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Choice patterns reveal qualitative individual differences among discounting of delayed gains, delayed losses, and probabilistic losses

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A new probabilistic losses questionnaire as well as Kirby's delayed gains questionnaire and a previously developed delayed losses questionnaire were administered to a large online sample. Almost all participants showed the *positive discounting* choice pattern expected on the Kirby questionnaire, decreasing their choice of a delayed gain as time to its receipt increased. In contrast, approximately 15% of the participants showed *negative discounting* on the delayed losses questionnaire and/or the probabilistic losses questionnaire, decreasing their choice of an immediate loss as time to a delayed loss decreased and/or decreasing their choice of a certain loss as likelihood of the probabilistic loss increased. Mixture model analysis confirmed the existence of these negative discounting subgroups. The inconsistent findings observed in previous research involving delayed/probabilistic losses may be due to differences in the proportion of negative discounters who participated in previous studies. Further research is needed to determine how negative discounting of delayed and probabilistic losses manifests itself in everyday decisions. It should be noted that the presence of individuals who show atypical choice patterns when losses are involved may pose challenges for efforts to modify discounting in order to ameliorate behavioral problems, especially because many such problems concern choices that have negative consequences, often delayed and/or probabilistic.

Key words: discounting, delayed losses, probabilistic losses, delayed gains, decision-making, humans

It is well-established that the subjective value of a delayed reward decreases with the time until its occurrence, a phenomenon referred to as delay discounting. A similar phenomenon appears to occur with delayed losses, as evidenced by the fact that many people choose to carry a credit-card balance despite the fact that purchases then tend to end up costing more. Something similar also occurs with probabilistic losses: The aversiveness of a probabilistic loss tends to decrease as the likelihood of the loss decreases, a phenomenon sometimes referred to as probability discounting. For example, if someone fails to declare all of their income, they pay less in taxes than if they had declared it all. They run the risk, however, that if caught, they will have to pay the taxes on all of their income plus a penalty, bringing their loss to more than if they had declared all of their income initially. People who choose to run that risk may be thought of as discounting the aversiveness of the probabilistic outcome.

Given that so many everyday decisions involve delayed or probabilistic losses, and thus may also involve discounting, it is perhaps surprising that such discounting has received relatively little attention in the literature compared to the discounting of gains. As Harris (2012) noted, moreover, the literature on losses is not only meager, but compared to the literature on choices involving gains, it is fraught with inconsistencies (e.g., Chapman, 1996; Hardisty & Weber, 2009; Harris, 2012; Mitchell & Wilson, 2010; Shead & Hodgins, 2009). There is, of course, an important similarity in the discounting of gains and losses: A simple hyperbolic function (Mazur, 1987) provides a relatively good description of the discounting of both delayed gains and delayed losses (e.g., Murphy et al., 2001), although recent research indicates that both are better described by a hyperboloid function in which the denominator of the hyperbola is raised to a power less than 1.0 (for a review, see Green, Myerson, & Vanderveldt, 2014).

Despite this similarity, there are also important differences between the discounting of delayed gains and losses. For example, it is well established that delayed losses are discounted at lower rates than delayed gains

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of the same size, a finding known as the *sign effect* (e.g., Benzion et al., 1989; Thaler, 1981), and this difference also has been observed with probabilistic gains and losses (e.g., Estle et al., 2006; Mitchell & Wilson, 2010). In addition, the amount of the outcome affects the discounting of delayed gains but not delayed losses (Green, Myerson, Oliveira, & Chang, 2014), and recent research suggests that the discounting of probabilistic losses also is relatively unaffected by the amount (Myerson et al., 2011). That is, unlike with gains, increasing the delay until a loss or decreasing its likelihood changes its subjective value by the same proportion, regardless of the amount involved.

Yet another major difference between gains and losses concerns individual differences in delay discounting. Although almost everyone discounts the value of a delayed gain, a significant proportion does not discount the aversiveness of a delayed loss. Moreover, with some aversive events (e.g., dental work), some people would prefer to get them over with as soon as possible rather than delay the experience. As Harris (2012) pointed out, the literature on the discounting of delayed gains is "large and generally consistent" in contrast to the literature on delayed losses, which "contains puzzles and apparent contradictions." In fact, it may be that the inconsistences in the literature on losses are due, in part, to the existence of subgroups of people who show different patterns of loss discounting (Myerson et al., 2017). Whereas relatively few studies have explored individual differences in the discounting of delayed losses, far fewer have examined differences in the discounting of probabilistic losses. Accordingly, the present effort focused on individual differences in the discounting of both delayed and probabilistic losses.

Myerson et al. (2017) identified three distinct patterns of responding in the discounting of delayed losses based on the way individuals chose between immediate, smaller payments and delayed, larger payments. In two relatively large samples of participants recruited and tested over the internet, a majority of Myerson et al.'s participants (61% and 55%) were increasingly likely to choose the delayed payment as the delay to the larger payment increased. For each of these individuals, there was a positive correlation between their choices of the immediate outcome on a specific question and the log k associated with that question.[1] Other participants (18% and 23%), however, were less likely to choose the delayed payment as the delay increased, as indicated by a negative correlation, and Myerson et al. labeled them *Debt Averse*. A third subgroup of participants (21% and 22%) always chose the immediate, smaller payment, and these participants were labeled *Minimizers*. The majority group was labeled *Loss Averse*, for lack of a better term, although this usage differs from that of economists, who use the term in the context of choices involving probabilistic outcomes.

In their laboratory study of the discounting of delayed monetary losses, Gonçalves and Silva (2015) used a three-group classification scheme similar to that used by Myerson et al. (2017). About 40% of the participants in the Gonçalves and Silva study showed a typical delay discounting pattern (loss becoming less aversive with delay), but another 40% showed initial discounting followed by a decrease in degree of discounting at increasingly longer delays (loss becoming more aversive with delay), and about 20% showed no discounting. The findings from both the Myerson et al. and

[1]Following Kirby (Kirby, 2009; Kirby & Maraković, 1996), the discounting rate parameters for the questions on the three questionnaires used in the present study were calculated as follows: If discounting were hyperbolic such that $V = A/(1 + bX)$, where V is the amount of an immediate, certain outcome equal in subjective value to a delayed or probabilistic outcome of amount A, X is the delay until or odds against that outcome, and b is a parameter governing the rate of decrease in V as X increases, then it follows algebraically that $b = (A\text{-}V)/A{*}X$. This formula may be used to calculate the value of b associated with a question that offers a choice between an immediate, certain amount of one amount, V, and another amount, A, when the delay until or odds against amount A is X. The value of b for each question is typically represented by k or h, depending on whether the outcome is delayed or probabilistic, respectively. It should be noted, however, that although it might appear the questionnaires were designed with a simple hyperbolic discounting function in mind, the underlying logic, while compatible with a simple hyperbolic model, is much more general. Indeed, Kirby intended his questionnaire to be theoretically neutral, and it was designed to be compatible with both hyperbolic and exponential discounting functions (Kirby & Maraković, 1996). Moreover, as Myerson et al. (2014) pointed out, the Kirby questionnaire also is compatible with other monotonic functions. Accordingly, in the present study the log b metric merely serves as a convenient index of how steeply someone who was indifferent between the options presented on a particular question discounted the delayed or probabilistic outcome on that question.

