

Decision Making in Mice (*Mus musculus*) Using Two-Dimensional Binary Choice Sets

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Abstract

Models of decision making have traditionally assumed a rational decision maker who will always try to maximize the return currency. However, various findings breach with the idea that decisions are made solely on the basis of rational, economic principles. One possible explanation for this breach is that the cognitive process of translating perceived values of an option from a physical to a cognitive scale happens in a nonlinear fashion. In this study we analyzed choice behavior in mice by investigating reward evaluation with respect to the dimensions "amount of reward" and "probability to receive a reward". To this end, we designed a two alternative forced choice experiment presenting individual mice with differently rewarding options using water from two water feeders as reward. We exposed the mice to four contexts with incongruent and neutral setups of reward dimension parameters to test if noneconomical

behavior could be observed. Our results show that the mice did not use absolute reward evaluation. Furthermore, the mice were only efficient in making economically correct decisions when exposed to options that varied in volume but not in probability.

1 Introduction

The study of animal decision making is a useful method for the study of economic decision making in humans (Kalenscher and van Wingerden, 2011). Traditionally, decision making models have assumed a rational decision maker who will always opt for the most profitable option. In this context, profitability is understood as an optimization process of maximizing benefits and minimizing costs (Schuck-Paim and Kacelnik, 2002). In natural environments, options usually vary in multiple dimensions. For example, an animal might have to decide between a foraging option A offering vast amounts of food on an infrequent basis and a foraging option B offering few amounts of food with certainty.

A common approach that allows comparisons between options varying in

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multiple dimensions is the assumption that animals use value based decision making. In this model, the decision maker assigns weights to each dimension and derives a single value for each option. Options are thereby reduced to a common currency referred to as utility. Assuming a rational decision maker this concludes that the common currency will be maximized within the decision process. In evolutionary terms the common currency for an animal has been assumed to be Net Energy Gain (NEG) or Fitness Level. Therefore, an animal will always try to optimize its energy intake or reproductive opportunities (Stephens and Krebs, 1986). However, recent studies have questioned the idea that humans and animals use rational based decision making. Various observations show that humans as well as other animals do not always make economical decisions (Cnaani et al., 2006; Kahneman and Tversky, 1979; Shafir and Yehonatan, 2014). To understand how noneconomical behavior can be explained, it is necessary to look at the cognitive aspects involved in the reward evaluation process. In order for an animal to evaluate rewards by value, it needs the ability to store obtained values in memory and it needs the ability to discriminate between options by the sensory information obtained. This requires a translation from the physical quantities of a reward to cognitive information (Nachev et al., 2013a,b). The relationship between physical and cognitive scales has been a major research area within the field of psychophysics and it has been found that the translation is often nonlinear (Nachev and Winter, 2012). Comparisons between options could occur on a physical or a cognitive scale which has to be accounted for, when forming theories of decision making. Context can have a strong impact on the value assigned to an option on a cognitive scale, while context would not affect the physical quantities of an option. For example, a food deprived animal presented with a specific food reward might later prefer this specific reward over a food reward of higher caloric potential. The information obtained in the food deprivation context might have been processed in a way so that the animal will continue to prefer this reward over other more rewarding options in the future. This example illustrates, that physical reward information are not sufficient to fully understand the processes involved in decision making. Context-dependent reward evaluation has been intensively studied in starlings as well as in hummingbirds and honey bees (Bateson et al., 2003; Kacelnik and Marsh, 2002; Pompilio and Kacelnik, 2010; Shafir et al., 2002). Due to the insufficiency of the absolute reward evaluation model, various alternatives have been proposed. Comparative reward evaluation assumes, that animals base their decisions on a priority dimension and only use in dimension comparisons (Shafir et al., 1993; Shafir and Yehonatan, 2014). Comparative reward evaluation would explain noneconomic behavior because even though the animal might take overall caloric value into account, its decision might differ from the optimal decision due to the impact of the priority dimension. For example, it was shown that deciding between nectar rewards in bumblebees is primarily influenced by sucrose concentration rather than by NEG (Cnaani et al., 2006). One advantage of comparative decision making is that it requires less computational effort, thus reducing

110 processing costs which could be beneficial
 111 for an animal. Comparative and context
 112 dependent reward evaluation offer possible
 113 explanations why objectively economic
 114 behavior is not always observed
 115 (Kahneman and Tversky, 1979; Shafir et al.,
 116 1993; Shafir and Yehonatan, 2014).
 117 Since we cannot directly measure subjective
 118 cognitive representations of rewards,
 119 researchers have instead focused on
 120 measuring behavioral output (Nachev et al.,
 121 2013b). In order to broaden our knowledge
 122 of when and how animals behave
 123 uneconomically, it is necessary to study a
 124 broad range of species.

125 Mice are fairly closely related to humans,
 126 show similar brain organization and
 127 economic behavior. Therefore, studies with
 128 mice could provide valuable insights to
 129 human decision making processes
 130 (de Visser et al., 2011; Zschummel, 2014).

131 The hypothesis that we test in the present
 132 study is that mice do not use absolute
 133 reward evaluation as it has been observed
 134 in bumblebees, starlings, humans and other
 135 species. To this end, we designed a
 136 two-alternative forced choice (2AFC)
 137 experiment presenting the mice with two
 138 differentially rewarding options. The
 139 rewards were provided by two water
 140 feeders that differed in the probability to
 141 give water and the water volume of a single
 142 reward. Naive mice have been observed to
 143 prefer probability over volume (Nachev,
 144 personal communication). In the present
 145 study we used non-naive mice that had
 146 previously been used in similar
 147 experiments. Assuming a learned certainty
 148 of eventual food rewards within the
 149 laboratory context we expected the mice's
 150 preference of probability over volume to
 151 decrease. We exposed the mice to four
 152 different contexts creating incongruent and
 153 neutral parameter conditions. If mice used

154 absolute reward evaluation and were able
 155 to distinguish between the relative
 156 intensities chosen for each dimension they
 157 should prefer the option that yielded the
 158 better average volume output. Each
 159 condition was tested for one day, followed
 160 by a reversal to avoid side biases. Our
 161 results are in accordance with our
 162 hypothesis and show that mice do not use
 163 absolute reward evaluation. Furthermore,
 164 mice decisions were only economically
 165 efficient when forced to decide between
 166 options that varied only within the volume
 167 dimension.

