No simple link between temporal discounting and body composition

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Abstract

Impulsive traits, broadly construed, are thought to play a role in under- and overweight. For example, the behavioural economic factor of delay discounting, which describes preferences between smaller sooner and larger later rewards, is thought to be predictive of body composition. However, the evidence base is mixed, consisting of studies with varying methodological approaches and effect sizes. Two studies ($N = 384$ and 401) explored the potential relationships between discounting for money, weight loss, and food rewards to body mass index or waist-to-height ratio measures. Three proposals are considered: 1) that discounting and body composition are correlated, 2) that discounting influences body composition even after accounting for the confounder of age, and 3) that discounting moderates the rate of weight gain over time. Using Bayesian methods, we find evidence against all 3 proposals for discounting of multiple commodities and two different measures of body composition. We test, and dismiss, the possibility that lack of evidence is due to higher evidence thresholds in Bayesian than Frequentist methods. These findings and the varied results in the literature suggest that if discounting and body composition are associated, it is probably through complex indirect pathways of mediating variables.

Keywords: Behavioural economics, temporal discounting, delay discounting, inter-temporal choice, body mass index, waist to height ratio, obesity, underweight.

Introduction

Obesity and under-weight are complex and widespread problems facing many societies. In the search to understand the behavioural factors contributing to these problems, impulsivity has emerged as a candidate involved in the onset and maintenance of obesity in particular, in children (Thamotharan, Lange, Zale, Huffhines, & Fields, 2013) and adults (Emery & Levine, 2017). Impulsivity however is a broadly defined personality construct consisting of many dimensions – there is disagreement about how to conceptualise the impulsivity construct but Sharma, Karkon, and Clark (2014) propose a 4-factor structure of inattention, inhibition, set shifting, and impulsive decision making. Our use of temporal discounting (how we value smaller sooner or

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Figure 1: Conceptual diagrams of the 3 proposals examined. Proposal 1: Does discount rate correlate with body composition (top)? Proposal 2: Does discount rate (along with other factors such as age) influence body composition (middle)? Proposal 3: Do discount rates moderate the rate of weight gain with age (bottom) in addition to option direct effects on body composition? This latter hypothesis is supported if an interaction between age and discount rate is found.

larger later rewards) of various commodities represents a focus on this latter impulsive decision making component.

Many studies on this topic could be thought of as evaluating Proposal 1 – that discount rates are associated with body composition (Figure 1, top), using either a correlational or a case-control approach with different BMI groups. Other studies assess Proposal 2 – that there is an association between discounting and BMI even when accounting for other predictor variables (Figure 1, middle) using a regression approach. Here we focus on age due to the robust finding that average BMI increases with age (Sutin, Ferrucci, Zonderman, & Terracciano, 2011). We could also test Proposal 3 – that higher discounting leads to behaviours resulting in a faster rate of BMI gain with age (Figure 1, bottom).

The role of discounting in obesity has been the focus of much attention, with 3 recent meta analyses, assessing Proposal 1, all finding modest effect sizes (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; McClelland et al., 2016; Tang, Chrzanowski-Smith, Hutchinson, Kee, & Hunter, 2018). However, all of these meta analyses highlight study heterogeneity as a concern – that is, the discounting studies use an array of different approaches, methods of measuring discount rates and discounting measures reported. For example, some use fixed questionnaire methods while others use adaptive computer based methods. Some report discount rate, some log transformed discount rate, and others the Area Under Curve (Myerson, Green, & Warusawitharana, 2001). Given this, it is unlikely that component studies can be considered as independent measurements of one underlying population level effect size. So while incredibly useful, meta analytic results require careful and cautious interpretation – differences between

participants, methodologies, or measures are likely to influence the true population level effect sizes.

In addition to this, even when solely focussing on findings published in 2020, there are a non-trivial set of studies reporting no association between discounting and BMI. [Myers, Beyl, Martin, Broyles, and Katzmarzyk \(2020\)](#) failed to find significant differences in discounting between obese/overweight and normal weight participants, controlling for level of food security. [Temple, Ziegler, Crandall, Mansouri, and Epstein \(2020\)](#) and [Balantekin, Ziegler, Crandall, and Temple \(2020\)](#) failed to find a significant correlation between BMI and delay discounting in a sample of non-obese adolescents. [Ross et al. \(2020\)](#) concluded that measures of impulsivity (including discounting) have limited clinical utility within behavioural weight management interventions. [Bjorlie and Fazzino \(2020\)](#) found that while some measures of impulsivity were associated with increases in a body roundness index in college freshmen, discounting was not. In a randomised control trial with weight loss intervention, [Pastore, Schurer, Tymula, Fuller, and Caterson \(2020\)](#) found no statistically significant correlation with BMI in adults with obesity and pre-diabetes. [Hollis-Hansen et al. \(2020\)](#) failed to find a statistically significant correlation between discounting and BMI in mothers. [Chang, Claassen, and Klein \(2020\)](#) found that neither discounting of money nor discounting of food rewards were statistically significantly correlated with BMI. And [Veillard and Vincent \(2020\)](#) provided evidence against Proposals 1, 2, and 3 using Bayesian analysis methods ¹.

There are, however, still compelling reasons why we might believe that a discounting/BMI relationship may exist. Firstly, it could be that (despite the findings of [Chang et al. \(2020\)](#)) discounting for food rewards has a stronger link to BMI than discounting of money or weight loss rewards. For example [Rasmussen, Lawyer, and Reilly \(2010\)](#) and [Hendrickson, Rasmussen, and Lawyer \(2015\)](#) found higher discount rates for food rewards in those with higher percent body fat levels, but this was not the case for monetary rewards. The hunger related hormone ghrelin ([Müller et al., 2015](#)) increases impulsivity for food in rats ([Anderberg et al., 2016](#)) and humans ([Cummings, Frayo, Marmonier, Aubert, & Chapelot, 2004](#)), and in turn hunger increases discount rates dramatically for food, and less so for other rewards ([Skrynka & Vincent, 2019](#)). Therefore before we can strongly rule out a relationship between discounting and BMI, we echo the call of [Barlow, Reeves, McKee, Galea, and Stuckler \(2016\)](#) to more fully understand the relationship of body composition and discounting of food rewards as compared to other commodities. Secondly, there is evidence that those with anorexia nervosa have lower discount rates in that they can defer rewards ([Steinglass et al., 2012](#)). A compelling study by [Decker, Figner, and Steinglass \(2015\)](#) showed that before treatment, patients with anorexia nervosa had lower discount rates than healthy controls, but after treatment and weight restoration, this group level difference in discount rates disappeared. [Bernardoni et al. \(2020\)](#) showed a dysfunctional ghrelin–discounting relationship in those with acute anorexia. Typically, those with higher ghrelin levels had greater preference for sooner rewards (higher discount rates), but this relationship was reversed in acute anorexia, potentially allowing short term food rewards to be resisted in favour of a (maladaptive) longer-term goal. Third, while the meta analyses mentioned above note considerable study-level heterogeneity, there are studies which do convincingly suggest discounting is correlated with weight status (e.g. [Jarmolowicz et al., 2014](#)). In summary, despite the results to the contrary, there are still compelling reasons to suspect a link between discounting and body composition.