Gonçalves and Silva studies clearly argue for the existence of subgroups of individuals who discount delayed losses in qualitatively different ways.

To our knowledge, there is no published study that has explored individual differences in the discounting of probabilistic losses. The aim of the current work, then, was to examine individual differences in both delay and probability discounting of losses. More specifically, we wanted first to replicate our previous findings of responding patterns with delayed losses while then determining whether different subgroups also would be observed when discounting involved probabilistic losses. To achieve this goal, we designed a new discounting questionnaire that was similar to that developed previously for studying delayed losses (Myerson et al., 2017). We also included an established questionnaire for studying delay discounting of gains (Kirby et al., 1999), so that we could examine the relations among the discounting of delayed gains, delayed losses, and probabilistic losses.

Notably, we augmented our previous use of within-person correlations and used a mixture modeling analytic approach (latent class regression) to determine whether there are subgroups of individuals in our sample who differ in the form of the relation between the likelihood of choosing a delayed or probabilistic outcome on a specific question and the logarithm of the value of the k (for delay) or h (for probability) parameter associated with the question. Finite mixture models can be applied to data where observations originate from various subgroups of a sample, but the subgroup affiliations are not known (Leisch, 2004). We combined mixture modeling with multilevel modeling to identify the subgroups that differed in their responses to questions varying in values of k or h (this approach is sometimes referred to as growth curve mixture modeling because it is often applied to longitudinal data but is more generally referred to as latent class mixed modeling). Previous efforts have also used a multilevel approach to discounting data (e.g., Kirkpatrick et al., 2018; Young, 2017; 2018) but have applied it to problems where the goal is to identify outliers or where group or subgroup affiliations are known (e.g., substance users and controls). In the present instance, however, mixture models are appropriate because the research question specifically concerns whether or not there are subgroups that differ in their discounting, and if so, how they can be best characterized.

Method

Participants

The participants (N = 428) were recruited from the pool of workers maintained by Amazon's Mechanical Turk (Behrend et al., 2011). All were 18 years of age or older, were using a computer with an IP address in the United States and had previous MTurk approval HIT rates of at least 85%.

Participants were compensated $0.50-0.60 based on the amount of time they spent in the study. The minimum amount of time needed to complete the study was established by three research assistants. Nine participants completed the study in less than the minimum amount of time needed by the research assistants, and their data were excluded from the analysis. Thus, the final sample consisted of 419 participants. One participant did not report gender, two did not report their age, five did not report their education, eight did not report their individual annual income, and six did not report their annual household income. Of those who reported the relevant demographic information, 51.1% were female; Mean age = 34.9 years, *SD* = 11.4; Mean education = 15.4 years, *SD* = 2.5; Mean individual annual income = $35,400, *SD* = 31,564; Mean household annual income = $59,500, *SD* = 45,347.

Materials

Three questionnaires were used to measure the discounting of delayed gains, delayed losses, and probabilistic losses.

Delayed Gains Questionnaire

A 27-item questionnaire developed by Kirby et al. (1999) was used to evaluate individuals' discounting of delayed gains. The items are divided into three sets of nine questions each, based on whether the delayed amount is small ($25, $30, or $35), medium ($50, $55, or $60), or large ($75, $80, or $85). As may be seen in Table 1, the items in each set correspond to nine logarithmically spaced values of the k parameter in a simple hyperbolic discounting function (Mazur, 1987). For each

Table 1

Question Order (Q), Immediate Amount (V_i), Delayed Amount (A_d), Duration of the Delay (D), and Values of k for Questions Involving Small, Medium, and Large Delayed Outcomes on the Kirby et al. (1999) Delayed Gains Questionnaire and the Myerson et al. (2017) Delayed Losses Questionnaire

Gains					Losses				
Q	V_i($)	A_d($)	D(days)	k	Q	V_i($)	A_d($)	D(mos)	k
Small Delayed Outcome									
13	34	35	186	0.00016	15	102	105	108	0.0000090
20	28	30	179	0.00040	8	84	90	106	0.000022
26	22	25	136	0.0010	2	66	75	78	0.000057
22	25	30	80	0.0025	6	75	90	46	0.00014
3	19	25	53	0.0060	25	59	75	26	0.00034
18	24	35	29	0.016	10	72	105	17	0.00089
5	14	25	19	0.041	23	41	75	12	0.0023
7	15	35	13	0.10	21	45	105	8	0.0055
11	11	30	7	0.25	17	33	90	4	0.014
Medium Delayed Outcome									
1	54	55	117	0.00016	27	162	165	68	0.0000090
6	47	50	160	0.00040	22	141	150	94	0.000022
24	54	60	111	0.0010	4	159	180	76	0.000057
16	49	60	89	0.0025	12	147	180	52	0.00014
10	40	55	62	0.0060	18	120	165	36	0.00034
21	34	50	30	0.016	7	103	150	17	0.00088
14	27	50	21	0.041	14	81	150	12	0.0023
8	25	60	14	0.10	20	75	180	8	0.0058
27	20	55	7	0.25	1	60	165	4	0.014
Large Delayed Outcome									
9	78	80	162	0.00016	19	234	240	94	0.0000090
17	80	85	157	0.00040	11	240	255	92	0.000022
12	67	75	119	0.0010	16	201	225	69	0.000057
15	69	85	91	0.0025	13	207	255	54	0.00014
2	55	75	61	0.0060	26	165	225	35	0.00034
25	54	80	30	0.016	3	162	240	18	0.00088
23	41	75	20	0.041	5	123	225	15	0.0018
19	33	80	14	0.10	9	99	240	8	0.0059
4	31	85	7	0.25	24	93	255	4	0.014

Note. For purposes of comparison, values of *k* are given in days for both gains and losses even though the delays for the loss questions seen by participants were given in months.

item, participants were asked to choose between an immediate, smaller gain and a delayed, larger gain (i.e., participants were asked, "Which would you prefer to receive?").

The proportion of items on which the delayed reward was chosen provided one measure of the degree to which an individual discounted delayed gains (Myerson et al., 2014). Although the proportion measure is strongly correlated with measures of *k*, it has the advantage that it does not require the assumption of a specific theoretical model (i.e., the simple hyperbola) and it can be used to measure negative discounting, which can be important when outcomes are losses rather than gains (Hardisty et al., 2013).

Delayed Losses Questionnaire

A 27-item questionnaire directly analogous to the delayed gains questionnaire and developed by Myerson et al. (2017) was used to evaluate individuals' discounting of delayed losses. The items are divided into three sets of nine questions each, based on whether the delayed loss is small ($75, $90, or $105), medium ($150, $165, or $180), or large ($225, $240, or $255). As may be seen in Table 1, the items in each set correspond to nine logarithmically spaced values of the *k* parameter in a simple hyperbolic discounting function (Mazur, 1987), even though that measure was not used for assessing discounting. The delays and amounts used in this questionnaire are greater than those used in the delayed gains questionnaire because of the sign effect (i.e., losses are discounted at a much lower rate than gains; e.g., Frederick et al., 2002). For each item, participants were asked to choose between an immediate, smaller loss and a delayed, larger loss (i.e., they were asked, "Which would you prefer to pay?"). The proportion of choices of the immediate payment was used as a measure of how steeply an individual discounted delayed losses.