1 Methods

2 Experimental Setup

3 In our experiment we used 8 female
 4 non-naive laboratory mice of the strain
 5 C57Bl6/NHsd. The mice, which were 20
 6 weeks of age, had been used for similar
 7 behavioral experiments before.

8 The mice were housed isolated in
 9 individually ventilated cages (IVCs). Each
 10 cage contained two water feeders which
 11 would be activated through nose pokes,
 12 while the water volume and reward
 13 probability could be programmed
 14 individually. The recorded information
 15 comprise the nose pokes on each feeder,
 16 together with a time stamp, the duration of
 17 each event and whether a reward was given
 18 or not. Further details on the cage setup as
 19 well as on the handling of the mice are
 20 found in Becker et al. (2016) and Clos et al.
 21 (2016). Differing from the experiments
 22 performed in those studies, we did not add
 23 any time delay or timeout. We also
 24 removed any separating walls between the
 25 feeders as we had observed them to cause
 26 strong left side biases.

27 Our experiment was designed, executed

28 and pre-evaluated as a collaborative work
 29 together with Sophie Leineweber, Falk
 30 Mielke and Nicola Vallon.

31 The experiment was designed so that the
 32 reward volumes differed between the two
 33 feeders. However, relative volume
 34 intensities were kept constant throughout
 35 the experiment and only the reward
 36 probabilities were varied instead. For the
 37 reverse experiments we swapped the
 38 parameters between the left and right
 39 feeder. The general idea was to subject the
 40 mice to four different setups in regard of
 41 the relative intensity ratio for volume $I_r(v)$
 42 and probability $I_r(p)$. In all our setups the
 43 probability dimension opposed the volume
 44 dimension so that the greater reward
 45 volume was combined with the lower
 46 probability and vice versa. We created three
 47 incongruent setups, where the $I_r(p)$
 48 differed from the $I_r(V)$ and one neutral
 49 setup where the $I_r(p)$ was equal to the
 50 $I_r(V)$ (Table 1). The relative intensities were
 51 calculated on the basis of equation 1.

$$I_r(x) = \frac{|x_1 - x_2|}{\frac{x_1 + x_2}{2}} \quad (1)$$

52 with x: conditions on the different
 53 feeders

54 We decided on the relative intensities to use
 55 in accordance with a psychometric curve
 56 obtained from previous experiments
 57 (Nachev and Rivalan, personal
 58 communication), fitted with a Weibull
 59 distribution (Weibull, 1951) (Figure 1).

60 Experimental Schedule

61 The mice were split into two groups of four
 62 mice, participating on our experiment for
 63 nine days one group at a time. Before the
 64 actual experiment started, the mice were
 65 given one day to adapt to their cages,
 66 without any differences on the reward

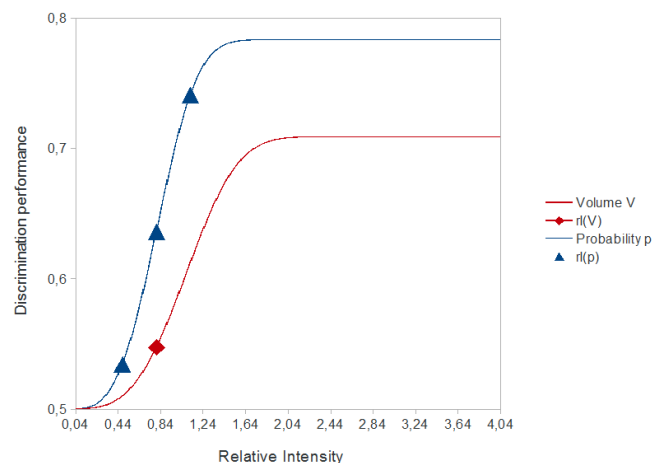


Figure 1: Psychometric function based on which the relative intensities were chosen. The relative intensities were chosen to cover the slope of the function, chosen values are indicated by different symbols for both used dimensions.

Table 1: Experimental setup, chosen values for the relative dimensions for volume and probability.

$I_r(V)$	$I_r(p)$	$I_r(p)/I_r(V)$	Setup
0.8	0.0	0.0	incongruent
0.8	0.5	0.6	incongruent
0.8	0.8	1.0	neutral
0.8	1.1	1.4	incongruent

67 volume between the feeders and a
 68 probability of one on both. Afterwards, the
 69 four setups were applied in a random order
 70 thus that ascending and descending orders
 71 of relative intensities were avoided and no
 72 mouse would get the same setup as another
 73 on the same day. Each setup was followed
 74 by its reversal the next day, to avoid side
 75 biases.

76 For the first group of mice, reward
 77 probabilities between 0.26 and 0.9 were
 78 chosen. Since we observed a lack of
 79 learning behavior we lowered the
 80 probabilities for the second group to values

81 between 0.1 and 0.35, hoping to thereby
 82 enforce learning behavior. The exact values
 83 are listed in Table 2.

Table 2: Values for volume and probability for both groups of mice

Feeder	Volume [ml]	Group 1 Probability	Group 2 Probability
1	6	0.3	0.15
2	14	0.3	0.15
1	6	0.5	0.25
2	14	0.3	0.15
1	6	0.7	0.35
2	14	0.3	0.15
1	6	0.9	0.35
2	14	0.26	0.1

84 At 4 pm each day the new set of
 85 experiments was started, the mice then had
 86 water access under the listed conditions for
 87 18 hours, during their nocturnal phase. To
 88 better understand the behavior of our mice,
 89 we captured two mice on video under
 90 infrared light during one night.

