a), non-decision time (t), drift rate (v), and bias (z) parameters. To explore whether the estimation of these parameters differed between participants as a function of apathy, we used HDDMRegressor, a function that allows for trial-by-trial DDM parameters to be estimated as a linear combination of observed predictor variables. Namely, drift rate was specified to be predicted by the three factor-derived composite value attribute scores described in the previous section (i.e., ΔEffort_comp, ΔShould_comp, ΔReward_comp), while boundary, because the direction of choice was arbitrary in our task, was regressed onto the absolute values of these composite scores. Additionally, apathy (AMI) and impulsivity (BIS) questionnaire scores were also added as interaction terms in separate models. Ten thousand samples were drawn from the posterior for each parameter across four chains, discarding the first two-thousand samples for burn-in and no thinning was applied. To identify the best-fitting model for our data, we compared several candidate models using the Deviance Information Criterion (DIC). The DIC is a widely used metric for model comparison in Bayesian statistics, where lower DIC values indicate a better fit to the data, accounting for model complexity. The models we compared were as follows:

- **Model 1:** *[drift rate ~ ΔEffort_comp + ΔShould_comp + ΔReward_comp + AMI + ΔEffort_comp:AMI + ΔShould_comp:AMI + ΔReward_comp:AMI], [boundary ~ |ΔEffort_comp| + |ΔShould_comp| + |ΔReward_comp| + AMI + |ΔEffort_comp|:AMI + |ΔShould_comp|:AMI + |ΔReward_comp|:AMI]*
- **Model 2:** *Model 1 + bias term* (starting point bias, indicates whether a decision-maker has a preference towards one of the choices prior to evidence accumulation)
- **Model 3:** *[drift rate ~ ΔEffort_comp + ΔShould_comp + ΔReward_comp + AMI + ΔEffort_comp:AMI + ΔShould_comp:AMI + ΔReward_comp:AMI] + bias term*

The DIC values for each model were as follows: Model 1: 11232.85; Model 2: 11197.06; Model 3: 11222.41. Based on these results, Model 2, the most complex model including the bias term, was selected. A similar model structure was used, replacing AMI with BIS, and a separate model comparison step also indicated that Model 2 best fit the data. To test for model convergence, we visually inspected traces of the posterior distributions and computed the R-hat (Gelman-Rubin) statistic to compare between-chain variance to within-chain variance. All reported coefficient estimates (*b* values) for the HDDM models are mean posterior values across participants, and 95% highest posterior-density (HPD) intervals. Bayesian p values (P) represent one minus the proportion of the posterior distribution that falls above or below zero (depending on the sign of the median posterior value: below zero if $\beta < 0$ and above if $\beta > 0$).

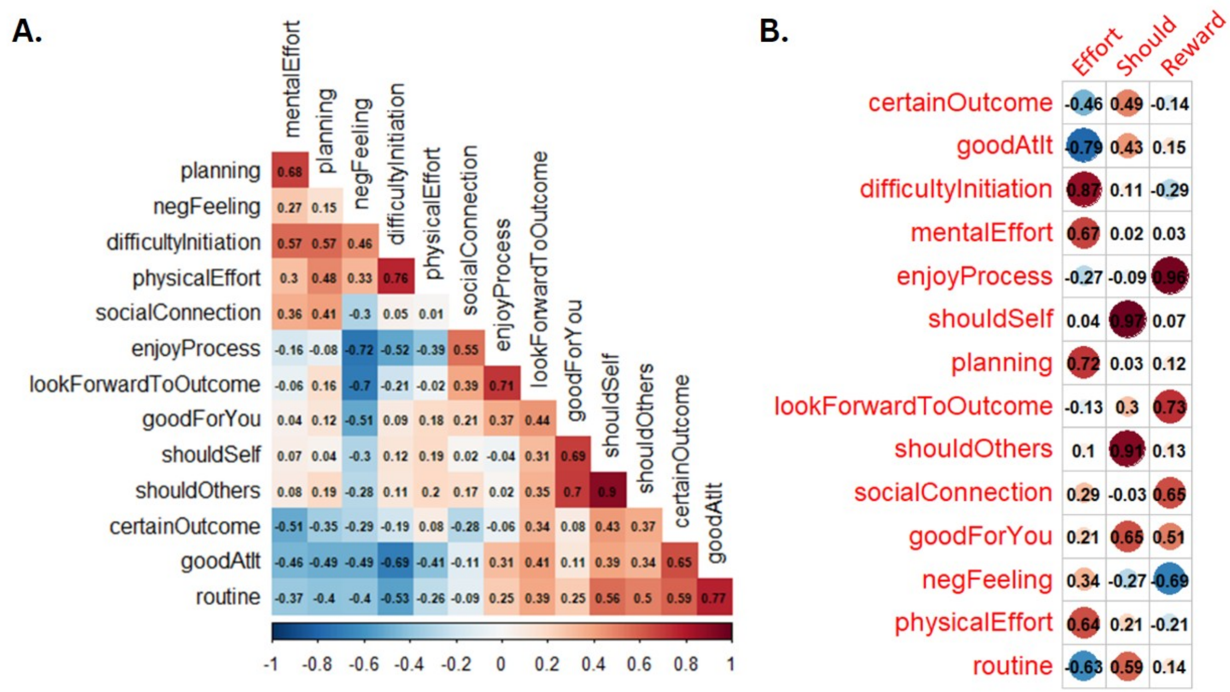
Results

Individual value attribute ratings and exploratory factor analysis

We found several strong correlations between attribute ratings averaged for each activity across participants. For instance, on average, an activity rated highly for the question "how much do you enjoy carrying out an activity?" was also rated highly for the question "how much do you look forward to the outcome of this activity?" ($r=0.71$, $p<0.001$; **Figure 2A** depicts the correlation matrix for all value attributes). To identify latent variables underlying the variation among value attributes, we conducted an exploratory factor analysis (EFA) on the rating data. The Cattell, Nelson, and Gorsuch's (CNG) test suggested a three-factor solution to best explain the variance between the 14 value attributes. The EFA showed the total variance in rating scores explained by the three factors to be 69.5%, with factor 1 explaining 26.4% variance, factor 2 explaining 22.9% variance, and factor 3 explaining 20.2% variance. We then used the pattern of value attribute loadings onto each factor to designate a label for each factor (**Figure 2B**). Factor 1 was labeled "Effort" based on the high positive loading of items related to the difficulty of initiating an activity, planning involved, and mental and physical effort. Factor 2 was labeled "Should" based on the high loading of items related to the sense of obligation to engage in an activity and to how good an activity is for you. Factor 3 was labeled "Reward" based on the high loading of items related to the positive anticipation of the outcome, the enjoyment from carrying it out, and the high negative loading of an item related to negative feeling elicited by an activity.