Therefore, the present work sought to further explore this possible relationship, and to go further in 3 main ways. Firstly, based upon [Rasmussen et al. \(2010\)](#) and [Hendrickson et al. \(2015\)](#), discount rates for food were measured, in addition to money and weight loss rewards.

¹[Veillard and Vincent \(2020\)](#) assessed if discounting moderated the rate of BMI gain with age but did not include a main effect of discounting in their linear model. Their data are reanalysed later in this paper with the addition of a main effect of discounting.

Table 1: Sample sizes associated with the discounting of different commodities (money, weight loss, and food). Values from [Veillard and Vincent \(2020\)](#) are as-is – no truncation of discount rates were used. Values for Study 1, Study 2 and the meta analyses are post-truncation of discount rates outside of the sensitive ranges (see Appendix). Outcome measures are body mass index (BMI), and log waist to height ratio, $\ln(\text{WHtR})$.

	Discounting commodity			Outcomes	
	Money	Weight Loss	Food	BMI	$\ln(\text{WHtR})$
Veillard and Vincent (2020)	381	257		✓	
Study 1	359		238	✓	✓
Study 2		253	235	✓	✓
Meta analysis	708	477	462	✓	

Secondly, discount rates are also influenced by many state-based factors, including hunger ([Skrynka & Vincent, 2019](#)), and so links between subjective hunger and discount rates were also explored. Third, the anthropometric measures were extended beyond BMI. Specifically, we recorded height, weight, and now waist measurements which allows waist-to-height ratio (WHtR) to be calculated. WHtR was shown by a meta analysis of 31 studies to be a better predictor of a range of cardiometabolic risk factors than BMI or waist measurements ([Ashwell, Gunn, & Gibson, 2011](#)). Two online studies were conducted – the first measured delay discounting for money and food, and the second measured delay discounting for weight loss rewards and food rewards (see Table 1). Data from [Veillard and Vincent \(2020\)](#) were reanalysed, resulting in the same conclusions being drawn. Finally, a meta analysis was conducted where data was pooled across studies to achieve even larger sample sizes.

Methods

Participants

Two online questionnaire studies were approved by the University of Dundee ethics committee. Participants were recruited using volunteer sampling by distributing the questionnaire through online social media, and no payments were offered. All submissions were anonymous, open to anyone aged 18 or over, and a total of 416 submissions were received for Study 1, and 440 for Study 2. Because of the recruitment methods the majority of participants responding were likely to be from the UK, but the possibility that some participants were from other countries cannot be excluded. There may have been some participant overlap between the current studies and [Veillard and Vincent \(2020\)](#), but it is unlikely as the data was collected one year apart. Data were collected between 16th Jan – 17th Feb 2020. As is common with online surveys exploring discounting and BMI, more women completed the survey than men. 336 females and 79 males completed Study 1, and 366 females and 73 males completed Study 2.

While the respondents were all unpaid volunteers, and therefore had some level of intrinsic motivation to complete the questionnaire accurately, strict exclusion criteria were used. Participants were removed if: their age was under 18, height was below 1.25m or above 2m, weight was less than 35kg or greater than 150kg, or waist was below 0.6m or above 1.5m.

Procedure

Two online questionnaire studies were conducted via www.onlinesurveys.ac.uk – the first measured discounting for hypothetical money and food rewards, the second measured discounting for hypothetical food and weight loss rewards. Both questionnaires asked for participants' age, and sex (assigned at birth), followed by the discounting tasks. Study 1 measured discounting of hypothetical monetary and of food rewards. Study 2 measured discounting of hypothetical weight loss and hypothetical food rewards. Participant's subjective hunger was then assessed. Finally height, weight and waist circumference measures were asked for – participants were free to enter in imperial or metric units. Asking for these anthropometric measures last could help to reduce salience of body composition when the discounting tasks and subjective hunger measures were taken.

Measures

Discounting tasks

Discounting of money was assessed via the 27-item monetary choice questionnaire (MCQ; Kirby, 2009). Discounting of food was assessed with the 27-item food choice questionnaire (FCQ; Hendrickson et al., 2015). Discounting of weight loss rewards uses a modified form the weight loss choice questionnaire (WCQ; Lim & Bruce, 2015)

Choices made in the WCQ, MCQ, and FCQ tasks were scored separately using a Python implementation of the Bayesian methods outlined in Vincent (2016), using the MCMC sampling software PyMC3 (Salvatier, Wiecki, & Fonnesbeck, 2016). We took the posterior mean as the estimated discount rate for each participant. Because discount rates are known to be highly positively skewed, we report natural log discount rates, $\ln(k) = \log_e(k)$.

During the scoring of the FCQ we found a very large proportion of participants fell outside the sensitive range of discount rates. On further inspection we found that the properties of the FCQ deviated somewhat from the MCQ. We chose to deal with this by using the relatively common approach of truncating discount rates falling outside the sensitive range of the discounting measures, and this is expanded upon in the Appendix.

Subjective hunger

Subjective hunger was assessed with the 15-item Food Craving Questionnaire-State (FCQ-S) measure (Cepeda-Benito, Gleaves, Williams, & Erath, 2000).

Body mass index

All height and weight measures data were converted to meters and kilograms, respectively. Body Mass Index was calculated as $\text{weight}/\text{height}^2$ resulting in BMI in units of kg m^{-2} .

Weight to height ratio

All height and waist circumference measures recorded were converted to meters. Initial analyses were conducted on waist-to-height ratios (WHtR). However, the simple ratio has undesirable properties² – the measure changes depend upon whether we look at waist/height or height/weight. Therefore we proceed with $\ln(\text{WHtR}) = \log_e(\text{weight}/\text{height})$ which is a unitless ratio. This did not affect the pattern of results, which we take to show that our findings are robust across both WHtR and $\ln(\text{WHtR})$ measures.