91 Data Analyses

92 We collected and distributed our data using
 93 an SQLite database (Hipp et al., 2015) as
 94 well as a GitHub account (GitHub Inc.,
 95 2015). Data Analysis has been done using R
 96 (R Core Team, 2015).

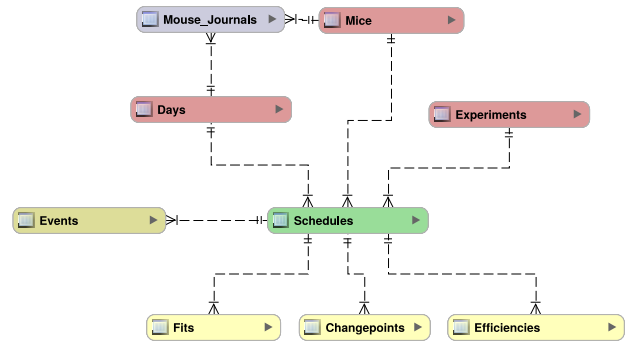


Figure 2: Structure of the database used for data analysis, which has been set up by Falk Mielke. The data as well as our analysis are accessible through GitHub as referenced below.

97 The collected data can be accessed via
 98 `https://github.com/falkm/mus_oeconomicus`.
 99 `//github.com/falkm/mus_oeconomicus`.
 100 The structure of the database is presented
 101 in Figure 2.

1 Results

2 Throughout the experiment all mice showed
 3 strong side biases while the side preferences
 4 varied for different mice. The alteration of
 5 the settings for the second group of mice
 6 even increased those biases. Mathematically,
 7 we broadly eliminated them by averaging
 8 over reverse experiments. However it is not
 9 possible to fully dispose of other influences
 10 besides the different rewarding options.

11 As can be seen on our video footage, the
 12 mice regularly poked repeatedly at the
 13 same feeder or sometimes switched freely
 14 between feeders, as there were no walls to
 15 hinder them. This behavior has been
 16 captured on video (see Appendix). In
 17 consequence we excluded events which
 18 occurred within a threshold of 4 seconds
 19 from the prior event.

20 Learning behavior

21 We had planned to analyse the learning
 22 behavior by calculating the cumulated

23 water intake over time or trials for the
 24 different mice under the varying settings.
 25 However, in the majority of cases, our
 26 results do not indicate a clear learning
 27 behavior over one testing period (one day
 28 each).

29 Instead, we did a changepoint analysis,
 30 using the approach proposed by Gallistel
 31 et al. (2004), by firstly calculating the
 32 cumulated sum of events at the feeder with
 33 the higher water volume (V_+) over trials,
 34 then calculating the change points and
 35 subsequently the slopes between them
 36 (Gallistel et al., 2004). A changepoint in this
 37 context is the point where the behavior
 38 changes, indicated by a change in the slope.
 39 It is calculated for each point as the earlier
 40 point that deviates maximally from the
 41 straight line between the start of the record
 42 and the latest point. For this calculation the
 43 R function "cp_wrapper" from the package
 44 "cpdetector" has been used (Nachev, 2015).
 45 We applied a binominal test with a decision
 46 criterion of $p=0.15$. The slope between the
 47 last two change points (the last relevant
 48 slope) was used for further analysis. As an
 49 event at the feeder V_+ counts plus one and
 50 an event at the feeder V_- counts as zero,
 51 ideally a steep slope would be expected if
 52 the volume favored side provides the
 53 (objectively) better option and a flat slope
 54 otherwise. An exemplary fit is illustrated in
 55 Figure 3.

56 For further analysis, we averaged the
 57 respective last slopes over those from the
 58 reversed experiments and then plotted our
 59 data for the $I_r(p)$ (Figure 4). Even if single
 60 mice adapted diversely to the different
 61 conditions, overall no significant variance
 62 can be detected (using ANOVA, binominal).
 63 A mean slope around 0.5 indicates that the
 64 feeders on average had been chosen
 65 randomly. There is no exception for any
 66 condition. However, the data are widely

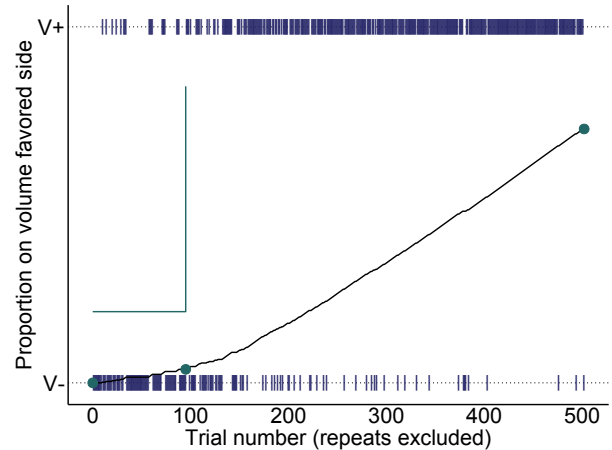


Figure 3: Exemplary changepoint analysis with equal probability on both feeders, cumulated sum of events at volume favored feeder. In this case, a change in the mouse's behavior after approximately 100 trials can be observed. This is reflected in the stepwise learning curve.

67 scattered for any condition that was tested,
 68 and individual mice reacted differently to
 69 the same conditions.

70 The absence of a clear learning effect in
 71 conjunction with the strong side biases led
 72 us to examine the explorative behavior of
 73 our mice over an expanded period of time,
 74 supposing they might integrate over longer
 75 timescales than the duration of one
 76 experimental setting (one day).