Figure 2

Relationship between Individual Value Attributes



Note. A) Correlation matrix representing the correlations between the 14 value attributes after averaging across activity. B) Value attribute factor loadings for the three factors (labelled Effort, Should and Reward based on pattern of attribute loadings) generated from the exploratory factor analysis.

Differences in value attribute scores predict choices and response times

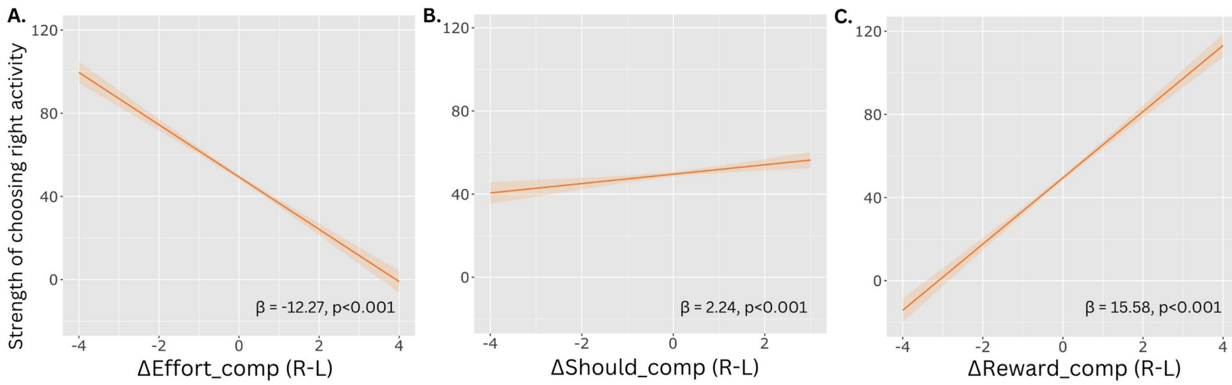
Next, to demonstrate the internal validity of the task, we wanted to confirm that the choices made between activities reflected the subjective ratings provided in the first phase. We conducted a mixed effects linear regression predicting the strength of choice preference for the activity presented on the right of the screen from the three factor-derived composite value attribute scores (Δvalue_comp, representing the factor-derived composite value attribute score for the right activity minus the rating for the left activity) in order to estimate their independent contributions to choice preference. This model also included the four external value attributes (moneyCost, timeCost, ageInterfering, healthInterfering) as nuisance variables. As shown in **Figure 3**, all three composite attribute scores significantly predicted choice even while controlling for the other two, but the magnitude of the relationships differed. ΔReward_comp was the most strongly predictive of choice behaviour (β= 15.58, $p<0.001$), such that a higher rating of reward-related value attributes for the right activity compared to the left activity was associated with a higher choice preference for the right activity. The effect of effort-related value attributes (ΔEffort_comp) was of similar magnitude and predicted choice in the expected direction with higher rating for Effort-related attributes of the right activity associated with higher choice rating for the left activity, i.e., participants indicated stronger choice preference for the lower effort activity (β=-12.27 $p<0.001$). The weakest relationship was observed for ΔShould_comp (β=2.24, $p<0.001$), although here too, the relationship was in the expected direction with higher rating of obligation-related attributes associated with stronger choice preference for that activity. Higher moneyCost (β=0.04, p=0.003) and higher timeCost ratings (β=0.06, $p<0.001$) were also associated with stronger choice preference, while controlling for all other value attributes. Neither ageInterfering (β=0.03, p=0.16) nor healthInterfering (β=-0.03, p=0.268) were significant predictors of choice preference. See **Supplementary Table 2** for the full model output.

We next examined choice response times (RT). We were interested in determining whether there was a relationship between value difference and choice RT such that a smaller difference in value ratings (i.e., activities that were rated similarly for specific value attributes) would be associated with longer RTs, reflecting a longer deliberation period for these presumably more "difficult" choices (Bakkour et al., 2019; da Silva Castanheira et al., 2022; De Martino et al., 2013). Finding such a relationship would suggest that participants were engaging in a process of deliberation involving comparisons of the different value attributes of interest, despite receiving no explicit reminder of the different value attributes previously rated. We conducted a mixed effects linear regression model predicting choice RTs from the three Δvalue_comp scores as above but taking here the absolute of the value differences to predict RT (|Δvalue_comp|, where 0 indicates that the two activities were rated equally on that composite value attribute score). As with the regressions on choice strength, we also included the four external value attributes in the model. We found that all three composite attribute scores significantly and independently predicted choice RTs such that, as expected, a greater difference in value attribute ratings related to effort (β=-179.88, $p<0.001$), obligation (β=-128.24, p=0.002), and reward (β=-213.31, $p<0.001$) were associated with faster choice RTs (**Figure 4**).

Finally, we also conducted univariate regression models for choice strength and choice RT with each of the individual attribute ratings to confirm the pattern of results obtained with the factor-derived composite scores. These results are presented in **Supplementary Figure 2** and show that all value attributes are significantly predictive of choice strength and that the relative ranking of value attribute effect sizes for the models predicting choice strength is similar to those predicting RT though in the latter case, not all attributes show significant effects.

Figure 3

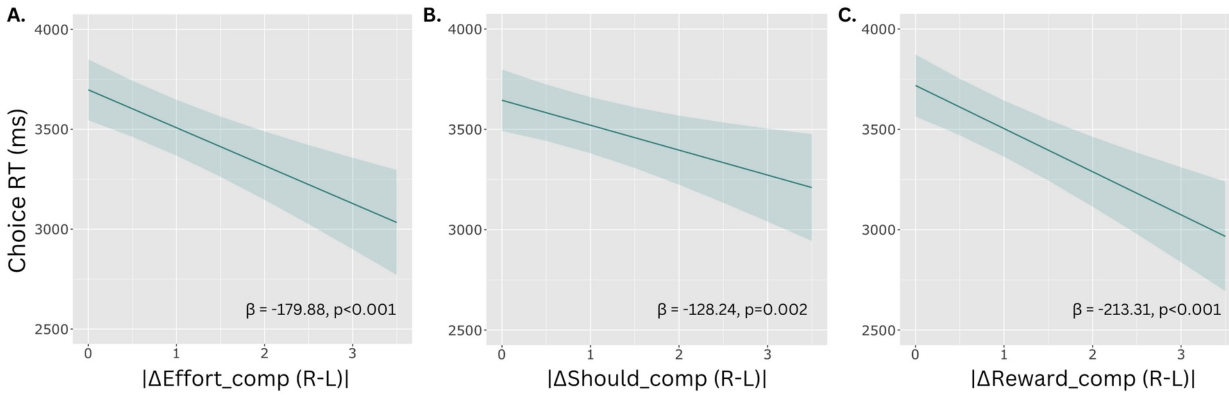
Relationship between Value Ratings and Choice Behaviour



Note. Choice behaviour plotted as a function of the difference in value attribute ratings for all three composite value attribute scores. (A) A higher rating for the effort-related value attributes for the right compared to the left activity was associated with a stronger choice towards the left activity, i.e., away from the right activity. (B) A higher rating for obligation-related value attributes for the right activity was associated with a stronger choice towards the right activity. (C) A higher rating for the reward-related value attributes of the right activity was also associated with a stronger choice towards the right activity. Solid lines represent the slope extracted from the mixed-effects regression model that included all three composite scores and shaded areas indicate the 95% confidence interval for the estimated values.