²The author thanks Jonathon Baron for this suggestion.

Analyses

All data and analysis code is available in the Online Supplementary Material (see Appendix). JASP files are provided (JASP Team, 2020), as is the Python code used to process raw data and to score discount rates.

Bayes Factors were used to quantify the relative predictive performance of H_1 and H_0 . The classification scheme of Lee and Wagenmakers (2014) is used – $BF_{10} > 1$ indicates support for H_1 , where values between 1-3 are considered as weak or anecdotal evidence, 3-10 are considered as moderate evidence, 10-30 are considered as strong evidence, 30-100 are considered as very strong evidence, and > 100 are considered as extreme evidence. Conversely, $BF_{10} < 1$ indicates support for H_0 , where values between 1-1/3 are considered as weak or anecdotal evidence, 1/3-1/10 are considered as moderate evidence, 1/10-1/30 are considered as strong evidence, 1/30-1/100 are considered as very strong evidence, and $< 1/100$ are considered as extreme evidence.

Study 1

Results

Properties of the dataset

After participant exclusion (see Methods) we had a total of 384 participants, although there were some missing data entries – see Table 2 for the descriptive statistics. The BMI of our sample was broadly reflective of the UK population as a whole. There was a positive skew, seen by the mean being higher than the median. The mean BMI of 26.1 was marginally below the English average of 27.5 (NHS, 2019), which is possibly due to younger participants being overrepresented in the dataset.

Table 2: Descriptive statistics for Study 1. Age is in years, BMI in kg m^{-2} . The discount rate k_{money} is in units of days^{-1} , k_{food} is in units of hours^{-1} , however after natural log transformation these are unitless ratios (see Vincent and Stewart (2020)).

	Age	BMI	$\ln(\text{WHtR})$	$\ln(k_{\text{money}})$	$\ln(k_{\text{food}})$
Valid	384	372	321	358	239
Missing	0	12	63	26	145
Mean	33.576	26.065	-0.734	-4.544	-1.646
Median	27.000	25.581	-0.763	-4.457	-1.619
Std. Deviation	14.390	5.305	0.147	1.314	0.619
Minimum	18.000	15.527	-1.013	-8.432	-3.485
Maximum	82.000	46.652	-0.271	-1.547	-0.524

Table 3 shows Bayesian correlations between the main measures. As one would expect we found extreme evidence in support of a positive correlation ($r = 0.773$, $BF_{10} = 2.56 \times 10^{61}$, $N = 321$) between the anthropometric measures (BMI and $\ln(\text{WHtR})$). There was extreme evidence in support of positive correlations between age and BMI ($r = 0.297$, $BF_{10} = 1.49 \times 10^6$, $N = 372$) and age and $\ln(\text{WHtR})$ ($r = 0.378$, $BF_{10} = 2.86 \times 10^9$, $N = 321$).

There was strong evidence that discounting for money and food rewards were correlated. However the correlation coefficient was modest, suggesting that these reflect different temporal discounting preferences as opposed to reflecting one overall discounting measure ($r = 0.214$, $BF_{10} = 16.9$, $N = 232$).

In terms of subjective hunger, there was strong evidence *against* a correlation (i.e. evidence for H_0) between BMI and state hunger ($r = -0.024$, $BF_{10} = 0.072$, $N = 372$). In other words, there was strong evidence that state hunger at time of survey completion was unrelated to BMI. This result was mirrored for $\ln(\text{WHtR})$ ($r = -0.007$, $BF_{10} = 0.07$, $N = 321$). There was very strong evidence for a slight negative correlation between age and subjective hunger when completing the survey, and we do not have any compelling theoretical explanation for this. There was also strong evidence against subjective hunger being correlated with discounting of money ($r = 0.034$, $BF_{10} = 0.081$, $N = 359$) and moderate evidence against subjective hunger being correlated with discounting of food ($r = 0.086$, $BF_{10} = 0.193$, $N = 238$).

Proposal 1

We test the notion that discount rates are correlated to BMI or $\ln(\text{WHtR})$ through use of Bayesian correlations (see Table 3). In terms of correlations between discounting and body composition, there was no compelling evidence for correlations between discounting of money and BMI, discounting of money and $\ln(\text{WHtR})$, discounting of food and BMI, nor discounting of food and $\ln(\text{WHtR})$.

Table 3: Bayesian Pearson correlations for Study 1, using 2-sided tests. A stretched-Beta prior width of 1 was used, corresponding to a uniform distribution over correlation coefficients.

		BMI	$\ln(\text{WHtR})$	Age	$\ln(k_{\text{money}})$	$\ln(k_{\text{food}})$
BMI	Pearson's r	—				
	BF_{10}	—				
$\ln(\text{WHtR})$	Pearson's r	0.773***	—			
	BF_{10}	2.562×10^{61}	—			
Age	Pearson's r	0.297***	0.378***	—		
	BF_{10}	1.489×10^6	2.862×10^9	—		
$\ln(k_{\text{money}})$	Pearson's r	0.110	0.093	0.054	—	
	BF_{10}	0.538	0.257	0.111	—	
$\ln(k_{\text{food}})$	Pearson's r	0.078	0.097	0.124	0.214*	—
	BF_{10}	0.165	0.222	0.492	16.877	—
FCQ-S	Pearson's r	-0.024	-0.007	-0.184**	0.034	0.086
	BF_{10}	0.072	0.070	45.955	0.081	0.193

* $BF_{10} > 10$, ** $BF_{10} > 30$, *** $BF_{10} > 100$

Proposals 2 and 3

Having failed to find compelling evidence for correlations between discounting and body composition, we tested Proposals 2 and 3 (Figure 1, middle, bottom) firstly for BMI, and then for $\ln(\text{WHtR})$ using Bayesian linear models. We included the following modelling terms – we explain using BMI but the same applies to the $\ln(\text{WHtR})$ outcome measure:

- age: A credibly positive main effect of age would indicate BMI increases with age.
- sex: A credibly positive main effect of sex would indicate a higher mean BMI for men.
- $\ln(k_{\text{money}})$: A credibly positive main effect would indicate support for Proposal 2, that people who discount money more have higher BMI.
- $\ln(k_{\text{food}})$: A credibly positive main effect would indicate support for Proposal 2, that people who discount food more have higher BMI.