Probabilistic Losses Questionnaire

Following the same procedure as that used to develop the delayed losses questionnaire, we developed a 27-item questionnaire to evaluate individuals' discounting of probabilistic losses (see Table 2). The items in this questionnaire also are divided into three sets of nine questions each, based on whether the probabilistic amount is small ($50, $60, or $70), medium ($100, $110, or $120), or large ($150, $160, or $170), and the items correspond to nine logarithmically spaced values of the *h* parameter in a simple hyperbolic model of probability discounting (Rachlin et al., 1991). For each item, participants were asked to choose between a certain, smaller loss and a larger, probabilistic loss. For example, they were asked, "Which would you prefer? Paying $32 for sure or 68% chance of having to pay $110 (32% chance of paying nothing)." The proportion of choices of the certain payment was used as a measure of how steeply each individual participant discounted probabilistic losses.

Table 2

Question Order (Q), Certain Amount (V_c), Probabilistic Amount (A_p), Probability of the Payment (P), and Values of h for Questions Involving Small, Medium, and Large Probabilistic Outcomes on the New Probabilistic Losses Questionnaire

		Losses		
Q	V_c($)	A_p($)	*P*	*h*
Small Probabilistic Outcome				
15	21	70	.05	0.1228
8	13	60	.05	0.1903
2	11	50	.08	0.3083
6	12	60	.11	0.4944
25	9	50	.15	0.8039
10	17	70	.29	1.2734
23	12	50	.39	2.0246
21	18	70	.53	3.2577
17	17	60	.67	5.1355
Medium Probabilistic Outcome				
27	33	110	.05	0.1228
22	24	100	.06	0.2021
4	26	120	.08	0.3144
12	24	120	.11	0.4944
18	22	110	.17	0.8193
7	21	100	.25	1.2540
14	25	100	.40	2.0000
20	27	120	.49	3.3094
1	32	110	.68	5.1797
Large Probabilistic Outcome				
19	48	160	.05	0.1228
11	42	170	.06	0.1945
16	36	150	.09	0.3132
13	28	170	.09	0.5016
26	29	150	.16	0.7947
3	36	160	.27	1.2740
5	35	150	.38	2.0138
9	36	160	.49	3.3094
24	46	170	.66	5.2327

Note. The *h* values were calculated using the odds against (*O*) having to make a payment, not the probability (*P*) of having to make a payment: $O = (1 - P)/P$.

Procedure

After reading information about the study and agreeing to participate, participants completed the three questionnaires. Because the main purpose of this study was to investigate individual differences in the discounting of different types of outcome, rather than group differences, all participants completed the questionnaires in the same order (a common practice in individual differences research; for the rationale, see Carlson & Moses 2001) in order to avoid "noise" from sequence effects to individuals' data: They completed the probabilistic losses questionnaire first, then the delayed gains questionnaire, and finally, the delayed losses questionnaire. Following completion of the three discounting questionnaires, the participants answered a series of demographic questions and were given a password to arrange for compensation. All data were collected using the internet survey platform Qualtrics.

Analyses

For each of the three questionnaires, the proportion of participants who chose the alternative used to measure individuals' discounting (i.e., the delayed gain, the immediate payment, or the certain payment) was calculated for each item. These measures, rather than the proportion of participants who chose the immediate gain, or the delayed or probabilistic loss, were selected because they correspond to the choices that some researchers assume reflect "self-control" and thus may shed light on the validity of that assumption. When plotted as a function of the log k or log h for the item, these proportions reveal whether the items on a questionnaire adequately assess preferences over the range of possible subjective values of the delayed or probabilistic outcome (Myerson et al., 2017). These proportions were fitted with a logistic growth function:

$$P = 1/\left[1 + e^{-\left(x - x_0 - x_1 * A_{\text{Medium}} - x_2 * A_{\text{Large}}\right) r}\right], \qquad (1)$$

where P, the dependent variable, is the proportion of choices; x is the logarithm of the discounting parameter values associated with the various questions; x_0, x_1, and x_2 are three intercept parameters that shift the curve horizontally depending on whether the amount is small, medium, or large, respectively; r is a rate parameter that describes the rate of increase in the proportion of choices; and A_{Medium} and A_{Large} are dichotomous variables that index the medium, and large amounts (for the small amount, $A_{\text{Medium}} = 0$ and $A_{\text{Large}} = 0$; for the medium amount, $A_{\text{Medium}} = 1$ and $A_{\text{Large}} = 0$; for the large amount, $A_{\text{Medium}} = 0$ and $A_{\text{Large}} = 1$). The values of x_1 and x_2 are used to evaluate whether there were significant differences as a function of amount. Following identification of positive and negative discounting subgroups on the two losses questionnaires, analogous analyses were conducted comparing the patterns of choices for participants in the different subgroups.

Major analyses were conducting using R Version 3.5.1 (R Core Team, 2018). The FlexMix (Version 2.3-15) software package (Leisch, 2004) was used to conduct mixture model analyses of the data from each questionnaire. The multilevel part of this analysis treated the item-level responses for a given questionnaire as nested within individuals. The item responses were modeled as a binomial logistic regression with the logarithm of k or h for specific questions (Wileyto et al., 2004) used as the predictor. The mixture model part of the analysis estimated component- (latent class) specific slopes and intercepts for the logistic regressions. For each questionnaire, these analyses were conducted assuming different numbers of hypothesized components to check the consistency of the resultant classifications, with a particular focus on whether negative discounting would be consistently observed.

We also examined whether participants in the different classes (i.e., the subgroups) revealed by mixture modelling of the data from a specific questionnaire differed with respect to their choices on the other two questionnaires. More specifically, we examined the correlations among choices as assessed by the different questionnaires to determine whether, within a subgroup, those who made more choices on one questionnaire also made more (or less) of those choices on the other questionnaires. All p values reported are corrected for multiple comparisons according to the false discovery rate method proposed by Benjamini and Hochberg (1995). Finally, we examined the degree to which membership in a subgroup (e.g., the negative discounting subgroup) on the delayed losses questionnaire corresponded with membership in other subgroups on the probabilistic losses questionnaire.

Results

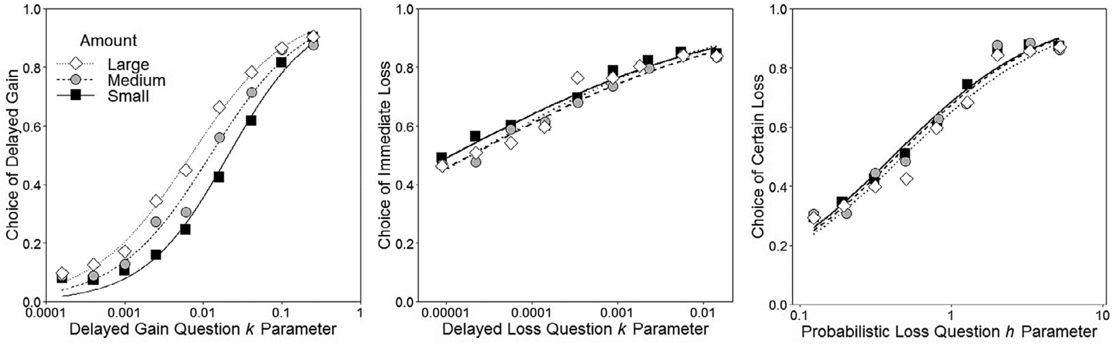
Magnitude Effects

The proportion of participants' choosing the delayed gain, immediate payment, and certain payment on each item for all three questionnaires is shown in Figure 1. As may be seen in the left panel, the proportion of participants who chose the delayed gain increased systematically as the k parameter for the corresponding questions increased and the delay decreased (see Table 1). The data were well described by Equation 1 ($R^2 = .99$), and both x_1 and x_2 were significantly different from zero (ps $< .01$), indicating a magnitude effect.