Figure 4

Relationship between Value Ratings and Choice Response Times



Note. Choice response times plotted as a function of the absolute difference in value attribute ratings for effort-related attributes (A); obligation-related attributes (B); and reward-related attributes (C). In all three cases, a higher absolute difference in the value rating between the two activities was associated with faster RTs. Solid lines represent the slope extracted from the mixed-effects regression model that included all three composite scores and shaded areas indicate the 95% confidence interval for the estimated values.

Apathy biases the relative weighting of effort during everyday value-based decision-making

To determine if apathy influenced the relative weighting of the different value attributes during choices, we ran a mixed effects linear regression model on choice preference that included all three Δvalue_comp scores, the z-scored AMI score, and their interactions. Additionally, because other mood symptoms affecting motivation are thought to be mechanistically related to apathy and often co-occur with apathy, the model also controlled for impulsivity and depression (z-scored BIS and GDS, respectively) as well as their interactions with each of the three Δvalue_comp scores. Indeed, in our sample AMI was weakly positively correlated with both BIS-11 ($r=0.24$, $p<0.01$) and with GDS ($r=0.30$ $p<0.01$).

The three composite value attribute scores remained independently predictive of choice strength in the same direction as reported above (**Table 3**). As expected, we observed no significant main effect of any of the mood symptom scores on choice preference, indicating that these scores did not induce a bias for choosing a side (i.e., left vs. right activity). We found a significant negative interaction between AMI scores and ΔEffort_comp (β=-1.65, p=0.004), indicating that higher apathy was associated with *increased* weighting of effort-related value attributes, resulting in further lowering of choice preference for activities rated high on effort-related attributes, when controlling for depression and impulsivity. Interestingly, we also found a nonsignificant but trending positive interaction between BIS scores and ΔEffort_comp (β=1.05, p=0.051) indicating that higher levels of impulsivity may be associated with an *under*-weighting of effort-related value attributes during choices when controlling for apathy and depression (note here that the positive β for the interaction leads to a lessening of the negative main effect of the ΔEffort_comp on choice preference). This suggests that apathy and impulsivity may exert opposing influences on the weighting of effort during everyday decisions, despite being weakly positively correlated to each other. Contrary to our predictions, there was no statistically significant interaction between apathy and the influence of reward-related attributes on choice preference (β=-0.89, p=0.193). There were no significant interactions between GDS scores and any of the three composite value attribute scores.

To examine if the effect of apathy and impulsivity on the weighting of effort was being driven by some of the effort-related attributes more than others, we first ran a regression model that included interactions with only AMI and BIS but not GDS, which confirmed that they interacted with the ΔEffort_comp term in opposite directions (**Figure 5, Supplementary Table 4**). Next, we conducted a set of exploratory regression models that again included both AMI and BIS, but this time replaced the ΔEffort_comp term with each of the individual attributes that were used for the composite score. These results are presented in **Supplementary Figure 3**. In the case of apathy, ΔdifficultyInitiation, Δplanning, and ΔmentalEffort showed significant negative interactions with AMI, but interestingly, ΔphysicalEffort did not. In the case of impulsivity, ΔdifficultyInitiation showed a nonsignificant but trending positive interaction with BIS. In summary, this suggests that the effect of both apathy and impulsivity on the weighting of effort-related attributes was mostly driven by the more cognitive aspects of effort rather than by the motor aspects of effort.

Table 3

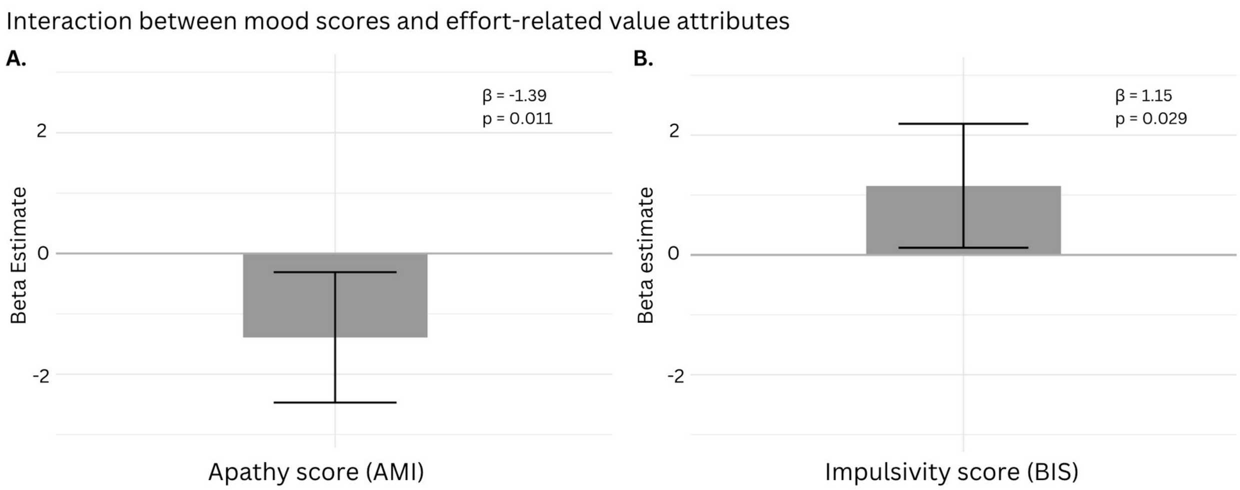
Results of the Mixed-effects Linear Regression Model Predicting Choice Strength