- $\text{age} \times \ln(k_{\text{money}})$: A credibly positive interaction term would indicate support for Proposal 3 – that discounting of money moderates the rate of BMI increase with age.
- $\text{age} \times \ln(k_{\text{food}})$: A credibly positive interaction term would indicate support for Proposal 3 – that discounting of food moderates the rate of BMI increase with age.

Table 4 (top) shows the best 5 models with BMI as the outcome variable. The best model consists of a main effect of age only. The next best model consists of main effects of age and sex, but this is approximately half as credible as the best model. Subsequent models become even less credible, with the third model being approximately 15 times less credible compared to the best model. In short, we find evidence for a main effect of age alone, and find no support for Proposal 2 (main effects of discounting) or Proposal 3 (interactions of age and discounting).

Table 4: Model Comparison for Study 1 with the outcome variables BMI (top) and $\ln(\text{WHtR})$ (bottom). Bayes Factors (BF_{10}) are presented relative to the best model. For each, the top 5 models are shown in descending order of goodness, $P(M|\text{data})$. Full tables are available in online Supplementary Materials (see Appendix).

Models	P(M)	P(M data)	BF_M	BF_{10}	error %
age	0.038	0.608	38.835	1.000	
sex + age	0.038	0.327	12.163	0.538	0.854
age + mcq	0.038	0.041	1.076	0.068	0.003
sex + age + mcq	0.038	0.023	0.590	0.038	1.221
age + fcq	0.038	5.256×10^{-6}	1.314×10^{-4}	8.640×10^{-6}	0.001
age	0.038	0.409	17.282	1.000	
age + fcq	0.038	0.105	2.929	0.257	0.002
sex + age	0.038	0.103	2.876	0.252	1.878
age + fcq + age * fcq	0.038	0.100	2.766	0.244	0.008
age + mcq	0.038	0.084	2.300	0.206	0.002

Table 4 (bottom) shows the best 5 models with $\ln(\text{WHtR})$ as the outcome variable, with essentially the same findings as for BMI. Namely, the best model consists of a main effect of age only. The next best model consists of main effects of age and $\ln(k_{\text{money}})$, but this is approximately 3.8 times less credible than the best model. Subsequent models become even less credible. It is worth pointing out that the relative credibility of the fourth model (for example) with main effects of age, $\ln(k_{\text{food}})$, and the interaction $\text{age} \times \ln(k_{\text{food}})$ is only ~ 4 times less credible than the main effects of age model. So while this cannot be considered as definitive evidence against this model, the evidence favours a main effects of age model. In short, we again find evidence for a main effect of age alone, and find no support for Proposal 2 (main effects of discounting) or Proposal 3 (discounting mediates rate of BMI gain over time).

Discussion

After participant exclusion we had data from 384 participants. We also truncated (i.e. set data as missing) discount rates whose values fell outside the sensitive ranges of the MCQ and FCQ. This highlighted that the range of sensitive values for the FCQ is very narrow (see Appendix), resulting in 146 participant's discount rates for food rewards being truncated, resulting in a still respectable sample size of 238 valid measurements. This does need to be born in mind however when we interpret the results in relation to discounting of food rewards.

A speculative prediction based upon the link between hunger and discount rates (Lu, Zhou, Pan, & Zhao, 2019; Skrynka & Vincent, 2019) would be that discount rates may have been

correlated to subjective hunger. This was effectively disproved however as we found evidence *against* a correlation between discounting (of money or food) and current state hunger, consistent with [Rasmussen et al. \(2010\)](#). We suspect that the absence of a correlation here could be due to the high levels of between-participant variance, so future work on discounting and subjective hunger would almost certainly require the use of a repeated measures design.

Consistent with the findings of [Veillard and Vincent \(2020\)](#), we did not find any evidence that discounting of money was related to BMI. Study 1 extended this to discounting of food rewards and to the $\ln(\text{WHtR})$ measure. Thus far, given the lack of evidence for relationships between discounting of food and BMI, discounting of money and $\ln(\text{WHtR})$, nor discounting of food and $\ln(\text{WHtR})$, we are far from a conclusive link between discounting and body composition.

The lack of connection between discounting and $\ln(\text{WHtR})$ was surprising given that $\ln(\text{WHtR})$ is a better predictor of cardiometabolic risk factors than BMI or waist measurements ([Ashwell et al., 2011](#)). It remains feasible that there could have been a relationship between $\ln(\text{WHtR})$ and discounting, but that self-reported waist measurements are inaccurate – a point that will be examined in the General Discussion.

Further, the lack of relationship between discounting for food rewards and body composition was also surprising given the findings of [Rasmussen et al. \(2010\)](#) and [Hendrickson et al. \(2015\)](#), but was consistent with [Chang et al. \(2020\)](#). If discounting of any commodity is related to body composition, then one would predict this to be discounting of food rewards. [Rasmussen et al. \(2010\)](#) and [Hendrickson et al. \(2015\)](#) report researcher-measured percent body fat and find a correlation, whereas [Chang et al. \(2020\)](#) report researcher-measured BMI and do not. So it is not clear that our use of self-reported BMI was the cause of failing to find a connection (indeed many studies reporting a correlation are based on self-reported BMI). It could feasibly be that case the the percent body fat is a better measure of the underlying construct which discounting influences, in which case we might have to disregard the literature reporting BMI rather than body fat measures. It could be that there was a connection between discounting for food and $\ln(\text{WHtR})$ but that the WCQ measure was problematic. We had to truncate the FCQ scores from 146 (38%) of the participants, which raises some questions about this measure, if not in general, then specifically for this participant sample, but there would still be the lack of association from ([Chang et al., 2020](#)) to account for.

Study 2

Study 2 was very similar to Study 1 – we explored possible relationships between discounting of food rewards using the FCQ ([Hendrickson et al., 2015](#)) (as in Study 1) and weight loss rewards with the WCQ ([Lim & Bruce, 2015](#)) (instead of money as in Study 1), and BMI and $\ln(\text{WHtR})$.

Results

Properties of the dataset

After participant exclusion (see Methods) we had a total of 401 participants. Table 5 shows the descriptive statistics. Again, the BMI distribution of this sample was broadly reflective of the UK population as a whole. There was a positive skew, seen by the mean being higher than the median. The mean BMI was similar to the English average of 27.5 ([NHS, 2019](#)), at 27.4.