The data for the delayed and probabilistic losses questionnaires, with choice of the immediate loss and the certain loss, respectively, as dependent variables, also were well fitted by Equation 1 ($R^2 = .96$ and $.97$, respectively; see the middle and right panels in Fig. 1), but in contrast to the results for the delayed gains questionnaire, there were no apparent magnitude effects for either of these questionnaires.

Figure 1

Proportions of Participants Choosing the Delayed Gain, the Immediate Loss, and the Certain Loss.



Note. Proportion of participants who chose the delayed gain on each question of the delayed gains questionnaire (left panel), the immediate loss on each question of the delayed losses questionnaire (middle panel), and the certain loss on each question of the probabilistic losses questionnaire (right panel), plotted as a function of the discounting parameter associated with that question. Note the logarithmic scaling of the discounting parameter in all three panels.

This was verified statistically; that is, x_1 and x_2 were not significantly different from zero (ps > .14), and Equation 1 did not provide a significantly better fit to the data than a reduced model in which four parameters were removed (i.e., x_1, x_2, A_{Medium}, and A_{Large}) to reflect the null hypothesis that there is no magnitude effect with delayed or probabilistic losses (for delayed losses, $F[2, 25] = 1.87$, $p > .29$; for probabilistic losses, $F[2, 25] = 1.10$, $p > .45$).

It may be noted that while the proportion of choices of the delayed gains increased from approximately 0.1 to approximately 0.9 in Figure 1, choices of the immediate loss and the certain loss on the Delayed Losses and Probabilistic Losses questionnaires varied across a more restricted range. Given the recent finding that subgroups with different choice patterns (Myerson et al., 2017) can give rise to such attenuated ranges, the differences in range between choices on gains and losses questionnaires observed here call for further analysis at the individual level. Indeed, when such analyses were conducted, they revealed subgroups of substantial size with different choice patterns in the case of the delayed losses questionnaire as well as in the case of the probabilistic losses questionnaire.

Choice Patterns

For the delayed gains questionnaire, analysis of the data from individual participants revealed that, as expected, most (90.0%) showed a positive correlation between their choices of the delayed gain and the logarithms of the k values for the different questions, indicating that their choice of the delayed gain increased as the delay decreased. In contrast to the relatively consistent choice patterns observed with delayed gains, analysis of the data from the delayed losses questionnaire revealed that although a majority of the participants (57.3%) showed the expected positive correlation between their choices and the logarithms of the k values for the different questions (reflecting more choices of a smaller, but immediate loss when the delay to the larger loss option was brief), the remaining participants consisted almost entirely of two subgroups: 15.3% showed a negative correlation, reflecting the opposite pattern (i.e., more choices of the immediate option when the delay was long), and 25.8% always chose the immediate payment. This pattern of results is consistent with that of Myerson et al. (2017) who concluded that the attenuated range of choices of the immediate loss like those seen in Figure 1 reflects the presence of different patterns of choices on the delayed losses questionnaire.

As may be seen in the right panel of Figure 1, the data from our new probabilistic losses questionnaire also spanned an attenuated range, albeit to a lesser degree than the delayed losses data, and analysis of the individual data from our new probabilistic losses questionnaire again revealed subgroups showing different choice patterns: 74.0% showed a positive correlation between their choices and the logarithms of the *h* values, indicating that they were less likely to choose the certain payment when the likelihood of having to pay the larger amount was low, and more likely to choose the certain, smaller payment when the probability of the large payment was high, as reflected in larger *h* values. The remaining participants consisted almost entirely of two subgroups: 12.6% showed a negative correlation, indicating that the likelihood of their choosing a probabilistic loss decreased as the probability of having to pay decreased, and 12.4% always chose the smaller, certain payment regardless of the *h* values.

Mixture model analyses revealed subgroups with similar characteristics to those revealed by the correlational measures. Figure 2 presents the results of these analyses for models with three to six latent classes for each of the three questionnaires. These numbers of classes were chosen based on changes in Bayesian Information Criterion measures (BICs) as the number of classes increased (see Table 3), reaching asymptote at six or seven classes. It should be noted that, like the BIC, both the Akaike Information Criterion and the Integrated Completed Likelihood Criterion showed a pattern of improvements in fit with increasing numbers of latent classes reaching asymptote at the same number of classes in each case. The curves depicted in the figure represent the logistic growth functions that describe the patterns of choices by members of each subgroup identified as a latent class by the mixture model analyses.[2]