	Choice Strength		
Predictors	*Estimates*	*CI*	*p*
Intercept	49.44	48.46 – 50.41	**<0.001**
AMI_total	0.45	-0.59 – 1.49	0.399
BIS_total	-0.41	-1.43 – 0.61	0.431
GDS_total	-0.40	-1.42 – 0.63	0.450
ΔEffort_comp	-10.84	-11.89 – -9.79	**<0.001**
ΔShould_comp	2.23	1.02 – 3.43	**<0.001**
ΔReward_comp	16.43	15.18 – 17.68	**<0.001**
AMI_total x ΔEffort_comp	-1.65	-2.77 – -0.53	**0.004**
AMI_total x ΔShould_comp	-0.51	-1.80 – 0.78	0.436
AMI_total x ΔReward_comp	-0.89	-2.24 – 0.45	0.193
BIS_total x ΔEffort_comp	1.05	-0.01 – 2.11	0.051
BIS_total x ΔShould_comp	0.50	-0.74 – 1.73	0.431
BIS_total x ΔReward_comp	-0.59	-1.90 – 0.72	0.376
GDS_total x ΔEffort_comp	0.84	-0.18 – 1.86	0.107
GDS_total x ΔShould_comp	0.23	-0.97 – 1.44	0.704
GDS_total x ΔReward_comp	-0.50	-1.79 – 0.79	0.445
Marginal R^2 / Conditional R^2	0.456 / 0.460		

Note. Regression coefficients from the mixed-effects linear regression model predicting choice strength from all three composite value attribute scores and their interactions with apathy (AMI), impulsivity (BIS), and depression (GDS). While controlling for BIS and GDS, higher AMI scores were associated with a more negative weighting of effort on choice strength. Bold p values denote significance at the 0.05 level.

Figure 5

Interaction between Effort-related Value Attributes and Mood Symptoms on Choice Strength



Note. Linear regression model: choice strength ~ Δvalue_comp scores + interactions with AMI and BIS. A) The beta estimate for the interaction between ΔEffort_comp and the Apathy Motivation Index (AMI) scores was negative indicating that higher apathy was associated with overweighting of the effect of effort on choice, leading to a lower preference for more effortful activities. B) The interaction between ΔEffort_comp and the Barratt Impulsivity Scale (BIS) scores positive indicating that higher impulsivity was associated with an underweighting of the effect of effort on choice, leading to a higher preference for more effortful activities. AMI and BIS scores were standardized. Error bars represent 95% confidence intervals.

Hierarchical drift diffusion modeling (HDDM) of choice behaviour and relationship to apathy

We applied a drift diffusion model to the choice data to determine if the three value dimensions and apathy exerted their effects on decision-making by selectively or differentially influencing evidence accumulation and response caution. This model included the effects of all three value dimensions on drift rate and decision boundary, as well as the interactions of these effects with participants' AMI scores. The model also estimated the non-decision time (b=1.968, 95% CI = [1.894, 2.050], P=0) and bias (b=0.544, 95% CI = [0.531, 0.556], P=0) parameters at the population level, which indicated a small overall bias for choosing the right over the left activity.

We first examined the effect of the three different domains of value on the rate of evidence accumulation (i.e., drift rate) and on response caution (i.e., decision boundary). In the context of our task, a negative drift rate indicated evidence accumulation towards the activity presented on the left side of the screen, and a positive drift rate indicated evidence accumulation towards the activity presented on the right. In line with our predictions, we found that larger ΔReward_comp (b=0.561, 95% CI = [0.510, 0.615], P=0) and ΔShould_comp (b=0.091, 95% CI = [0.0439, -0.136], P=0) scores (indicating higher ratings for these dimensions of value for the activity presented on the right) were associated with an increase in drift rate in the positive direction, i.e., towards the activity rated higher for reward and obligation. The betas reported here represent the population-level mean of the regression coefficient estimates, while the P=0 denotes that the posterior distributions for the regression coefficients of ΔReward_comp and ΔShould_comp were 100% above zero, indicating strong probability that higher reward and obligation ratings increased the drift rate towards that activity (**Figure 6A)**. Meanwhile, we found that larger differences in Effort_comp significantly shifted the drift rate in the negative direction, i.e., towards the activity rated as less effortful, with the posterior distribution for the regression coefficient of ΔEffort_comp being 100% below zero (b=-0.366, 95% CI = [-0.408, -0.323], P=0) (**Figure 6A)**. Of note, the relative magnitude of the effect of the three composite value attribute scores on the drift rate parameter mirrored their relative effects on choice preference in the linear regression models (i.e., Reward > Effort > Should).

With respect to decision boundary, we predicted that more ambiguous choices (i.e., with smaller |Δvalue_comp|) would be associated with increased decision boundaries (i.e., greater response caution). Surprisingly, however, greater absolute differences of both effort-related (b=0.102, 95% CI = [0.018, 0.188], P=0.02) and reward-related (b=0.238, 95% CI = [0.139, 0.343], P=0) value attributes were associated with significantly increased decision boundaries (**Figure 6B**). |ΔShould_comp| was not associated with changes in boundary (b=0.08, 95% CI = [-0.077, 0.094], P=0.43). These results suggest that differences in value influence not only the rate of evidence accumulation but also response caution. Specifically, larger differences in effort, reward and obligation-related value were associated with faster evidence accumulation (i.e., shorter time to reach decision boundary), yet paradoxically, larger value differences were also associated with higher decision boundary. Although the effects of value differences on drift rate and decision boundary are not directly comparable, the strong relationships observed between larger value differences and shorter RTs in the linear regressions above suggest that the impact of value on drift rate predominates over its effect on decision boundary.

Next, we examined whether apathy interacted with the influence of effort on either evidence accumulation or on response caution. AMI showed a small interaction with the effect of ΔEffort_comp on drift rate, such that higher AMI scores were associated with a faster drift rate towards the *less* effortful activity (b=-0.030, 95% CI = [-0.070, 0.010], P=0.07). While the 95% CI includes zero, the Bayesian posterior probability (P=0.07) suggests that it is relatively more likely (93% chance) than not that higher apathy is associated with a small bias in evidence accumulation *away* from more effortful activities. Consistent with the regression models on choice strength, there were no interactions between AMI and ΔShould_comp (b=-0.018, 95% CI = [-0.063, 0.026], P=0.21) nor with ΔReward_comp