Table 6 shows the correlations and Bayes Factors for the main predictor and outcome variables of Study 2. As one would expect, we found extreme evidence in support of a positive correlation between BMI and $\ln(\text{WHtR})$ ($r = 0.807$, $BF_{10} = 3.387 \times 10^{74}$, $N = 335$). There was extreme evidence in support of positive correlations between age and BMI ($r = 0.331$, $BF_{10} = 4.2 \times 10^8$, $N = 393$) and age and $\ln(\text{WHtR})$ ($r = 0.423$, $BF_{10} = 1.372 \times 10^{13}$, $N = 338$).

Table 5: Descriptive statistics for Study 2

	Age	BMI	ln(WHtR)	ln(k_{food})	ln(k_{weight})
Valid	401	393	338	234	253
Missing	0	8	63	167	148
Mean	33.870	27.413	-0.705	-1.463	-2.832
Median	27.000	26.079	-0.720	-1.289	-2.805
Std. Deviation	14.653	6.562	0.167	0.600	1.004
Minimum	18.000	13.841	-1.042	-3.481	-4.991
Maximum	73.000	51.564	-0.174	-0.506	0.177

There was moderate evidence against a correlation between food and weight loss rewards, with a modest correlation coefficient ($r = 0.102$, $BF_{10} = 0.231$, $N = 175$). This suggests not only that these measures do not reflect domain general discounting, but also that preferences for food or weight loss sooner rather than later are uncorrelated across participants.

Table 6: Bayesian Pearson correlations for Study 2, using 2-sided tests. A stretched-Beta prior width of 1 was used, corresponding to a uniform distribution over correlation coefficients.

Variable		BMI	log_WHtR	Age	fcq	wcq
BMI	Pearson's r	–				
	BF ₁₀	–				
ln(WHtR)	Pearson's r	0.807***	–			
	BF ₁₀	3.387×10^{74}	–			
Age	Pearson's r	0.331***	0.432***	–		
	BF ₁₀	4.203×10^8	6.373×10^{13}	–		
ln(k_{food})	Pearson's r	-0.019	-0.008	0.015	–	
	BF ₁₀	0.086	0.088	0.084	–	
ln(k_{weight})	Pearson's r	0.008	-0.013	0.020	0.105	–
	BF ₁₀	0.080	0.087	0.083	0.244	–
FCQ-S	Pearson's r	0.128	0.159	0.007	0.057	0.011
	BF ₁₀	1.574	4.965	0.063	0.118	0.080

* BF₁₀ > 10, ** BF₁₀ > 30, *** BF₁₀ > 100

Proposal 1

Based upon the Bayes Factors ($BF_{10} < 1/10$), we found strong evidence *against* any of the 4 correlations between discounting for food or weight loss and BMI and ln(WHtR), see Table 6.

Proposals 2 and 3

We used the same procedure to test Proposals 2 and 3 as in Study 1, namely running a Bayesian linear regression with multiple model terms. The only difference was the use discounting predictors ln(k_{food}) (in common with Study 1) and ln(k_{weight}) (as opposed to discounting of money in Study 1).

Table 7 (top) shows the best 5 models with BMI as the outcome variable. The best model consists of a main effect of age only. The next best model has an additional main effect of sex,

Table 7: Model comparison for Study 2 with the outcome variable BMI (top) and ln(WHtR) (bottom). For each, the top 5 models are shown in descending order of goodness, $P(M|\text{data})$. Bayes Factors (BF_{10}) are presented relative to the best model. Full tables are available in online Supplementary Materials (see Appendix).

Models	P(M)	P(M data)	BF_M	BF_{10}	error %
age	0.038	0.861	155.321	1.000	
sex + age	0.038	0.139	4.021	0.161	1.296
age + fcq	0.038	6.914×10^{-5}	0.002	8.027×10^{-5}	0.003
sex + age + fcq	0.038	3.022×10^{-5}	7.555×10^{-4}	3.508×10^{-5}	1.206
age + wcq	0.038	4.970×10^{-7}	1.243×10^{-5}	5.770×10^{-7}	0.002
age	0.038	0.520	27.094	1.000	
sex + age	0.038	0.126	3.604	0.242	0.884
age + fcq	0.038	0.105	2.927	0.201	0.008
age + wcq	0.038	0.088	2.422	0.170	0.008
age + fcq + age * fcq	0.038	0.034	0.873	0.065	0.008

but this is approximately 6 times less credible. All other models become vastly less credible compared to the best (main effects of age) model.

Table 7 (bottom) shows the best 5 models with ln(WHtR) as the outcome variable. The best model consists of a main effect of age only. The next best model has an additional main effect of sex, but this is approximately 4 times less credible. All other models become progressively less credible compared to the best (main effects of age) model.

Discussion

As in Study 1, we again found consistent evidence against Proposals 1, 2, or 3 again for discounting of food, but now additionally for discounting of weight loss. Namely, there was no credible evidence for correlations (see Table 6), and there was no evidence for main effects or interaction terms with either BMI or ln(WHtR) (see Table 7) as the outcome variable. The lack of relationship between discounting of weight loss and BMI is consistent with the findings of both [Lim and Bruce \(2015\)](#) and [Veillard and Vincent \(2020\)](#). And it would appear that this also extends to the ln(WHtR) measure.

We again had to exclude quite a lot of participant's WCQ scores (148 of 401, 37%) because they fell outside of the sensitive range (see Methods and Appendix). At this point it is not clear whether we have found strong evidence against a role of discounting of food rewards, or if we have detected a potential problem with the WCQ score and failed to find evidence for a relationship because of its narrow range of sensitivity (see Appendix).

Reanalysis of [Veillard and Vincent \(2020\)](#)

The conclusions of [Veillard and Vincent \(2020\)](#) were based upon assessing a main effect of age and an interaction of age and discount rates, with a main effect of discount rates omitted. To confirm that this did not affect the research conclusions we conducted a reanalysis with both main effects and the interaction, just like those run in Study 1 and Study 2.

Table 8 shows the Bayes Factors for the resulting top 5 models. The best model consists of a main effect of age and sex. The next best model (a main effect of age alone) has similar credibility ($BF_{10} = 0.712$, relative to the best model). The third and fourth best models include main effects of sex, age, and either discount rate, but these now become approximately 6.8–7.8

times less credible relative to the best model. While this would not count as very strong evidence *against* either of the main effects, it is certainly not compelling evidence *for* main effects of discount rates. In short, the conclusions of [Veillard and Vincent \(2020\)](#) are robust when adding main effects of discount rates into a Bayesian linear model – the data is most consistent with a main effects of age and sex model with no compelling evidence for Proposal 2 (main effects) or Proposal 3 (interactions).