77 Therefore, for each day and each mouse, we
 78 calculated the ratio of events at the less
 79 frequented feeder to events at the preferred
 80 one. Then for each day, counting the day a
 81 mouse started to participate in the
 82 experiment as day one, we averaged over
 83 the event ratios from the different mice.
 84 Figure 5 illustrates how these mean ratios
 85 changed over the days of the experiment.

86 A higher mean events ratio means that the
 87 mice were more explorative that day. As
 88 illustrated by Figure 5(a), if averaged over
 89 all 8 mice, the mean events ratio decreases
 90 over the days of experiment, meaning that
 91 the mice explored less over time. In Figure

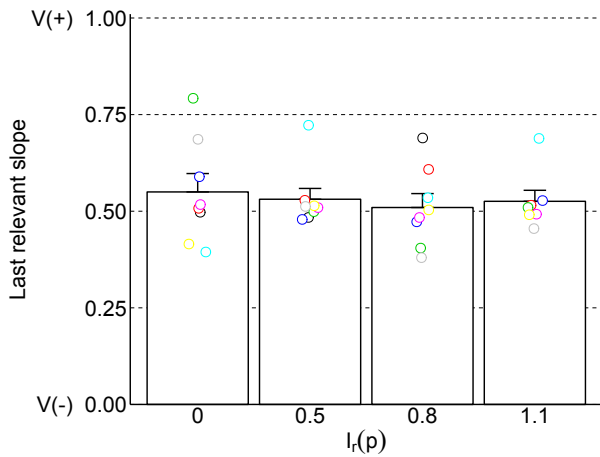
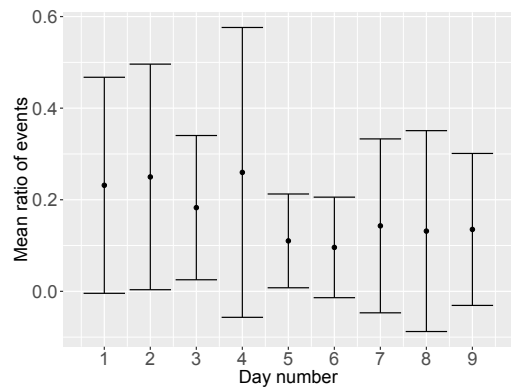
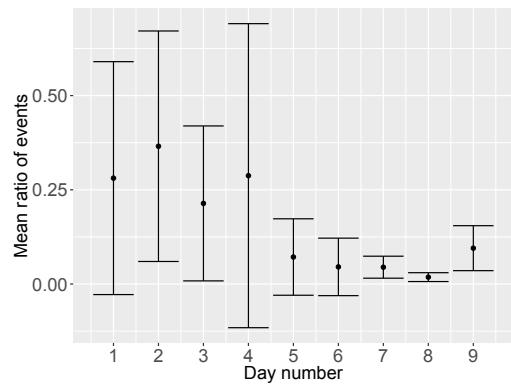


Figure 4: Slope analysis for different $I_r(p)$. Dots represent single datapoints, each color represents one mouse. The economical choices would have been: Feeder V_+ for $I_r(p) = 0.0$ and $I_r(p) = 0.5$ (slope > 0.5), feeder V_- for $I_r(p) = 1.1$ (slope < 0.5) and both feeders equally for $I_r(p) = I_r(V) = 0.8$ (slope ≈ 0.5). Nonetheless no significant variance could be detected (tested with ANOVA). A mean slope around 0.5 indicates that the feeders on average had been chosen randomly.

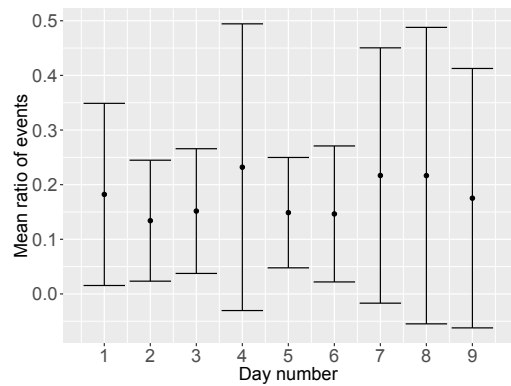
92 5(b) and 5(c) the two groups of mice are
 93 presented separately. Since there were only
 94 4 mice in each group, no statistical
 95 approaches can be made for those two
 96 separate groups. Even so, we wanted to
 97 examine the behavior of each group
 98 because the lower probabilities, which have
 99 been used as parameter settings in the
 100 second group, might have influenced the
 101 mice's behavior crucially. The plots indeed
 102 indicate that group 1 is mainly responsible
 103 for the decrease over time in 5(a) while no
 104 clear conclusion on the explorative
 105 behavior over time for group 2 is possible.
 106 All in all, the mean ratios for group 2 are
 107 lower than in group 1 and the explorative
 108 behavior possibly even increased over time.



(a) Averaged over all mice



(b) Averaged over group 1



(c) Averaged over group 2

Figure 5: Exploration behavior over days of the experimental phase, illustrated by the ratios of events and their standard deviation. (a) Events ratio - averaged over all 8 mice - decreases over the days of experiment. (b) Events ratio averaged over the 4 mice from group 1, who seem to be mainly responsible for the decrease over time in (a). (c) Events ratio averaged over the 4 mice from group 2. No clear tendency over time, mean ratios are lower than in group 1.