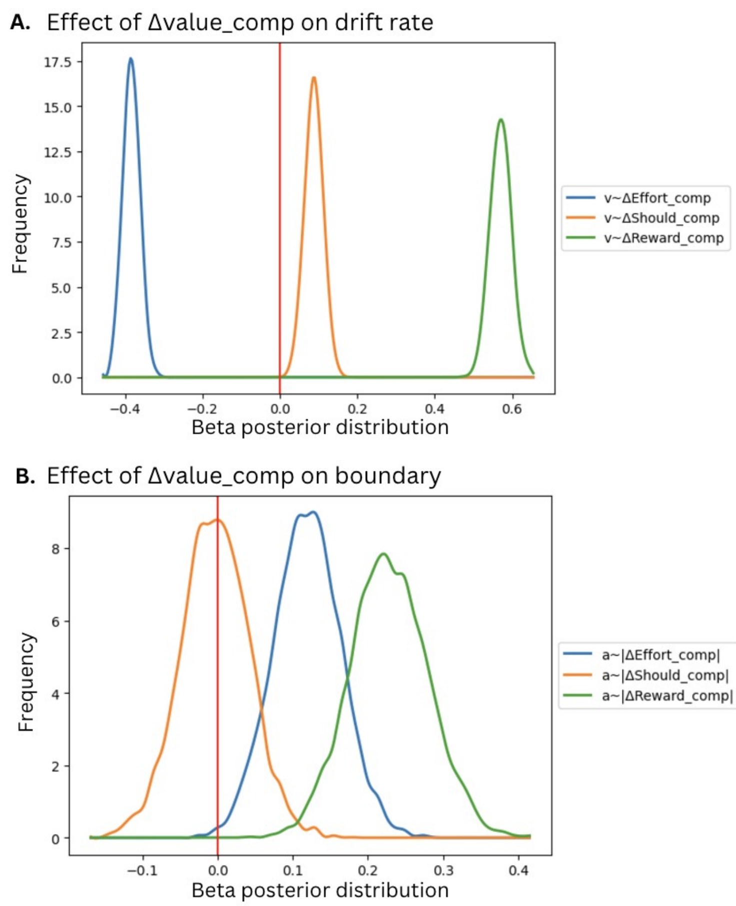
(b=-0.004, 95% CI = [-0.055, 0.047], P=0.44, **Figure 7A**). In the case of decision boundary, apathy did not interact with any of the three value dimensions (**see Table 4**). Importantly, there were no significant main effects of AMI on the drift rate parameter (b=0.016, 95% CI = [-0.017, 0.049], P=0.17) nor on decision boundary (b=0.054, 95% CI = [-0.075, 0.185], P=0.21); in other words, apathy itself was not associated with altered evidence accumulation or response caution**.**

Because our regression models had found that impulsivity modulated the effect of effort on choice in a direction opposite to that of apathy, we conducted a second HDDM model that replaced AMI with BIS to confirm this finding and to determine whether the interaction between impulsivity and effort was similarly confined to modulating the effect of effort on drift rate (**Table 5**). Consistent with the linear regression models, there was an interaction between BIS and ΔEffort_comp such that higher impulsivity was associated with a faster drift rate towards the *more* effortful activity (b=0.035, 95% CI = [-0.005, 0.074], P=0.04; **Figure 7B**), while there were no interactions with ΔShould_comp (b=0.022, 95% CI = [-0.024, 0.068], P=0.18) nor ΔReward_comp (b=-0.035, 95% CI = [-0.088, 0.017], P=0.10). Additionally, in the case of decision boundary, the model indicated a strong probability for a negative interaction between impulsivity and |ΔEffort_comp| (b=-0.084, 95% CI = [-0.166, 0.004], P=0.02), but not |ΔShould_comp| or |ΔReward_comp| (**Figure 8B**). With respect to the main effect of impulsivity on decisional processes, there was no association between BIS and drift rate (b=-0.006, 95% CI = [-0.041, 0.029], P=0.36) but interestingly, higher BIS was associated with higher decision boundary (b=0.103, 95% CI = [-0.016, 0.228], P=0.05).

In summary, the above results linking mood symptoms to cognitive mechanisms underlying decision making are consistent with those of the linear regression models on choice behaviour in that apathy and impulsivity selectively modulated the effect of effort-related value attributes (but not reward nor obligation-related attributes) on choice behaviour, and did so in opposite directions.

Figure 6

Relationship between Composite Value Attribute Scores and HDDM Parameters



Note. This figure demonstrates posterior distribution plots derived from a single model: drift rate ~ (Δvalue_comp scores)*AMI; boundary ~ (|Δvalue_comp scores|) *AMI. A) Posterior distribution plot for the regression coefficients representing the main effect of each of the Δvalue_comp scores on drift rate. This plot shows that higher ΔEffort_comp is associated with slowing of drift rate towards more effortful activities, whereas higher ΔReward_comp and higher ΔShould_comp scores are associated with faster drift rate towards more rewarding activities and towards those perceived as having greater obligation. B) Posterior distribution plot for the regression coefficients representing the main effect of each of the Δvalue_comp scores on boundary. Higher absolute differences in Effort and Reward_comp scores were associated with a higher boundary.

Table 4

Parameter Estimates for the HDDM Model Predicting Drift Rate and Boundary from Composite Value Attribute Scores and Interactions with AMI

Coefficient	*b*	95% CI	Bayesian P
Nondecision time (t)			
Intercept	**1.968**	**[1.894, 2.046]**	**.000**
Bias (z)			
Intercept	**0.544**	**[0.531, 0.556]**	**.000**
Drift rate (v)			
Intercept	**-0.090**	**[-0.118, -0.046]**	**.000**
AMI	0.016	[-0.017, 0.049]	.170
ΔEffort_comp	**-0.366**	**[-0.408, -0.323]**	**.000**
ΔShould_comp	**0.091**	**[0.044, 0.136]**	**.000**
ΔReward_comp	**0.561**	**[0.510, 0.615]**	**.000**
ΔEffort_comp x AMI	-0.030	[-0.070, 0.010]	.071
ΔShould_comp x AMI	-0.018	[-0.063, 0.026]	.207
ΔReward_comp x AMI	-0.004	[-0.055, 0.047]	.440
Boundary (a)			
Intercept	**2.534**	**[2.409, 2.661]**	**.000**
AMI	0.054	[-0.075, 0.185]	.213
|ΔEffort_comp|	**0.10**	**[0.018,**	**.001**

	2	**0.188]**	
|ΔShould_comp|	0.008	[-0.077, 0.094]	.425
|ΔReward_comp|	**0.238**	**[0.139, 0.343]**	**.000**
|ΔEffort_comp| x AMI	-0.032	[-0.120, 0.058]	.237
|ΔShould_comp| x AMI	0.004	[-0.086, 0.094]	.472
|ΔReward_comp| x AMI	0.049	[-0.058, 0.154]	.176

Note. Bayesian p values (P) represent one minus the proportion of the posterior distribution that falls above or below zero (depending on the sign of the median posterior value: below zero if b < 0 and above if b > 0). Bold P values denote significance at the 0.05 level.