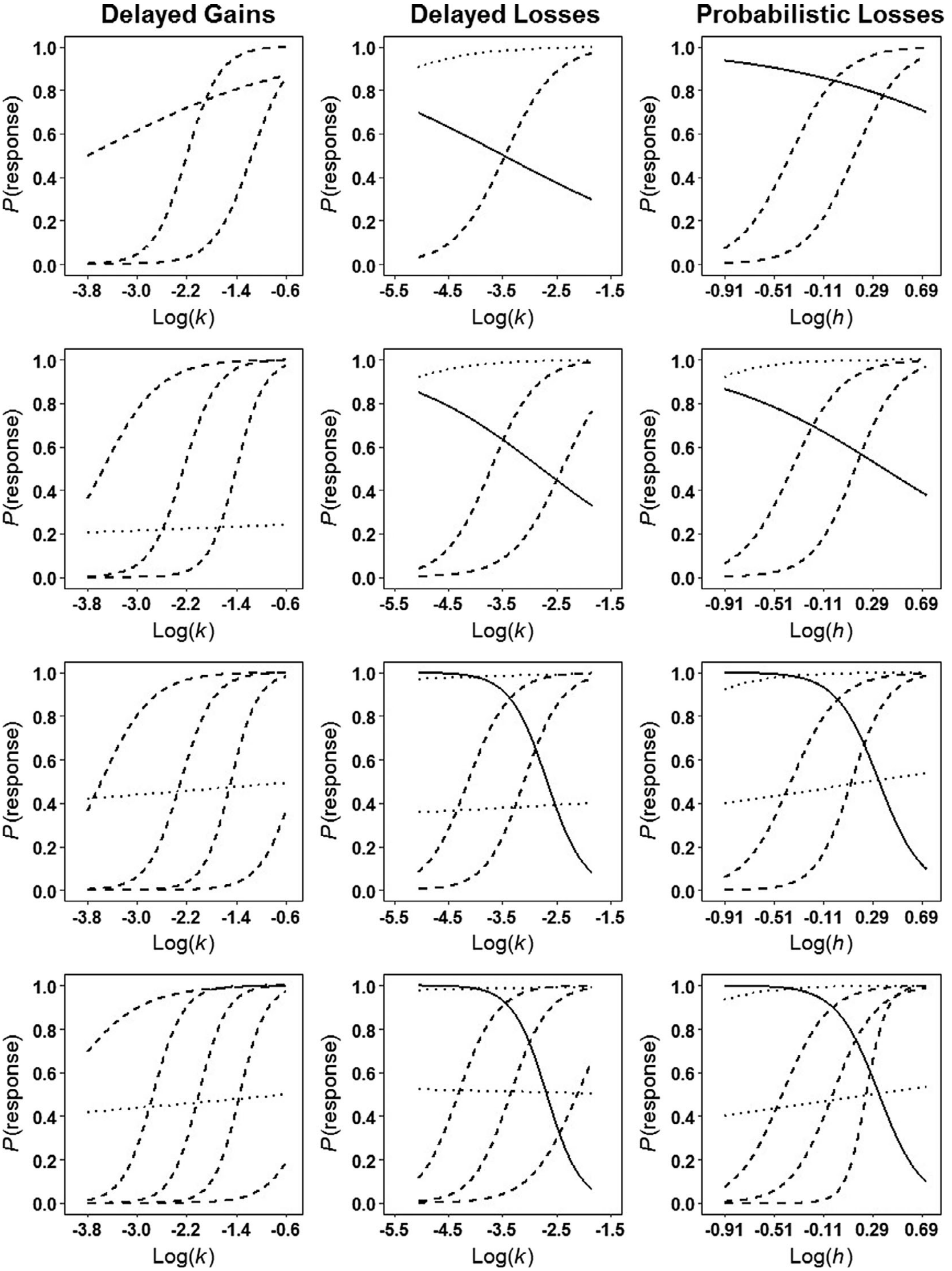
For the delayed losses and probabilistic losses questionnaires, negative discounting subgroups (i.e., subgroups of participants whose choice of the immediate or the certain option decreased as the delay until or odds against a loss increased) were observed for all numbers of latent classes. Indeed, as the number of classes increased, discounting by these subgroups (which correspond to the negative-correlation subgroups reported above) tended to become even more negative. Notably, there was no evidence for negative subgroups in the mixture model analyses of the data from the delayed gains questionnaire regardless of the number of latent classes.

Further analyses focused on mixture models with four latent classes because although further increases in the number of latent classes continued to improve the fit of the mixture models up to six or seven classes, these improvements were negatively accelerated and tended to merely increase the number of positive subgroups or identify subgroups of participants who were relatively insensitive to changes in delay or probability, as indicated by functions that were relatively flat. The quality of the classification provided by models with four latent classes was quite high, as indicated by the corresponding entropy measures, which were greater than .93 for all three questionnaires. The entropy measure (Celeux & Soromenho, 1996) provided by FlexMix (Leisch, 2004) ranges from 0.0 to 1.0, where values close to 1.0 indicate accurate classification as well as good separation between classes.

For the delayed gains questionnaire, the four latent classes consisted of three that showed increasing logistic growth curves and one that was characterized by a relatively horizontal curve, biased towards choosing the immediate gain. For both of the losses questionnaires, the four classes consisted of two increasing logistic growth curves, a negative discounting curve, and a relatively horizontal curve biased towards choosing the immediate or certain outcome. The parameters of these curves as well as the mixing proportions (the proportion of the sample in each latent class or subgroup) are provided in Table 4. For each questionnaire, the order of the four classes in the table is based on the rate parameter of the logistic growth function such that if there is a class that showed negative discounting, its parameters and mixing

[2]The curves in Figure 2 represent logistic growth functions. In biology, such functions are commonly written in the form: $y(x) = 1/[1 + \left(\frac{1}{y0} - 1\right) e^{-r\ x}]$. In the present case, *x* represents the log *k* for a specific question, *y* is the probability of a response to that question (either choosing the delayed outcome when that outcome is a gain or choosing the immediate or certain outcome when it is a loss), *r* is the parameter governing the rate of growth in *y*, and *y*0 is the intercept of the logistic growth function (i.e., the value of *y* when $x = 0$). Note that when the function is written in this form, it may immediately be seen that when $x = 0$, the equation simplifies to $y = y0$. It also is to be noted that the slope, *b*1, of the logistic regression equation, logit (*P*) = *b*0 + *b*1* *x*, is the rate parameter, *r*, in the above logistic growth function. The intercept (*b*0) of the logistic regression equation is the natural logarithm of the odds in favor of a response when $x = 0$: *ln* [*y*0/(1-*y*0)] = logit (*y*0).

Figure 2
Logistic Growth Functions for Different Subgroups.



Note. Logistic growth functions for the different subgroups identified by mixture models with different numbers of latent classes, ranging from three in the top row to six in the bottom row.

Table 3

Bayesian Information Criterion (BIC) Fit Statistics for Mixture Models with Different Numbers of Latent Classes

	Delayed Gains	Delayed Losses	Probabilistic Losses
Latent classes	BIC	BIC	BIC
1	10850	13230	12862
2	8833	9694	9852
3	7836	8617	9067
4	7252	7950	8366
5	6862	7688	8005
6	6625	7409	7890
7	6595	7409	7890
8	6595		

proportion will be found in the rightmost column of the table.

Following the use of mixture models to identify members of the different subgroups, we used mixed models to fit each individual's data on each losses questionnaire with a logistic growth function analogous to those used in the mixture modeling. The data from the two positive discounting subgroups were combined into one larger subgroup, and the choices of the individuals whose logistic regression slopes represent the 25th, 50th, and 75th percentiles of the distribution of slopes for their subgroup are depicted in Figure 3.

Table 4

Growth Rate (r) and Intercept (y0) Parameters as well as Mixing Proportions (m) and Entropy Values for the Mixture Models with Four Latent Classes

	Class 1	Class 2	Class 3	Class 4
Delayed Gains: entropy = 0.9369				
m	0.341	0.401	0.129	0.129
$y0$	0.9980	0.9998	0.9996	0.2473
r	4.447	3.713	2.216	0.064
Delayed Losses: entropy = 0.9667				
m	0.332	0.134	0.377	0.158
$y0$	0.9999	0.9943	0.9997	0.1067
r	2.389	2.157	1.123	-0.762
Probabilistic Losses: entropy = 0.9494				
m	0.351	0.332	0.167	0.150
$y0$	0.2958	0.8563	0.9947	0.6323
r	5.838	4.941	3.046	-1.445

Note. The mixing proportion, m, is the number of participants in a specific subgroup divided by the number in the whole sample; $y0$ and r are the parameters of the logistic growth function as presented in Footnote 2.