109 **Efficiency**

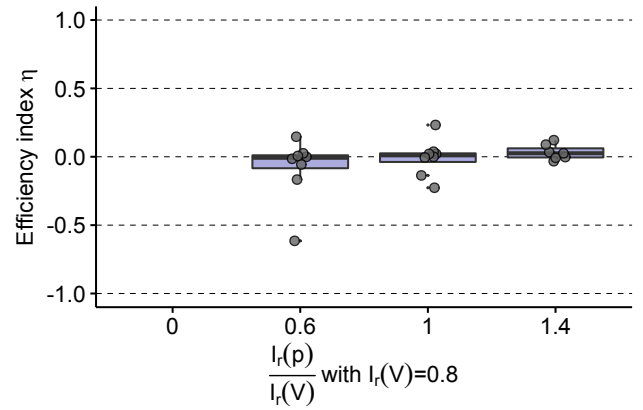
110 Due to the lack of a clear learning effect, we
 111 decided against a psychometrical analysis.
 112 Instead we calculated the efficiency of the
 113 mice under the different reward parameter
 114 conditions, regarding the dimensions
 115 Volume and Probability as well as the
 116 combination of the two dimensions,
 117 Volume×Probability.

118 To calculate the efficiencies, we first
 119 calculated the sum of the infimum,
 120 supremum and the actual drinking
 121 performance over the events for volume,
 122 probability and the combination of both
 123 (volume×probability). The infimum being
 124 the lowest possible value the mouse might
 125 have chosen, the supremum being the
 126 highest possible value and the actual
 127 drinking performance being the option the
 128 mouse actually did choose. We then
 129 calculated the efficiency index using
 130 equation 2. A high efficiency index
 131 indicates that the mice did prefer the better
 132 option in regard to the chosen dimension, a
 133 negativ index indicates that the mice
 134 preferred the other one while an index
 135 around 0 indicates that the mice treated
 136 both options equally.

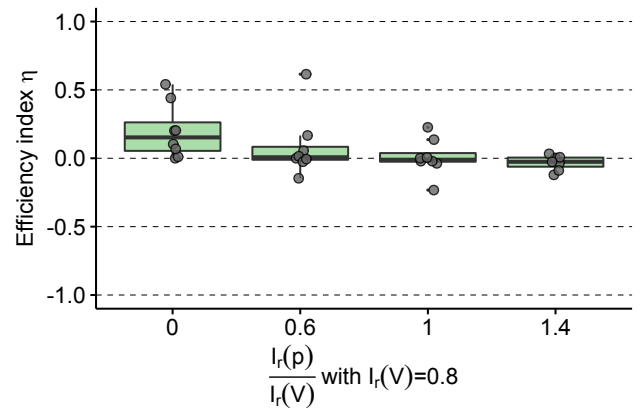
$$\eta(x) := 2 \times \frac{x - \inf(x)}{\sup(x) - \inf(x)} - 1 \quad (2)$$

137 with $x \subset \{V, p, Vp\}$

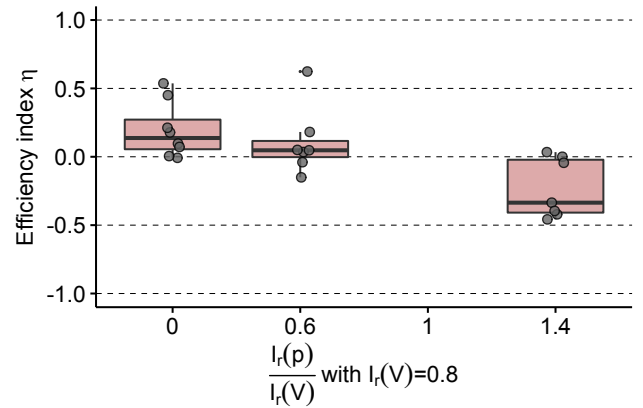
138 The results are presented in Figure 6.
 139 While there is no significant difference in
 140 the efficiency index, in regard to the
 141 dimension probability - for each
 142 $I_r(p)/I_r(V)$ the index stays around 0 -
 143 there is a difference in regard to the
 144 dimensions volume and
 145 volume×probability. The smaller the
 146 $I_r(p)/I_r(V)$, which means an $I_r(p)$ near 0,
 147 the more efficient were the mice in regard
 148 to the dimension of volume, while they



(a) regarded dimension: probability



(b) regarded dimension: volume



(c) regarded dimension: volume×probability

Figure 6: Efficiencies for different $I_r(p)/I_r(V)$, regarding (a) probability, (b) volume and (c) volume×probability. The results indicate that the mice treat the dimension of probability randomly and only distinguish for volume if $I_r(p)/I_r(V) \approx 0$. Regarding the combined dimensions, the mice are highly inefficient, when $I_r(p)/I_r(V)$ is highest.

149 started choosing randomly if the $I_r(p)$
 150 increased. Regarding the combined
 151 dimensions volume \times probability this means
 152 the mice have been efficient for a
 153 $I_r(p)/I_r(V)$ around 0 but are highly
 154 inefficient for a $I_r(p)/I_r(V)$ around 1.4
 155 where the $I_r(p)$ is largest. Nonetheless, the
 156 data again are widely scattered and single
 157 mice performed differently.

1 Discussion

2 Our findings support the initial hypothesis
 3 that mice do not use absolute reward
 4 evaluation. If so, they would have been
 5 expected to choose the altogether more
 6 profitable option more frequently
 7 throughout all tested conditions. However,
 8 as our efficiency analysis shows (see Figure
 9 6), this was not the case. Not choosing the
 10 economically correct option more often
 11 than other options based on a universal
 12 "currency" has also been observed in other
 13 species (Bateson et al., 2003; Cnaani et al.,
 14 2006; Shafir et al., 2002). The universal
 15 currency to compare different options
 16 across various dimensions is usually NEG,
 17 as is the case for our experiments, because
 18 the mice only eat when having access to
 19 water.