Table 5

Parameter Estimates for the HDDM Model Predicting Drift Rate and Boundary from Composite Value Attribute Scores and Interactions with BIS

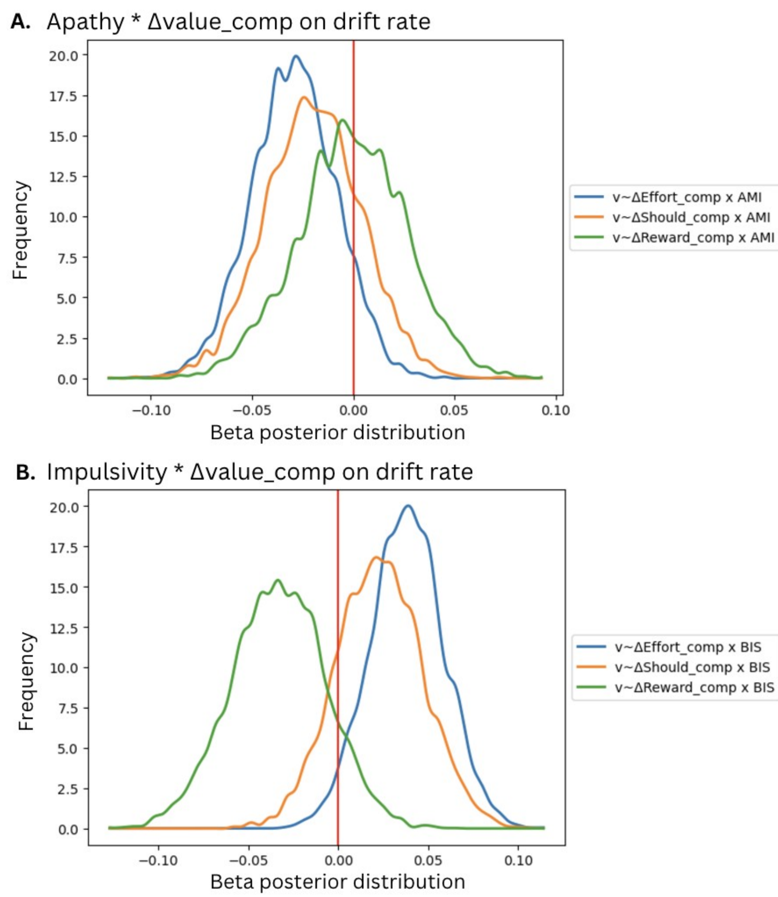
Coefficient	*b*	95% CI	Bayesian P
Nondecision time (t)			
Intercept	**1.967**	**[1.892, 2.043]**	**.000**
Bias (z)			
Intercept	**0.541**	**[0.527, 0.554]**	**.000**
Drift rate (v)			
Intercept	**-0.078**	**[-0.127, -0.035]**	**.000**
BIS	-0.006	[-0.041, 0.029]	.361
ΔEffort_comp	**-0.376**	**[-0.419, -0.334]**	**.000**
ΔShould_comp	**0.087**	**[0.041, 0.132]**	**.000**
ΔReward_comp	**0.56**	**[0.508,**	**.000**

	2	**0.614]**	
ΔEffort_comp x BIS	**0.035**	**[-0.005, 0.074]**	**.040**
ΔShould_comp x BIS	0.022	[-0.024, 0.068]	.181
ΔReward_comp x BIS	-0.035	[-0.088, 0.017]	.097
Boundary (a)			
Intercept	**2.534**	**[2.409, 2.669]**	**.000**
BIS	**0.103**	**[-0.016, 0.228]**	**.047**
|ΔEffort_comp|	**0.117**	**[0.030, 0.204]**	**.003**
|ΔShould_comp|	0.004	[-0.083, 0.086]	.461
|ΔReward_comp|	**0.231**	**[0.131, 0.332]**	**.000**
|ΔEffort_comp| x BIS	**-0.084**	**[-0.166, 0.004]**	**.018**
|ΔShould_comp| x BIS	-0.031	[-0.113, 0.054]	.233
|ΔReward_comp| x BIS	0.022	[-0.075, 0.119]	.321

Note. Bayesian p values (P) represent one minus the proportion of the posterior distribution that falls above or below zero (depending on the sign of the median posterior value: below zero if b < 0 and above if b > 0). Bold P values denote significance at the 0.05 level.

Figure 7.

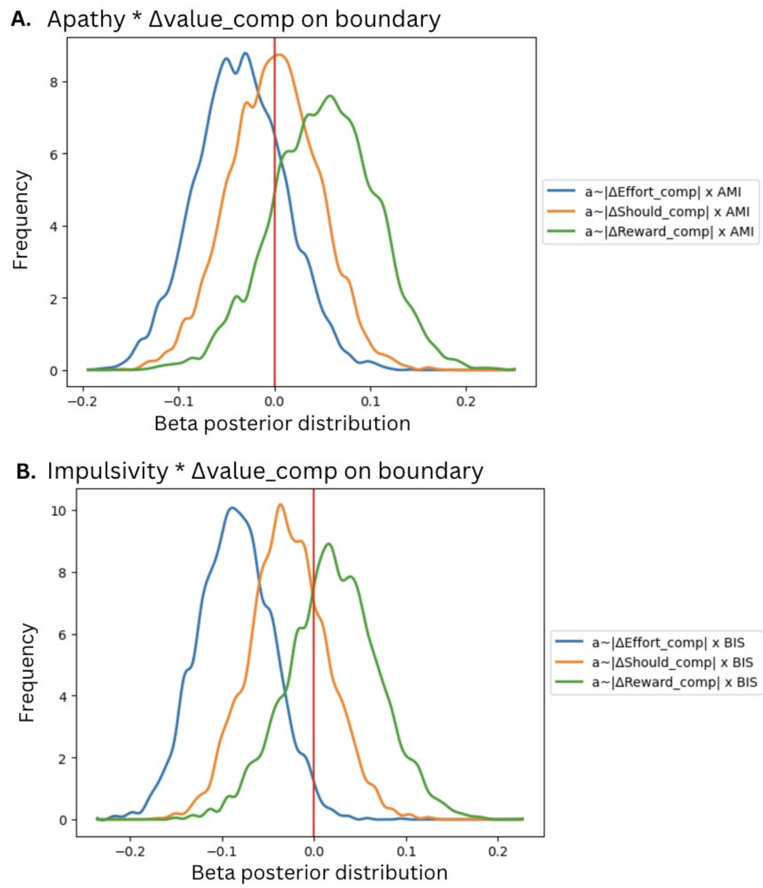
Interaction Effect of Composite Value Attribute Scores and Apathy or Impulsivity on Drift Rate



Note. Posterior distribution plots were derived from two separate HDDM models which predicted drift rate from the Δvalue_comp scores with interactions with either apathy or impulsivity. A) Similar to the results of the linear regression model, the HDDM model indicated a relatively high probability of an interaction between apathy and ΔEffort_comp such that higher apathy amplified the negative influence of effort, leading to in a greater slowing of the drift rate towards the more effortful activity. B) The HDDM model indicated a strong probability of a positive interaction effect between impulsivity and ΔEffort_comp such that higher impulsivity amplified the positive influence of effort on drift rate, resulting in a greater speeding of drift rate towards the more effortful activity.