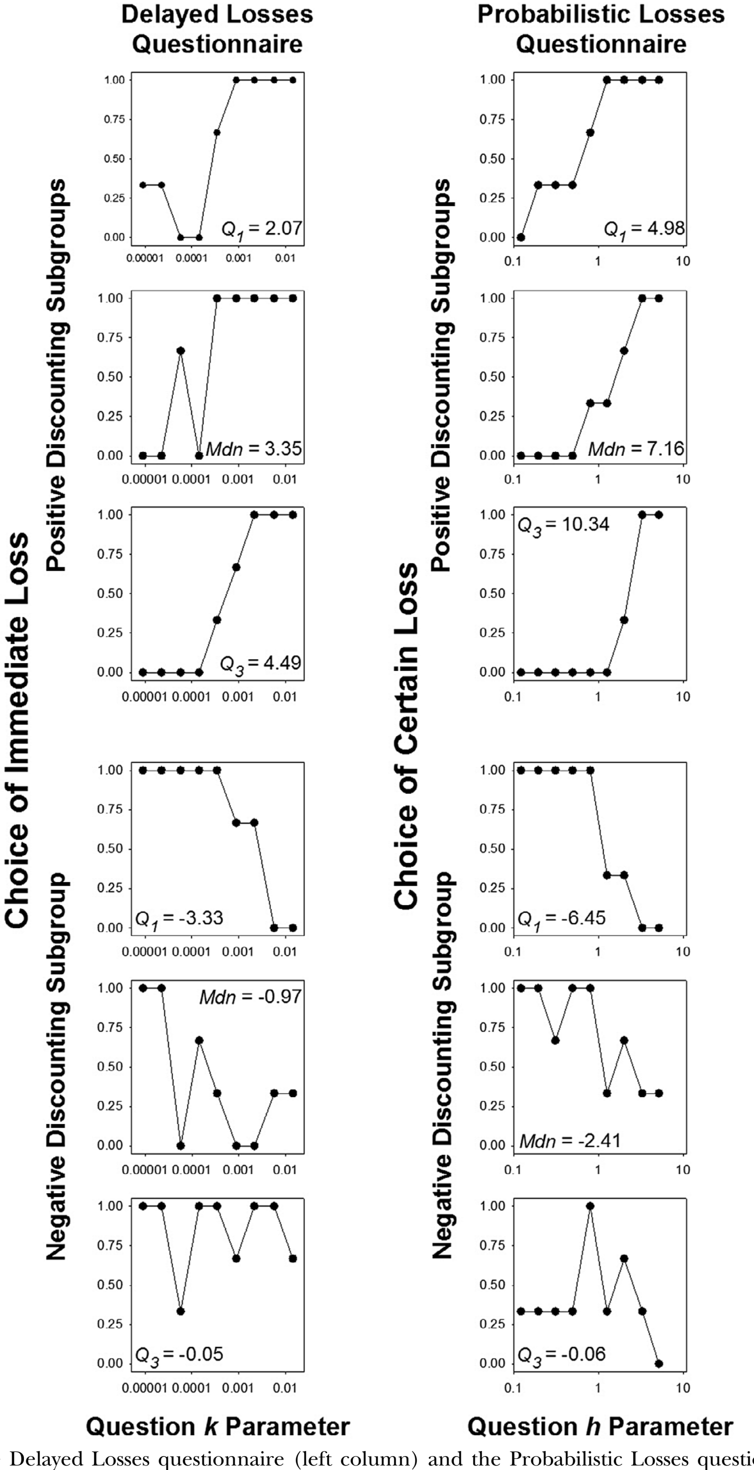
The presence of subgroups characterized by increasing and decreasing logistic growth functions when the choice options involve delayed or probabilistic losses explains the attenuated ranges of responses on these two questionnaires seen in Figure 1. For example, the data from the smaller negative discounting subgroup (n = 66) on the delayed losses questionnaire (see the upper right panel of Fig. 4), when combined with the data from the two positive discounting subgroups (upper left panel of Fig. 4; total n = 195), results in the attenuated sigmoidal curve seen in the combined data shown in the middle panel of Figure 1. Similarly, with the probabilistic losses questionnaire, the data from the smaller negative discounting subgroup (bottom right panel of Fig. 4; n = 63) combined with the data from the two positive discounting subgroups (bottom left panel of Fig. 4; total n = 286), results in the attenuated curve seen in the combined data shown in the right panel of Figure 1.

Correlations Between Different Types of Discounting

In the sample as a whole, the number of choices of the larger, delayed gain on the delayed gains questionnaire was not significantly correlated either with the number of choices of the immediate loss on the delayed losses questionnaire (r = .01) or with the number of choices of the certain loss on the probabilistic losses questionnaire (r = -.09), although there was a weak positive correlation between choices on the delayed and probabilistic losses questionnaires (r = .13, p < .01). However, different patterns of correlations were observed when the corresponding data for the subgroups on the two losses questionnaires identified by the mixture model with four latent classes were analyzed separately.

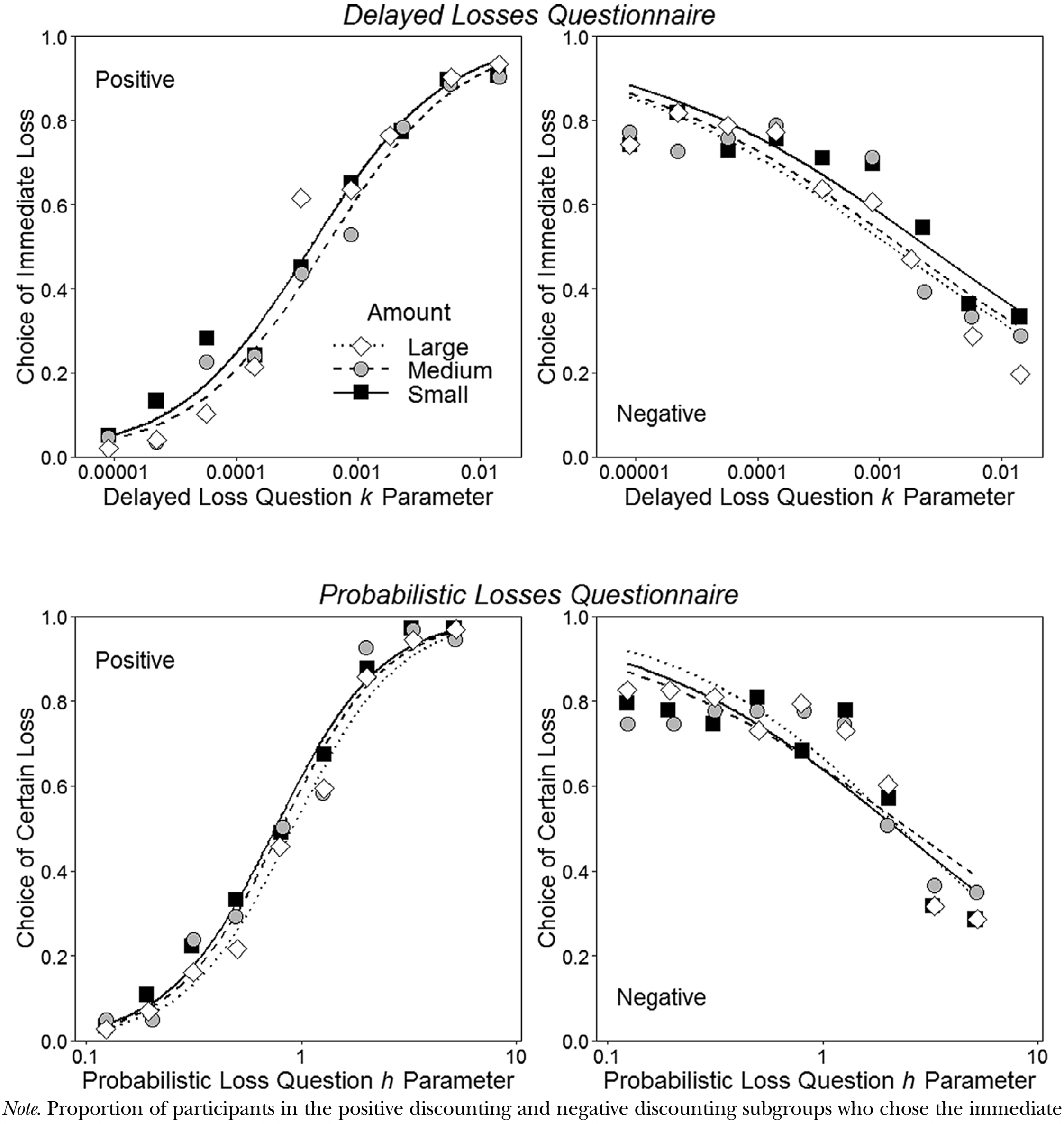
None of the correlations involving the subgroups on the Delayed Losses questionnaire were significant (all ps > .14), although the sample sizes for the subgroups were necessarily smaller than for the sample as a whole. For the positive discounting subgroups on the Probabilistic Losses questionnaire, however, there was a positive correlation between participants' choices on delayed losses and delayed gains questionnaires (r = .22, p < .01), whereas for the negative discounting subgroup, that