20 Slope analysis revealed that, on average, all
 21 mice did choose both available reward
 22 options as if by chance and independently
 23 from relative intensity of probability. This
 24 observation was also apparent in the
 25 efficiency analysis, solely when
 26 probabilities of both feeders were equal
 27 did the mice choose the economically more
 28 profitable option more frequently and thus
 29 achieved an above average total water
 30 intake. This behavior implies that, for equal
 31 probabilities, they were able to discriminate
 32 between the offered options and identify
 33 the more rewarding choice. As this was not

34 the case for the other settings, we could
 35 assume that our mice were not able to
 36 discriminate the offered choices when
 37 probability came into play. This inability
 38 could be due either to the introduction of
 39 another dimension or, in particular, that
 40 this dimension was probability. However,
 41 in earlier experiments mice were able to
 42 differentiate between choices that differed
 43 in probability (Zschummel, 2014; Nachev
 44 and Rivalan, personal communication).
 45 Another explanation for the lower
 46 efficiencies associated with the probability
 47 dimension could be that the mice were able
 48 to discriminate between the offered options,
 49 but the differences were not relevant to
 50 them. However, it should seem more
 51 reasonable to assume that discriminating
 52 between probabilities rather than differing
 53 volumes would be important to mice, as the
 54 water sources encountered in natural
 55 environments do not require a good ability
 56 to discriminate volume due to their usually
 57 large amount of water (Zschummel, 2014).
 58 Alternatively, the observed behavior could
 59 have been driven by influences unrelated to
 60 our setup and thus uncontrollable by us.
 61 Such influences can rarely be ruled out
 62 completely when studying mice, as they
 63 are complex animals, though well-studied,
 64 and their behavior is often obscure.

65 It is notable that the mice tested in the first
 66 week explored the offered choices more in
 67 the earlier days of testing, with an
 68 increasing side bias towards the end of the
 69 experimentation phase (Figure 5b). The
 70 mice tested in the second week were less
 71 explorative altogether and did not show a
 72 decrease or increase in their exploration
 73 behavior over time. The higher exploration
 74 habit in the mice of week 1 might indicate
 75 that they integrated the rewards over a
 76 longer period than one day and came to
 77 choose one favorite feeder after some time.

78 A possible reason for the differing 122 much effort. Other changes to increase the
 79 exploration behavior between the two 123 physical effort for the mice to reach the
 80 groups could have been the altered 124 feeders could be considered, e. g. placing
 81 conditions. In the first week, the mice 125 the feeders further apart or making them
 82 might not have felt pressured enough to 126 less accessible by placing them higher up.
 83 choose a preferred feeder, because they 127 This way the mice would have to climb up
 84 received sufficient water from both feeders 128 first (which they are able to, as can be seen
 85 regardless of treatment. In the second 129 in the video footage) and therefore would
 86 group, however, due to much lower 130 require much more effort and energy to
 87 probabilities the pressure to select an 131 access the feeder, which could presumably
 88 option was considerably higher and 132 lead to a greater desire to make the
 89 therefore the mice from week 2 might have 133 economically right choice. Additionally, to
 90 been forced to reconsider their choice more 134 prevent repeated nose pokes, a delay of
 91 often. Another strategy which could be 135 rewards rather than probability could be
 92 considered influential here is win-stay; a 136 introduced, or, an activation key added,
 93 more explorative behavior during the 137 resultinh in the necessity to carry out
 94 beginning of an experimental phase, as has 138 another activity first to activate either one
 95 been observed for the mice from week 1, 139 of the feeders, e. g. another poke hole
 96 has been found for rats in an earlier study 140 located somewhere else in the cage.
 97 (Moustgaard and Hau, 2009). For the mice 141 Furthermore, future studies should include
 98 of the second week, which had already 142 congruent settings, as this might shed light
 99 been exposed to another choice-experiment 143 on the discrimination ability of mice
 100 in the prior week, it could be possible that 144 regarding different dimensions. If mice still
 101 they had already developed a win-stay 145 do not perform above average with
 102 strategy during the preceding experiment, 146 congruent settings, this would mean that
 103 which they applied in our experiment. 147 the lower efficiency for all settings
 104 However, as the mice in general did not 148 including a relative intensity of probability
 105 perform well in discriminating between 149 over zero in this study, is due to the
 106 offered options and thus choosing the more 150 introduction of another (random)
 107 rewarding one, other factors have to be 151 dimension. Since we do not know if the
 108 considered. Side preferences were apparent 152 underlying reason for the lacking efficiency
 109 in all mice, but do not generally distort the 153 regarding all settings including a relative
 110 results as long as sampling still occurred - 154 intensity of probability over zero, is the
 111 assuming, of course, that the mice based 155 introduction of the dimension 'probability'
 112 their decisions on the used dimensions. 156 or only the introduction of another
 113 Still, to reduce side bias and enforce a 157 dimension, the mice should be tested with
 114 stronger need to choose between options, 158 several different dimensions. To conduct a
 115 the initial short walls between the nose 159 psychometric analysis, both used
 116 poke-holes could be reintroduced to 160 dimensions should be tested with
 117 separate each hole and another short wall 161 congruent conditions, with the relative
 118 could be added instead of the long wall 162 intensity for one dimension set to zero
 119 from the initial setup. This way, the mice 163 constantly, while varying the I_{rel} of the
 120 would not be able to just sit in front of the 164 other.
 121 feeders and switch between them without 165 Keeping the mice in single cages could

166 have also influenced them in some way; on
 167 the one hand, they were not in competition
 168 with other mice for the water rewards,
 169 which might have led them to decide more
 170 freely. On the other hand, they could still
 171 see the neighboring mice through the
 172 plastic walls of their cages which might
 173 have had an influence. Furthermore, mice
 174 are social animals, therefore keeping them
 175 in single cages might affect their (choice)
 176 behavior.

177 Summary

178 As hypothesized earlier, our results show
 179 that mice do not use absolute reward
 180 evaluation. To find out, if mice can
 181 superiorly discriminate volume rather than
 182 probability or if incongruent conditions or
 183 the mix of two dimensions blocked the
 184 ability to discriminate probability, further
 185 research is necessary.