Table 8: Reanalysis of data from [Veillard and Vincent \(2020\)](#), showing the top 5 models in descending order of goodness, $P(M|\text{data})$. Bayes Factors (BF_{10}) are presented relative to the best model. Full tables are available in online Supplementary Materials (see Appendix).

Models	P(M)	P(M data)	BF_M	BF_{10}	error %
sex + age	0.038	0.425	18.511	1.000	
age	0.038	0.303	10.869	0.712	0.916
sex + logk_money + age	0.038	0.062	1.657	0.146	1.396
sex + logk_weight + age	0.038	0.054	1.431	0.127	2.071
logk_money + age	0.038	0.051	1.352	0.121	0.916

Meta analysis

The findings thus far do not provide any support for a link between discounting (for 3 different commodities) and body composition (assessed by BMI and $\ln(\text{WHtR})$). In an attempt to summarise what we know, integrating over Study 1, Study 2 and previous data from [Veillard and Vincent \(2020\)](#), we conducted meta analyses. Data were pooled for the discounting of money, weight loss, and food and their possible relations to BMI were analysed with similar Bayesian linear models as before (see Table 1 for an overview).

We ran 3 Bayesian linear models, akin to those before, with BMI as the outcome variable, with main effects of age, sex, and discount rate. Interactions between discount rates and ages were included. The 3 separate models correspond to discounting for money, food, and weight loss rewards, were run separately as all measures were not available for all participants.

Results

In terms of discounting for money, consistent with all previous findings we found that the best model consisted of a main effect of age only (see Table 9, top). Interestingly, a model with an additional main effect of $\ln(k_{\text{money}})$ was only 1.2 times less credible than the best model ($BF_{10} = 0.852$, relative to the best model). So while a main effect of discounting for money cannot be firmly ruled out, another way of viewing this is that by adding discounting of money as a main effect to a main effect of age does not meaningfully improve the predictive performance of the model relative to the main effect of age only model.

The same basic finding occurred with the discounting of food measure (see Table 9, middle) – the best model was a main effect of age alone. The next best model has an additional main effect of sex, is approximately 1.4 times less credible in comparison. The third best model, with a main effect of age and $\ln(k_{\text{food}})$ is approximately 7 times less credible.

The same basic finding also occurred with discounting of weight loss (see Table 9, bottom) – the best model was a main effect of age alone. The second best model was approximately two times less credible with an additional main effect of sex. The third best model, with a main effect of age and $\ln(k_{\text{weight}})$ is approximately 9 times less credible.

Table 9: Model comparison for the meta analyses for discounting of money (top), food (middle), and weight loss (bottom). For each, the top 5 models are shown in descending order of goodness, $P(M|\text{data})$. Bayes Factors (BF_{10}) are presented relative to the best model. Full tables are available in online Supplementary Materials (see Appendix).

Models	P(M)	P(M data)	BF_M	BF_{10}	error %
age	0.100	0.423	6.598	1.000	
age + mcq	0.100	0.360	5.072	0.852	0.013
sex + age	0.100	0.069	0.672	0.164	0.993
sex + age + mcq	0.100	0.068	0.655	0.160	1.123
age + mcq + age * mcq	0.100	0.066	0.638	0.156	0.015
age	0.100	0.500	8.988	1.000	
sex + age	0.100	0.352	4.899	0.705	2.163
age + fcq	0.100	0.069	0.663	0.137	0.002
sex + age + fcq	0.100	0.048	0.452	0.096	1.122
age + fcq + age * fcq	0.100	0.019	0.170	0.037	6.384×10^{-4}
age	0.100	0.591	13.019	1.000	
sex + age	0.100	0.292	3.709	0.494	0.869
age + wcq	0.100	0.066	0.634	0.111	0.008
sex + age + wcq	0.100	0.030	0.281	0.051	1.340
age + wcq + age * wcq	0.100	0.014	0.127	0.023	0.009

Discussion

This pooling of data and the correspondingly larger sample sizes resulted in a lack of compelling evidence for relationships between discounting and BMI – age was the only consistently credible predictor of BMI in these datasets. We must conclude that any link between discounting and BMI (see Figure 1) is either weak to non-existent, or much more complex than the correlation, main effects, or moderation analyses are able to capture.

Frequentist versus Bayesian inference methods

Nearly all previous studies arrived at their research conclusions through Frequentist analyses, whereas we used Bayesian analyses. Can this partly or wholly explain why we conclude that there is no relationship between discounting and BMI? In order to investigate this, Table 10 shows a summary of correlations between discounting and body composition measures. The conclusions were classified as in agreement if $p < 0.05$ and $BF_{10} > 3$, or if $p \geq 0.05$ and $BF_{10} < 1$. In order to maximise comparability to the Frequentist correlations, we use 2-tailed approaches and the Bayesian correlations used a uniform prior over correlation coefficients.

There are disagreements in the research conclusions reached through Frequentist and Bayesian methods in only 2 cases – when correlating BMI and $\ln(k_{\text{money}})$. This is particularly pronounced in the meta analysis with a high sample size of $N = 708$. A Bayesian analysis would conclude that there are zero correlations between any of the datasets across both body composition measures and all 3 of the discounting measures (MCQ, FCQ, WCQ). For example, the Bayesian correlation between BMI and $\ln(k_{\text{money}})$ for the meta analysis shows that the $r \neq 0$ hypothesis only has 1.312 times more credibility than the $r = 0$ hypothesis, barely anything at all. In contrast, the Frequentist analysis would conclude that the correlation $r = 0.097$ is significant at the $p < 0.01$ level. Although this Frequentist analysis would also have to concede

Table 10: Summary table of Frequentist and Bayesian correlations between discounting and body composition (Proposal 1). Bayesian correlations used a uniform prior to maximise comparability with the Frequentists correlations. The correlation coefficients and sample sizes are show in columns r and n , respectively. BF_{10} shows the relative credibility for $H_1 : r \neq 0$ relative to $H_0 : r = 0$ such that values below 1 indicate greater relative credibility for $r = 0$.