Figure 3
Individuals' Choices on the Delayed and Probabilistic Losses Questionnaires.



Note. Choices on the Delayed Losses questionnaire (left column) and the Probabilistic Losses questionnaire (right column) of the individuals whose logistic regression slopes represent the 25th, 50th, and 75th percentiles of the distribution of slopes for the positive discounting subgroups (upper three rows) and the negative discounting subgroups (lower three rows). Data points represent the proportions of choices on the three items from the small, medium, and large amount conditions that had similar *k*s (left column) and *h*s (right column).

Figure 4
Participants in Positive and Negative Subgroups Choosing Immediate Losses and Certain Losses.



Note. Proportion of participants in the positive discounting and negative discounting subgroups who chose the immediate loss on each question of the delayed losses questionnaire (top panels), and proportion of participants in the positive and negative subgroups who chose the certain loss on each question of the probabilistic losses questionnaire (bottom panels), plotted as a function of the discounting parameter associated with that question.

correlation was negative (r = -.45, $p < .01$). These positive and negative correlations may cancel each other out in the data from the whole sample (which also contains subgroups that show nearly exclusive choice of an immediate or certain loss), giving rise to the nonsignificant correlation observed for the whole sample. Finally, the choices of participants in the negative discounting subgroup on the delayed and probabilistic losses questionnaires were significantly correlated (r = .35, $p < .05$), whereas the corresponding choices of participants in the positive discounting subgroups were not (r = .04, p = .57).

Table 5

Cross Tabulation of the Delayed Losses and Probabilistic Losses Subgroups

	Probabilistic Losses		
	Positive (n = 286)	Negative (n = 63)	Other (n = 70)
Delayed Losses			
Positive (n = 195)	155	14	26
Negative (n = 66)	30	30	6
Other (n = 158)	101	19	38

Co-membership in Subgroups

The present results raise the question of whether people who show an atypical pattern of choices on one losses questionnaire also show an atypical choice pattern on the other losses questionnaire. For example, are members of the negative discounting subgroup on the delayed losses questionnaire likely to be members of the negative discounting subgroup on the probabilistic losses questionnaire? The answer to this question may be seen in the cross-tabulation table (Table 5), which presents the numbers of participants in the negative discounting subgroups on the two losses questionnaires, the numbers in the two positive discounting subgroups (collapsed), and the numbers in the Other subgroup whose functions were relatively flat. The number of participants who were members of the negative discounting subgroup on both losses questionnaires (rather than one of the other subgroups) differed significantly from that expected based on chance alone: $X^2(1) = 53.95$, $p < .001$, reflecting the fact that there were 30 participants who were members of both negative discounting groups whereas 9.9 were expected. It should be noted, however, that although being a member of the negative discounting subgroup on one losses questionnaire increased the likelihood of being a member of the negative discounting subgroup on the other losses questionnaire, nevertheless for each questionnaire, over half of the negative discounters were not negative discounters on the other questionnaire.

Demographic Differences

Finally, for both the delayed and probabilistic losses questionnaires, Pearson's chi-squared tests were used to compare the numbers of male and female participants in the combined positive subgroups with those for the negative subgroup, and Welch two-sample t-tests were used to assess demographic differences. The subgroups did not differ in gender, education, individual income, and household annual income on either questionnaire (all ps > .31). Notably, however, the positive discounting subgroups were significantly older than the negative discounting subgroup on both the delayed losses questionnaire, $t(120.77) = 2.54$, $p = .03$ (mean ages 36.2 and 32.2 years, respectively), and the probabilistic losses questionnaire, $t(124.55) = 4.99$, $p < .01$ (mean ages 36.0 and 29.8 years, respectively).

Discussion

To examine individual differences in choices involving probabilistic losses and examine how such choices are related to choices involving delayed gains and losses, we developed a 27-item probabilistic losses questionnaire modeled on those developed by Kirby et al. (1999) for delayed gains and Myerson et al. (2017) for delayed losses. Our new questionnaire proved to be valid in that choices of the certain payment changed systematically as a function of the h parameter of the question, and as in previous laboratory studies of the discounting of probabilistic losses, no magnitude effect was observed (Estle et al., 2006). In addition to capturing quantitative differences in the degree of discounting, the questionnaire also revealed subgroups of individuals with qualitatively different choice patterns.

Further, we replicated the previous finding of subgroups in the discounting of delayed losses (Myerson et al., 2017). In that study, approximately 20% showed negative discounting (and were termed Debt Averse) and in the present study approximately 15%

showed negative discounting of delayed losses. When a similar identification procedure was applied to the results from the discounting of probabilistic losses, the existence of subgroups with different choice patterns was again observed. Notably, 13% of the participants showed negative discounting of probabilistic losses (i.e., choices of the certain loss decreased as the likelihood of a probabilistic loss increased). The presence of subgroups that show patterns of discounting different from the majority of individuals is an important finding in part because it may explain the inconsistencies in the loss discounting literature noted by Harris (2012).

Because of the arbitrariness of criteria for identifying typical and atypical discounting based on correlations, the present study used mixture model analysis to identify subgroups of participants showing different patterns of discounting. Such analyses yield probabilistic models of the presence of subpopulations within an overall population when these subgroups are not known in advance. Similar to the subgroups revealed by correlations, mixture modeling assuming four latent classes of choice patterns revealed that 16% of the participants were members of the negative discounting subgroup on the delayed losses questionnaire and 15% were members of the negative discounting subgroup on the probabilistic losses questionnaire. These findings immediately raise two important questions: First, how many people show the typical positive discounting pattern for both delayed and probabilistic losses, and second, do people who show negative discounting on one losses questionnaire also show negative discounting on the other losses questionnaire?