1 References

2 Bateson M, Healy SD, Hurly TA (2003). Context-
 3 dependent foraging decisions in rufous
 4 hummingbirds. P Roy Soc London
 5 270:1271–1276

6 Becker E, Eltner F, Kraft J, Mieske P (2016). Mice
 7 exhibit side-biased behavior in a decision-
 8 making task under risk. *Gruppe 1B*

9 Clos C, Haas K, Jusyte M, Púčiková V (2016).
 10 Assessment of immediate and long-term
 11 advantages and disadvantages of mice on
 12 a RGT-inspired gambling task. *Gruppe 1A*

13 Cnaani J, Thomson JD, Papaj DR (2006)
 14 Flower choice and learning in foraging
 15 bumblebees: effects of variation in nectar
 16 volume and concentration. *Ethology*
 17 112:278–285

18 de Visser L, Homberg JR, Mitsogiannis M, Zeeb
 19 FD, Rivalan M, Fitoussi A, Galhardo V,

20 van den Bos R, Winstanley CA, Dellu-
 21 Hagedorn F (2011) Rodent versions of
 22 the iowa gambling task: opportunities
 23 and challenges for the understanding of
 24 decision-making. *Front Neurosci* 5:109

25 Gallistel CR, Fairhurst S, Balsam P (2004)
 26 The learning curve: implications of a
 27 quantitative analysis. *P Natl Acad Sci USA*
 28 101:13124-31

29 GitHub Inc. (2015) GitHub. <https://github.com/>
 30

31 Hipp R, Kennedy D, Mistachkin J (2015) SQLite
 32 (Version: 3.10). SQLite Development Team

33 Kacelnik A, Marsh B (2002) Cost can increase
 34 preference in starlings. *Anim Behav* 63:245–
 35 250

36 Kalenscher T, van Wingerden M (2011) Why
 37 we should use animals to study economic
 38 decision making - a perspective. *Front*
 39 *Neurosci* 5:82

40 Moustgaard A, Hau J (2009) Introduction of
 41 habits in rats by a forced-choice procedure
 42 in T-maze and the effect of pre-test free
 43 exploration. *Behav Process* 81:104-107

44 Nachev V (2015) cpdetectorr: Change point
 45 estimation from sequences of choices.

46 Nachev V, Stich KP, Winter Y (2013) Weber's law,
 47 the magnitude effect and discrimination
 48 of sugar concentrations in nectar-feeding
 49 animals. *PLoS one* 8:e74144

50 Nachev V, Thomson JDJ, Winter Y (2013)
 51 The psychophysics of sugar concentration
 52 discrimination and contrast evaluation in
 53 bumblebees. *Anim Cogn* 16:417-427

54 Nachev V, Winter Y (2012) The psychophysics
 55 of uneconomical choice: non-linear reward
 56 evaluation by a nectar feeder. *Anim Cogn*
 57 15:393–400

- 58 Pompilio L, Kacelnik A (2010) Context-
 59 dependent utility overrides absolute
 60 memory as a determinant of choice. *P Natl*
 61 *Acad Sci USA* 107:508–12
- 62 Kahneman D, Tversky A (1979) Prospect
 63 theory: an analysis of decision under risk.
 64 *Econometrica* 47:263–291
- 65 R Core Team (2015) R: A language and
 66 environment for statistical computing.
 67 R Foundation for Statistical Computing,
 68 Vienna, Austria
- 69 Schuck-Paim C, Kacelnik A (2002). Rationality in
 70 risk-sensitive foraging choices by starlings.
 71 *Anim Behav* 64:869–879
- 72 Shafir EB, Osherson DN, Smith EE (1993)
 73 The Advantage Model: A Comparative
 74 Theory of Evaluation and Choice under
 75 Risk. *Organ Behav Hum Dec* 55:325–378
- 76 Shafir S, Waite TA, Smith BH (2002). Context-
 77 dependent violations of rational choice
 78 in honeybees (*Apis mellifera*) and gray
 79 jays (*Perisoreus canadensis*). *Behav Ecology*
 80 *Sociobiol* 51:180–187
- 81 Shafir S, Yehonatan L (2014) Comparative
 82 evaluations of reward dimensions in honey
 83 bees: evidence from two-alternative forced
 84 choice proboscis-extension conditioning.
 85 *Anim Cogn* 17:633–644
- 86 Stephens DW, Krebs JR (1986) Foraging theory.
 87 Princeton University Press
- 88 Weibull, WA (1951) Statistical Distribution
 89 Function of Wide Applicability. *J Appl*
 90 *Mech*
- 91 Zschummel, M (2014) Discrimination of
 92 reward-volumes and -probabilities in *Mus*
 93 *musculus*.

1 Appendix

2 Video

3 http://amor.cms.hu-berlin.de/~mielkefa/Sem9/CEB/20151208_165418_Mouse83all.mp4

4 • At 10:40 repeated nose poking behavior and feeder changing can be observed.

5 Source Code

6 The relevant source code for this paper accessed through
7 https://github.com/Claartje/ceb_paper_1/tree/master/paper/relevant%20Code

8

9 The code for the calculation of the mean events ratios is given as an example below:

10

```

11 ##### Connection to database - Code from Falk Mielke #####
12 ## in this example, the dplyr way is chosen.
13 require('dplyr')
14
15 ##### database connection #####
16 ## go to the folder of the current file
17 setwd(dirname(parent.frame(2)$ofile))
18
19 ## load the SQL interface helpers
20 source('../././database/SimplerSQLQuery.r')
21
22 ## connect the database, in this case you choose to return a dplyr tbl object
23 sql_connection <- SQL_TBL$new(drv = RSQLite::SQLite(),
24 dbname = "../././database/data.db")
25 if(!sql_connection$connected) print ("something went wrong! no connection.")
26
27 # print(sql_connection$tables)
28
29 ## load the tables with master data
30 experiments = sql_connection$LoadTable("Experiments")
31 schedule = sql_connection$LoadTable("Schedules")
32 days = sql_connection$Run("SELECT day_nr,
33 start_date,
34 block FROM Days;") # alternative: run an SQL query
35
36 ## load the data table
37 events = sql_connection$LoadTable("Events")
38 events$date_time <- as.POSIXct(strptime(events$date_time, "%Y-%m-%d %H:%M:%S"))
39 # (unfortunately, SQLite is incapable of reliable date/time handling.
40 # Was saved as string.)