Figure 8.

Interaction Effect of Composite Value Attribute Scores and Apathy or Impulsivity on Boundary



Note. Posterior distribution plots were derived from two separate HDDM models which predicted boundary from the absolute difference in value_comp scores with interactions with either apathy or impulsivity. A) Apathy did not interact with the influence of |Δvalue_comp| scores on boundary. B) The HDDM model indicated a strong probability of a negative interaction effect between impulsivity and ΔEffort_comp such that higher impulsivity reduced the positive influence of effort on boundary, resulting in lower response caution during less ambiguous choices.

Discussion

We developed a novel task to quantify the independent influence of different domains of value on decisions about everyday activities and used this task to determine if apathy biases the valuation process during decisions about everyday activities. We found that ratings of attributes related to effort, reward and obligation predicted choices between different everyday activities. We also found that apathy was associated with *over*-weighting of effort-related attributes such that more apathetic individuals were *less* likely to choose high effort activities and had slower rates of evidence accumulation towards these activities. Furthermore, the influence of apathy on the valuation process was selective to the effort domain as there was no influence of apathy on weighting of reward- nor obligation-related attributes. In contrast, impulsivity was independently associated an *under*-weighting of effort-related attributes while controlling for apathy and depression. These results suggest that apathy leads to reduced engagement in everyday activities because of a selective over-weighting of effort-related attributes. By using more naturalistic stimuli and exploring a wider range of value attributes our results also provide an important bridge linking the behavioural patterns observed in highly controlled laboratory-based decision-making tasks to the altered everyday behavioural patterns characteristic of apathy.

Novel task captures multi-attribute decision-making about everyday activities

In this study, we introduced a novel decision-making task that used everyday activities as the choice stimuli. The goal was to create a task that more closely represents the everyday context where the effects of neuropsychiatric syndromes, like apathy, manifest themselves. We found that attributes related to effort, reward, and obligation independently contributed to decisions between typical everyday activities. These results extend the general framework of effort-based decision making, which explores how humans integrate costs and benefits when deciding to act, in several ways. First, we extend this framework to more typical everyday actions. Most prior studies have relied on laboratory tasks in which the actions being evaluated are simple ones such as gripping a dynamometer or engaging in a working memory problem for which there are not direct equivalents in everyday life. Here, we used a range of typical everyday activities and replicated the finding that effort and reward are indeed important determinants of decisions to engage in everyday activities (Bonnelle et al., 2015; Le Heron, Apps, et al., 2018; Muhammed et al., 2016). Second, we were able to expand the typical operational definitions of effort and reward by using a large set of self-rated value attributes to which we applied a factor analysis. The latent factor representing reward, which was a strong predictor of choice, included attributes such as enjoying the process of the activity, looking forward to its outcome, and the potential for social connection, thereby extending the concept of 'benefits' beyond the usual monetary rewards employed in tasks. Similarly, the latent factor representing 'effort' included not only attributes related to the physical and mental effort required of the activity, but also the difficulty in initiating an activity, the degree of planning involved and (in the opposite direction) the degree to which one felt qualified to perform the activity. It is important to note that in addition to showing that the latent factors representing effort and reward strongly predicted choice, each of the individual attributes represented by these latent factors were also significant predictors of choice. This may partly be explained by the fact that attribute ratings were correlated to one another; however, only seven (out of 96) attribute pairs exceeded a moderate correlation of 0.6, which suggests that the more comprehensive set of attributes explored in this task meaningfully expands the landscape of costs and benefits driving choices.

In addition to effort and reward, whose roles are well-established in value-based decisions, we identified a third domain of value related to the sense of obligation that also independently predicted choice. We were interested in including attributes that would capture the social influences presumably at play in decisions about every actions. Indeed, even decisions about the most routine everyday activities, like brushing one's teeth or doing the dishes, can impact social relationships and are therefore inherently social. The attributes represented by this latent factor, and which influenced choice, included whether individuals thought they should engage in an activity, whether others thought they should, and whether an activity was perceived as good for them. This relates to the concept of conformity to social norms, which has been shown to play an important role in decision-making (Ruff & Fehr, 2014) but has primarily been studied by imposing the sense of conformity on participants (e.g., by providing false normative feedback to induce biases) rather than by extracting self-report ratings, thereby limiting the ecological validity of the tasks (Cialdini & Goldstein, 2004; Toelch & Dolan, 2015). One limitation of our design is that we did not fully survey the range of social factors potentially contributing to decisions. For instance, we did not assess prosocial factors, i.e., how much choosing to engage in an activity could benefit someone else (Lockwood 2017). Although the version of the task presented here was designed to capture attributes already thought to be relevant in the context of apathy (i.e., reward and effort) and to preliminarily expand the notion of value to include social factors, we believe that the strength of this task design is that it is readily modifiable to incorporate different domains of value and/or different everyday activities relevant for a particular population (e.g. younger vs older adults) or disorder (e.g., Parkinson's disease vs. schizophrenia).

Our results also suggest that our task successfully captured a deliberative decision-making process involving the integration of multiple value attributes to guide choice. Because the decisions represented in the choice phase of the task (e.g., "Go to the park" vs. "Do a load of laundry") were necessarily theoretical and could not be enforced, this could have resulted in participants following a simple choice heuristic for the mere purposes of completing the task (e.g., always choosing the more highly enjoyed task). It was therefore important to demonstrate that individuals nonetheless engaged in deliberative multi-attribute decision-making. Several features of the choice behaviour suggest that they did: First, we found multiple instances where attributes that were not correlated [e.g., enjoyProcess and shouldSelf, r=-0.04] or only weakly correlated [e.g., difficultyInitiation and lookForwardToOutcome, r=-0.21] nonetheless *both* were related to choices. Second, we observed a relationship between value ratings and choice response times such that decisions between two activities rated similarly for a particular value attribute were slower than decisions where the value difference was large, suggesting that the longer response times reflected the longer deliberation required for these 'harder' decisions (Bakkour et al., 2019; Basten et al., 2010). Third, we found evidence that the drift diffusion model provided a good fit for the choice and response time behaviour suggesting that participants were sequentially sampling the attributes in service of preference-based choices (Basten et al., 2010; Milosavljevic et al., 2010). These findings indicate that, despite the rather complex nature of the decisions required of participants in our task, participants were not reducing their choices to a single dimension for the purposes of completing the task, and instead, were engaged in a process of deliberation.