With respect to the first question, nearly half of the participants (47%) were members of the positive discounting subgroups on the delayed losses questionnaire, and approximately two-thirds (68%) were members of the positive discounting subgroups on the probabilistic losses questionnaire. Although this is substantial, clearly many people do not show positive discounting when losses are involved. With respect to the second question, the majority of those in one negative discounting subgroup were not members of the other negative discounting subgroup, although co-membership in the two subgroups was more likely than predicted by chance. Thus, for the most part, an individual's choice pattern when probabilistic losses are involved is relatively independent of their pattern of choices when delayed losses are involved. Choices involving delayed and probabilistic losses are similar in that first, a magnitude effect is generally not observed in both cases, and second, discounting is well described by a hyperboloid function in studies using adjusting-amount procedures (Green, Myerson, Oliveira, & Chang, 2014), but the independence of choice patterns at the individual level argues for differences in the decision-making processes involved.

No previous study has explored individual differences in the discounting of probabilistic losses, and consequently our subgroup classification requires replication. We are optimistic, however, given that the results for the delayed losses questionnaire revealed the same subgroups reported by Myerson et al. (2017), validating the current approach. In addition, examination of the same participants' choices on the delayed gains questionnaire failed to reveal any subgroups comprising a sizeable percentage of participants, again replicating the Myerson et al. study and further increasing our confidence in the present approach. Taken together, all of these findings are consistent with the proposal that individuals differ qualitatively in their discounting of losses, both delayed and probabilistic, whereas they differ only quantitatively in their discounting of gains, although an examination of individual choice patterns with probabilistic gains clearly is needed.

Previous findings using adjusting-amount procedures suggest that the degree to which individuals discount delayed losses is not correlated with the degree to which they discount probabilistic losses (Green, Myerson, Oliveira, & Chang, 2014; Mitchell & Wilson, 2010), whereas in the present study, with a much larger sample (N = 419), there was a weak, albeit significant, correlation between choices on the delayed and probabilistic losses questionnaires (r = .13). It should be noted, however, that the participants in the positive and negative discounting subgroups on the Probabilistic Losses questionnaire showed different patterns of correlations among their choices on the three different questionnaires, with negative, positive, and nonsignificant correlations all being observed. The differences among these correlations provide independent evidence that the subgroups differ in their discounting, and like the different choice patterns associated with these subgroups, argue against simply combining data without examining it for differences among individuals.

Magnitude effects have played an important role in the study of discounting: With delayed gains, discounting decreases as the delayed amount increases, whereas with probabilistic gains, discounting increases as the probabilistic amount increases, indicating that although discounting is well described by the same hyperboloid function, different decision-making processes must be involved (for a review, see Green & Myerson, 2010). Additional evidence of the theoretical significance of magnitude effects is provided by the finding that whereas delayed and probabilistic gains show different effects of amount, with losses, neither delayed nor probabilistic losses showed magnitude effects, suggesting that again, different decision-making processes must be involved when choices involve losses rather than gains (e.g., Green, Myerson, & Vanderveldt, 2014). Notably, although the positive and negative discounting subgroups revealed by the mixture model analyses of the two losses questionnaires differed in their choice patterns, they were consistent in that no magnitude effects were observed (see Fig. 3). Thus, the present results demonstrate that whereas the various subgroups differ in multiple ways, they do not differ with respect to the absence of a magnitude effect when losses, either delayed or probabilistic, are involved.

Our results demonstrate the importance of taking individual differences into account in studying the relations among different discounting tasks, with implications for studying differences in discounting between demographic and other groups (e.g., substance abusers and controls). For example, the literature shows inconsistent findings regarding the correlation between the discounting of delayed gains and delayed losses. Although we failed to find a significant correlation between the discounting of delayed gains and delayed losses in the sample as a whole, we found negative, positive, and nonsignificant correlations for different subgroups. Our results suggest that having different percentages of the subgroups in a sample will have the effect of changing the correlations observed in the whole sample. Thus, any differences between studies may well be due to differences in the sizes of the subgroups (as well as reflecting sampling error).

Several important issues will require further study. One of these is determining, for each of the three questionnaires, how many theoretically meaningful subgroups there are. Our mixture model analyses revealed that the fit continued to improve as the number of latent classes was increased up to as many as six or seven subgroups. However, the largest improvements came when the number was increased from three to four classes, and therefore further analyses were based on models with four subgroups, although for certain analyses (e.g., co-membership), the positive discounting subgroups were treated as a single group. In future research, other analytic techniques (e.g., structural equation models, latent growth curve analyses, Bayesian modeling) may be needed to help resolve what is ultimately a theoretical issue. An important clue to how many meaningful classes there are on both the gains and losses questionnaires may also come from research on how different patterns of positive and negative discounting manifest themselves in everyday decision-making. Given the fact that negative discounters are in the minority, such research may need larger samples than are typically used in laboratory studies, and recruitment of internet samples like those used in the current investigation may be required.

The present findings strongly suggest that researchers studying discounting should examine the choice patterns of their participants, particularly when losses are involved, in order to more clearly understand the basis for the results that they observe in their samples as a whole. These issues may be especially critical when interventions that may modify discounting are being considered. Should we expect interventions to be equally effective on different subgroups? Will interventions modify choice patterns or alter the proportion of people in different subgroups? Although the present study has focused on subgroups that differ in their choice patterns when losses are involved, it is possible that subgroups also may be observed when the discounting of different kinds of gains (e.g., consumable vs. non-consumable rewards) is examined.

Conclusion

The present results show that people differ primarily quantitatively in their discounting of delayed gains but differ strongly, qualitatively as well as quantitatively, in their discounting of delayed and probabilistic losses. There was a magnitude effect in the discounting of delayed gains, but not in the discounting of delayed or probabilistic losses. Although most participants increasingly discounted the value of a gain as the delay to its receipt increased, they evaluated delayed and probabilistic losses differently. Many people increasingly discounted the value of a loss with increases in its delay and in the odds against its receipt; however, for others, the aversiveness of a loss actually increased with its delay and the odds against receiving it. There also were people who did not discount the aversiveness of losses with delay or probability, or did so only slightly. When these differences in evaluation of delayed and probabilistic losses were taken into account, different relations among the choices of delayed gains, delayed losses, and probabilistic losses emerged, which may well lead to a resolution of the inconsistent findings in the literature on the discounting of losses.

Taken together, our results suggest that the processes underlying the discounting of delayed gains, delayed losses, and probabilistic losses are different, and that not only do these differences have implications for understanding individual differences in decision-making, but individual differences have implications for understanding the processes that give rise to discounting at a more molar level. Finally, it cannot be overemphasized how important choices involving losses are in everyday life, and the present findings suggest that different people make these choices in different ways. Researchers are beginning to examine procedures that modify discounting with the goal of ameliorating behavioral problems (see Rung & Madden, 2018). We would point out that many problem behaviors are problems precisely because people's choices sometimes have negative consequences, often delayed and/or probabilistic, and thus understanding individual differences in discounting losses may prove critical.

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