```

```

41
42 mice = sql_connection$LoadTable("Mice")
43
44 ## when everything's done with SQL:
45 sql_connection$Close()
46
47 ##### Claculate ratio of events - Code from Clara Jongen #####
48 #merge tables
49 alldata<-merge(experiments,schedule)%>%
50 merge(days)%>%
51 merge(events)%>%
52 merge(mice)
53
54 #Count Number of events
55 data<-alldata%>%
56 filter(exclude==F)%>%
57 group_by(day_nr,mouse_nr,side)
58
59 eventsSummary<-summarise(data, length(event_duration_s))
60
61 #filter for events on left and right side
62 eventsLeft<-eventsSummary%>%
63 filter(side=="l")%>%
64 group_by(day_nr,mouse_nr)
65
66 eventsRight<-eventsSummary%>%
67 filter(side=="r")%>%
68 group_by(day_nr,mouse_nr)
69
70 ####Calculate ratio events
71 # divide number of events on less prefered side
72 # through number of events on prefered side
73
74 eventsRatio<-(ifelse(eventsLeft$`length(event_duration_s)`>
75 eventsRight$`length(event_duration_s)` ,
76 eventsRight$`length(event_duration_s)`/eventsLeft$`length(event_duration_s)` ,
77 eventsLeft$`length(event_duration_s)`/eventsRight$`length(event_duration_s)` ) )
78
79 eventsRatio<-data.table(cbind(eventsLeft$day_nr,eventsLeft$mouse_nr,eventsRatio))
80 names(eventsRatio)[1]<-c("day_nr")
81 names(eventsRatio)[2]<-c("mouse_nr")
82
83 #split tables for mice of first and second week
84 eventsRatio_mice1<-eventsRatio%>%

```



```

85 subset(mouse_nr==1|mouse_nr==2|mouse_nr==3|mouse_nr==4)%>%
86 mutate(day_nr=day_nr-1)
87 eventsRatio_mice2<-eventsRatio%>%
88 subset(mouse_nr==5|mouse_nr==6|mouse_nr==7|mouse_nr==8)%>%
89 mutate(day_nr=day_nr-9)
90
91 ###calculate mean events ratios
92 #for mice of first week
93 mean_mice1<-eventsRatio_mice1%>%group_by(day_nr)%>%
94 summarise(mean=mean(eventsRatio),
95 st_deviation=sd(eventsRatio))%>%
96 mutate(lower=mean-st_deviation,
97 upper=st_deviation+mean)
98
99 #for mice of second week
100 mean_mice2<-eventsRatio_mice2%>%group_by(day_nr)%>%
101 summarise(mean=mean(eventsRatio),
102 st_deviation=sd(eventsRatio))%>%
103 mutate(lower=mean-st_deviation,
104 upper=st_deviation+mean)
105
106 #calculate mean ratio over mice of all weeks
107 meanMice<-full_join(eventsRatio_mice1,eventsRatio_mice2)%>%
108 group_by(day_nr)%>%
109 summarise(mean=mean(eventsRatio),
110 st_deviation=sd(eventsRatio))%>%
111 mutate(lower=mean-st_deviation,
112 upper=st_deviation+mean)
113
114 #####Plot Data#####
115 require('ggplot2')
116
117 # Plot for all mice
118
119 meanMice %>% ggplot(aes(day_nr,mean)) +
120 xlab("Day number") +
121 ylab("Mean ratio of events") +
122 scale_x_continuous(breaks = 1:9) +
123 geom_point()+
124 geom_errorbar(aes(ymin = lower,
125 ymax = upper))->meanMicePlot
126 print(meanMicePlot)
127 ggsave( sprintf("meanMice.pdf")
128 , plot = meanMicePlot

```

```
129 , width = 16
130 , height = 12
131 , units = "cm"
132 , dpi = 150
133 , device = cairo_pdf
134 )
135
136 #Plot for mice of first week
137
138 mean_mice1 %>% ggplot(aes(day_nr,mean)) +
139 xlab("Day number") +
140 ylab("Mean ratio of events") +
141 scale_x_continuous(breaks = 1:9) +
142 geom_point() +
143 geom_errorbar(aes(ymin = lower,
144 ymax = upper))->meanMice1Plot
145 print(meanMice1Plot)
146 ggsave( sprintf("meanMice1.pdf")
147 , plot = meanMice1Plot
148 , width = 16
149 , height = 12
150 , units = "cm"
151 , dpi = 150
152 , device = cairo_pdf
153 )
154
155 #Plot for mice of second week
156
157 mean_mice2 %>% ggplot(aes(day_nr,mean)) +
158 xlab("Day number") +
159 ylab("Mean ratio of events") +
160 scale_x_continuous(breaks = 1:9) +
161 geom_point() +
162 geom_errorbar(aes(ymin = lower,
163 ymax = upper))-> meanMice2Plot
164 print(meanMice2Plot)
165 ggsave( sprintf("meanMice2.pdf")
166 , plot = meanMice2Plot
167 , width = 16
168 , height = 12
169 , units = "cm"
170 , dpi = 150
171 , device = cairo_pdf
172 )
```

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Role Assignment

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