Apathy is associated with selective over-weighting of effort-related attributes

Using regression models predicting choice preference, we found that apathy was associated with a selective over-weighting of effort-related value attributes during decisions between everyday activities while controlling for impulsivity and/or depression. Drift diffusion modeling similarly showed that apathy enhanced the slowing effect of effort on evidence accumulation. This is broadly consistent with recent studies using laboratory tasks to manipulate effort (motor or cognitive), which have generally found that, across healthy and clinical populations, apathy is associated with a greater sensitivity to effort resulting in reduced willingness to expend cognitive effort, though some findings are inconsistent across populations (Apps et al., 2015; Bogdanov et al., 2022; Bonnelle et al., 2015, 2016; Culbreth et al., 2016; Hartmann et al., 2015; Saleh et al., 2021). To our knowledge, only one prior study has examined the effect of apathy on drift rate in a value-based decision-making task (Saleh et al., 2021). Instead of the selective modulatory effect on effort that we observed, this study showed that apathy had an overall effect of slowing the drift rate. This difference in findings may be in part due to the fact that the range of severity of apathy symptoms was considerably lower in our study compared to theirs, suggesting that the influence of apathy on decision making may not be uniform across the spectrum of severity. Interestingly, we found that among the effort-related value attributes, it was primarily the more cognitive aspects of effort (i.e., attributes related to perceived difficulty in initiating the activity, mental effort required, and amount of planning required) rather than the motor aspects of effort that were driving the effect of apathy on effort. That the effects of apathy were weaker for the motor effort aspects of value contrasts with studies relying on motor effort manipulations in which apathy has been shown to be associated with increased sensitivity to motor effort (Bonnelle et al., 2016). One possible explanation for this discrepancy is that though apathy may affect the sensitivity to both motor and mental aspects of effort, in the everyday decision context, cognitive effort requirements may be more prominent drivers of choice. Given the complexity of real-world decisions, future research quantifying the joint contributions of different types of effort will be required to determine whether cognitive and motor effort are evaluated in similar ways and the degree to which individual differences determine their relative weighting.

Contrary to our predictions, we found no relationship between apathy and the weighting of reward-related attributes during decision making. This contrasts with previous studies where reward has been directly manipulated in the form of monetary or point incentives and which have shown that apathy is associated with reduced incentivization by reward to produce effort (Adam et al., 2013; Le Heron, Manohar, et al., 2018; Rochat et al., 2013; Saleh et al., 2021; Wong et al., 2023). Interestingly, it has also been shown that individuals with apathy have a reduced sensitivity to monetary reward, even when reward is isolated from any possible effects of effort requirement (Muhammed et al., 2016, 2021) though not all studies have shown this pattern (Le Bouc et al., 2023). A possible explanation for the discrepancy between past studies and ours regarding the relationship between apathy and reward may lie in the operationalization of reward-related variables in the task. Most studies have operationalized reward as a secondary, financial reward to be gained from carrying out an action and have directly manipulated the reward levels (Le Heron, Manohar, et al., 2018; Le Heron, Plant, et al., 2018; Muhammed et al., 2016, 2021; Saleh et al., 2021). In contrast, because our interest was in decisions about typical everyday activities and because we relied on self-report ratings, we necessarily focused on the more intrinsically rewarding aspects of activities (e.g., enjoyment of the process, looking forward to the outcome, social connection). As a result, one possible explanation for the absence of a relationship between apathy and reward weighting in our study is that apathy has domain-specific effects on reward sensitivity. For instance, one recent study showed that apathetic patients with frontotemporal dementia had reduced sensitivity to monetary rewards, but not to other forms of reward (Le Bouc et al., 2023). Given the important role of reward in incentivizing behaviour, more work is needed to investigate whether the effects of reward observed in laboratory tasks generalize to the effects of reward in everyday life, and whether factors like age or specific brain disorders might differentially affect specific domains of reward.

Opposing effects of apathy and impulsivity on effort valuation

Because apathy often manifests with other neuropsychiatric symptoms, notably, anhedonia, depression, and impulsivity (Husain & Roiser, 2018;

Lanctôt et al., 2023; Petitet et al., 2021), we examined whether these symptoms influenced the weighting of value attributes independently of apathy. Impulsivity was found to have an independent effect on the weighting of value attributes when controlling for apathy and/or depression. More specifically, though impulsivity and apathy were weakly positively correlated, impulsivity was associated with a significant under-weighting of effort-related attributes, an effect in direct opposition to that of apathy. Results from the drift diffusion model applied to the choice phase behaviour yielded similar results: the effect of effort on the speed of evidence accumulation was increased by apathy but decreased by impulsivity. Whereas apathy is defined as a reduction in self-generated actions, impulsivity is often described as the tendency to act rashly without forethought, leading to excessive actions (Dalley et al., 2011). The opposing influences of apathy and impulsivity on behaviour, as well as observations that dopaminergic drugs appear to improve symptoms of apathy while triggering impulsive and compulsive behaviours in Parkinson's disease patients, have led to the hypothesis that apathy and impulsivity have related but opposing underlying cognitive mechanisms (Sierra et al., 2015; Sinha et al., 2013; Volkmann et al., 2010; Voon et al., 2011). More recently, however, this view has been challenged by findings suggesting that apathy and impulsivity can co-occur in both neurological and healthy populations (Kok et al., 2021; Petitet et al., 2021; Scott et al., 2020). Interestingly, despite influencing effort weighting in opposite directions in our task, apathy and impulsivity were positively (though weakly) correlated in our sample of healthy older adults (R=0.24). Although these findings should be interpreted cautiously because levels of apathy and impulsivity were low for most participants, our results suggest that apathy and impulsivity result from distinct cognitive mechanisms that converge on the evaluation of effort and its impact on decision making. Further work is needed in samples representing a broader range of severity of these symptoms to better understand these relationships.

Conclusion

This study provides new insights into the way that apathy alters value attribute integration during everyday decision making. We found that apathy was selectively associated with the over-weighting of effort resulting in an avoidance of higher effort-associated activities and faster decisional processes when choosing to avoid these activities. We found an opposite pattern for impulsivity. An important next step will be to determine whether these biases in valuation generalize to populations where these mood symptoms are clinically significant and whether the pattern of biases is consistent between different populations. For instance, it is conceivable that the dopamine neuron loss of Parkinson’s disease and the frontal lobe degeneration of frontotemporal dementia, two diseases where apathy and impulsivity are common, would differentially impact the sensitivity to different domains of value. Overall, we believe that our novel laboratory task involving more naturalistic stimuli representing everyday decisions provides an imminently modifiable blueprint that can be used to bridge between typical laboratory decision making tasks, where a necessarily limited set of value dimensions are fully manipulated by the experimenter, and the everyday decisions in which maladaptive behaviours such as apathy manifest themselves.

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