Dataset	Correlation	r	n	p-value	BF_{10}	Agreement?
Study 1	BMI, MCQ	0.114	321	0.034	0.635	no
Study 1	BMI, FCQ	0.100	230	0.131	0.257	yes
Study 1	ln(WHtR), MCQ	0.082	297	0.159	0.195	yes
Study 1	ln(WHtR), FCQ	0.108	196	0.133	0.273	yes
Study 2	BMI, WCQ	0.008	246	0.903	0.080	yes
Study 2	BMI, FCQ	-0.019	232	0.777	0.086	yes
Study 2	ln(WHtR), WCQ	-0.013	217	0.847	0.087	yes
Study 2	ln(WHtR), FCQ	-0.008	203	0.911	0.088	yes
Veillard & Vincent	BMI, MCQ	0.059	381	0.247	0.125	yes
Veillard & Vincent	BMI, WCQ	0.016	257	0.797	0.081	yes
Meta Analysis	BMI, MCQ	0.097	708	0.010	1.312	no
Meta Analysis	BMI, FCQ	0.044	462	0.352	0.090	yes
Meta Analysis	BMI, WCQ	0.041	477	0.377	0.085	yes

that an $r^2 = 0.00941$ (0.94% explained variance) is on the low side. This approach would then also have to explain why it is only discounting of money that is related to BMI, and none of the other combinations of discounting commodities or for the ln(WHtR) measure. So even if we were to side with the Frequentist analyses, we would have to concede that the discounting/body composition relationship is not a robust one. The reader is referred elsewhere for an in-depth exploration of the differences between Frequentist and Bayesian approaches ([van Zyl, 2018](#); [Wagenmakers, Lee, Lodewyckx, & Iverson, 2008](#)).

General discussion

Findings

One of the most robust findings was the strong relationship between age and body composition (see [Sutin et al., 2011](#)). Because of this we strongly suggest that further research on discounting and body composition avoid *only* examining correlations and take the approach of other papers which incorporate other predictor variables using multiple regression or path analysis approaches, for example. While we restricted our focus to accommodate the influence of age on BMI, it could be prudent to add additional predictors, as some multiple-regression based analysis studies have done. We also evaluated the presence or absence of an interaction between age and discounting, which acts as a test of the process model that discount rates moderate the rate of weight gain over time. Having done so, we still lack evidence of a relationship between discount rates and BMI.

Overall, we found no compelling evidence that discounting (for money, weight loss, or food rewards) had any relationship with either BMI or ln(WHtR). In terms of discounting for money, Study 1, [Veillard and Vincent \(2020\)](#), and the meta analysis all found evidence against a relationship with BMI. In terms of discounting of weight loss rewards, [Lim and Bruce \(2015\)](#), [Veillard and Vincent \(2020\)](#), and Study 2 indicate that there is no link between discounting of weight loss and BMI. In terms of discounting for food, both Study 1 and 2 found no evidence for a relationship with BMI or ln(WHtR).

Limitations in measures?

One plausible reason for not finding any links, other than age, to BMI could be its inherent limitations as a measure (Garn, Leonard, & Hawthorne, 1986), or imprecision in its measurement. For example, there is evidence that men overestimate their height and women underestimate their weight (Brener, McManus, Galuska, Lowry, & Wechsler, 2003; Gosse, 2014; Shiely, Hayes, Perry, & Kelleher, 2013; Wen & Kowaleski-Jones, 2012). That said, there is also evidence suggesting that self-reported BMI is an acceptable measure (Bolton-Smith, 2000; Olfert et al., 2018). As noted by Veillard and Vincent (2020), studies covered in the meta analyses (Amlung et al., 2016; McClelland et al., 2016; Tang et al., 2018) show both correlations and no correlations regardless of whether BMI is measured by self-report or in a lab. Therefore the discrepancies in the literature are not likely to be due to methodological differences in BMI measurement.

The potential limitations of BMI motivates the use of alternative anthropometric measures. Rasmussen et al. (2010) found that discount rates for food were correlated with percent body fat, but not BMI. This inspired the measurement of WHtR (possible with questionnaire designs) which has been shown to be a more accurate predictor of cardiometabolic risk factors than BMI (Ashwell et al., 2011). However future work should consider the Body Roundness Index (Thomas et al., 2013) as an improved measure of body composition, overcoming some of the limitations of BMI, which we were unaware of at the time of conducting our study.

It remains feasible that there could have been a relationship between discount rates and $\ln(\text{WHtR})$, but that self-reported waist measurements are inaccurate. That said, Rimm et al. (1990) found high correlations between self- and technician-taken measurements of 0.95 for men and 0.89 for women. Similarly, Kushi, Kaye, Folsom, Soler, and Prineas (1998) found average measurement errors between self- and technician-measurement was only 0.59 ($CI_{95\%}$: 0.20, 0.98) inches. Therefore it is perhaps not so easy to attribute the lack of findings between discounting of $\ln(\text{WHtR})$ and discounting to inaccurate self-reported waist measurements. So while measurement error *might* account for the discrepancy in the findings and that of Rasmussen et al. (2010) and Hendrickson et al. (2015), it is more likely that there were simply different participant characteristics. If so, this suggests that we will either need very large sample sizes to resolve the issue, or that we aggregate over multiple studies with clear methodological consistency.

Could it be that eliciting discount rates by the Kirby (2009) 27-item questionnaire was not a precise enough measure to detect relationships between discounting of money and BMI? One of the downsides of this measure is that it is not as precise as either fixed questionnaires with more questions or computerised adaptive methods. However, there are some benefits from using it in an online survey context: firstly, the relatively low number of questions helps retain participants through the full survey and is less taxing than measures with more questions; secondly, it also has relatively high test-re-test reliability both over 1 week and 1 year (Kirby, 2009). Because of its wide use, any issues of precision with the measure would also have affected the many empirical studies which use it – this includes many studies reporting a relationship between discounting of money and BMI (e.g. Bickel et al., 2012; Chabris, Laibson, Morris, Schuldt, & Taubinsky, 2008; Jarmolowicz et al., 2014), and so it seems unlikely that our evidence against a relationship is caused by use of the MCQ.

Truncation of discounting measures

It was surprising that so many of the participants exhibited discount rates for food rewards outside of the sensitive range of the WCQ (Hendrickson et al., 2015). We investigated this by examining the discounting questions and by running parameter recovery simulations (see Appendix). This narrow sensitive range of discount rates does raise a question mark over the measure. While we did have to truncate a large proportion of the participant's data (146 of 384

in Study 1; 148 of 401 in Study 2) we still had respectable sample sizes (238 and 253) where a relationship between discounting for food rewards and body composition could have been found. That said, by definition it is the participants with lowest and highest discount rates that were truncated, so it is feasible that a relationship was obscured by this issue. In summary, there is scope for future studies to employ a modified WCQ sensitive to a broader range of discount rates.

What should we believe?

No association between discounting and BMI

The present results, along with many other studies (such as [Balantekin et al., 2020](#); [Chang et al., 2020](#); [Hollis-Hansen et al., 2020](#); [Myers et al., 2020](#); [Pastore et al., 2020](#); [Temple et al., 2020](#), and more) suggest that there is no true statistical association between discounting and body composition. If so, the small-medium effect size suggested by meta analyses would have to be explained away by some combination of p-hacking or publication bias, or the file-drawer problem ([Francis, 2012, 2013](#); [Rosenthal, 1979](#); [Simmons, Nelson, & Simonsohn, 2011](#)). There is, at present, no distinct evidence for publication bias from meta analyses however. And so on balance, it seems unwise to fully accept the idea that there is no statistical association between discounting and body composition until further meta-analytic or other evidence is in.

A simple association between discounting and BMI

If there is a true association between discounting and BMI then we could perhaps explain away those studies which do not find an association as artifactual. We should in fact expect a small proportion of ‘false negative’ studies from time to time, especially if the true underlying effect size is small. This does seem implausible given the number of studies finding no simple association, but this can be empirically resolved by future meta analyses.

If we were to be satisfied that there is indeed a small statistical association between discounting and BMI, then how useful is this? The association on its own is not useful, satisfying, or explanatory unless it tells us about the behaviours or other mechanisms which mediate this relationship. Nor is it practicable knowledge until we are sure about the causal direction of the relationship.

An indirect association between discounting and BMI

There is no mechanism by which preferences in an inter-temporal choice task can *directly* influence BMI – therefore there has to be mediating mechanisms and behaviours. If the causal direction is discounting→BMI, it could be that the profiles of participants (in terms of their mediating behaviours such as diet, exercise, food addiction) are dissimilar from one study to the next. Such differences in participant profiles from one study to the next could (in part) account for the heterogeneity in findings in the literature.

This becomes even more plausible when we consider causal pathways and mediating variables between discounting and BMI in more detail ([Meule, 2017](#)). For example, [Meule and Blechert \(2017\)](#) found no direct effect of discounting upon impulsivity (as measured by the Barratt Impulsivity Scale; [Barratt, 1959](#)) and BMI, but there was an indirect effect through multiple mediators: BIS → food cravings → perceived self-regulatory success → BMI (see also [Meule, Hofmann, Weghuber, & Blechert, 2016](#)). [Murphy, Stojek, and MacKillop \(2014\)](#) found no direct effect between impulsive personality traits, but did find indirect effects via the mediator of food addiction. And [VanderBroek-Stice, Stojek, Beach, vanDellen, and MacKillop \(2017\)](#) found that discounting and BMI were not correlated, but there was an indirect pathway of

discounting → food addiction → BMI. The balance of evidence suggests that the link between discounting and BMI is complex, and that varied participant composition between studies may account for the variability in findings present in the literature. We believe, in line with (Meule, 2017), that it is this complex relationship which explains the varied strengths of association between discounting and BMI in the literature.

There are however significant challenges in drawing causal conclusions from observational data (Rohrer, 2018), and there are significant inferential and experimental issues with mediation analysis which has not always been appreciated (Bullock, Green, & Ha, 2010). So it may be that the way forward will require rigorous and attentive causal inference methods applied to high powered studies, potentially requiring creative experimental manipulations.

Conclusion

The findings presented in this study do not provide compelling evidence for a simple association between delay discounting and body composition. This was the case for discounting for money, weight loss, and food rewards, where body composition was measured by BMI and ln(WHtR). However, there are reasons to suspect that discounting is related to body composition in a more complex manner. We suggest that a productive way forward would be to progress our understanding of the causal pathways between discounting (and other impulsivity constructs) and body composition.

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Competing interests

The author declares no competing interests.

Appendix

Data and code availability

All data and code is available from the Open Science Foundation, <https://osf.io/vtf6j/>.

Truncation of discounting scores

There are two strategies available when discounting behaviour extends beyond the sensitive range of a discounting measure – censoring or truncation. Censoring discount rates (set discount rates at the floor or ceiling values) can cause significant bias in subsequent correlation or regression analyses. Therefore we chose to truncate (exclude) participants who's responses fell outside of the sensitive range of the FCQ, as well as the MCQ and the WCQ.

One way to do this would be to exclude participants who always responded with the immediate or delayed reward options, however we conducted a parameter recovery simulation to determine the range of discount rates the measures are sensitive to (see Appendix). Based on this, we set discount rates outside of the sensitive ranges for each particular commodity as missing data.

This resulted in nearly 40% of FCQ scores being truncated (set to missing) 146 out of 384. Full details are provided in the row labelled ‘missing’ in Tables 2 (Study 1) and 5 (Study 2).

Establishing sensitive ranges of discounting tests with parameter recovery simulations

In order to evaluate the range of discount rates that the MCQ (Kirby, 2009), WCQ (Lim & Bruce, 2015), and FCQ (Hendrickson et al., 2015) measures are sensitive to, we conducted parameter recovery simulations. For each measure we generated a set of 150 uniformly spaced true $\ln(k)$ values for simulated participants. For each true value, we simulated the responses to the questions according to a stochastic hyperbolic discounter. These simulated behavioural data were then scored individually using Bayesian parameter estimation outlined in Vincent (2016). Figure 2 shows that each of the measures is only sensitive to a certain range of discount rates. Outside of these ranges it is not possible to accurately recover the discount rate because of floor or ceiling effects, that is, all choices would be either delayed or immediate, respectively.

The MCQ is able to accurately measure $\ln(k)$ discount rates spanning between -8.5 and -1.5, where k is in units of days^{-1} (Figure 2, top row). The FCQ is able to accurately measure $\ln(k)$ discount rates spanning between -3.5 and -0.5, where k is in units of hours^{-1} (Figure 2, second row). The modified WCQ is able to accurately measure $\ln(k)$ discount rates spanning between -5.0 and 0.5, where k is in units of days^{-1} (Figure 2, third row). We also conducted a parameter recovery simulation for the modified WCQ used in Study 2. It was able to accurately measure $\ln(k)$ discount rates spanning between -4 and 0.5, where k is in units of days^{-1} (Figure 2, bottom row).

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Figure 2: Parameter recovery simulations (left column) to determine the reliable range of discount rates measurable by the MCQ, FCQ, WCQ, and the modified WCQ used in Study 2. The x-axis and y-axes show the true and recovered discount rates – perfect recovery would fall along the solid line. Points and error bars represent the posterior mean and 95% Bayesian credible intervals. Plots in the right column visualise the distribution of questions in each discounting test.

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