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Evaluating Everyday Behaviors with Delayed and/or Probabilistic Consequences Through a Discounting Framework

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by

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Dedicated to my wife Meng-Ju and my daughter Suri.

ABSTRACT OF THE DISSERTATION

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Professor Leonard Green, Chair

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Delay and probability discounting refer to the decrease in subjective value of an outcome as the time until its occurrence increases and the likelihood of its occurrence decreases, respectively. Significant differences between the discounting of gains and losses, either delayed or probabilistic, have been documented in the literature. A recent study that investigated similarities and differences between the discounting of delayed gains, delayed losses, and probabilistic losses, found qualitative individual differences (i.e., subgroups) present only in the discounting of losses (Yeh et al., 2020). The current study expanded the previous investigation of subgroups to the discounting of probabilistic gains (Experiment 1) and examined to what extent the discounting of gains and losses, both delayed and probabilistic, are associated with everyday behaviors that involve delayed and/or probabilistic consequences (Experiment 2). Across two experiments, there was no evidence of subgroups either in the discounting of delayed gains or in the discounting of probabilistic gains, whereas a considerable number of individuals showed atypical discounting both in the discounting of delayed losses and in the discounting of

probabilistic losses, consistent with the notion that subgroups were present only in the discounting of losses. Regarding the associations between degree of discounting and everyday behaviors that involve delayed and/or probabilistic consequences, only 2 out of 204 regression coefficients (4 types of discounting tasks x 51 everyday behaviors investigated) reached statistical significance after correcting for multiple testing. Furthermore, neither degree of discounting nor the demographic variables (i.e., gender, age, years of education, and household income) were strong predictors for everyday behaviors, and degree of discounting only accounted for limited proportions of variance beyond the demographic variables. Our findings provide support for studying the discounting of losses by subgroups while showing degree of discounting alone is not sufficient to predict individuals' everyday behaviors.

Chapter 1: Introduction

Everyday options between which people choose often vary along three distinct dimensions: magnitude, delay, and probability. For example, a choice between keeping money in a savings account and putting it into the stock market involves evaluating the consequences that differ in terms of magnitude, delay, and probability. To reveal the decision-making processes underlying these choices, a discounting framework in behavioral economics, a field developed from both psychology and economics, has emerged in the past decades (Frederick et al., 2002; Green & Myerson, 2004). This framework captures important characteristics of choice behavior and provides researchers a reliable method to systematically investigate both human decision-making processes and psychopathologies of various maladaptive behaviors (e.g., addiction; pathological gambling; Madden & Bickel, 2010).

Although gains and losses are equally important to our everyday decisions, it is to be noted that the overwhelming majority of discounting studies have focused on gains, and the literature on losses is not only meager but fraught with inconsistencies (Harris, 2012). In a recent study that investigated similarities and differences between the discounting of delayed gains, delayed losses, and probabilistic losses, substantial individual differences (i.e., subgroups) were found in the discounting of losses but not in the discounting of gains (Yeh et al., 2020). The existence of subgroups is critical for understanding the differences between the discounting of gains and losses and may explain some of the "inconsistencies" in the literature. The present work involved a systematic replication of Yeh et al. and extended the investigation to the discounting of probabilistic gains. Furthermore, to what extent the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses as well as the presence of subgroups relate to everyday behaviors that involve delayed and/or probabilistic consequences was examined in the current study.

1.1 The Discounting Framework

The behavioral economic literature has shown that individuals discount the nominal value of a delayed outcome as the time until its occurrence increases, termed *intertemporal discounting* or *delay discounting*, as well as discount the nominal value of a probabilistic outcome as the likelihood of its occurrence decreases, termed *probability discounting*. Although the current work focuses on delay and probability discounting, it should be noted that the discounting framework has been extended to study decision-making processes that involve discounting over social distance (i.e., the degree to which individuals share common interests), termed *social discounting* (e.g., Jones & Rachlin, 2006), and discounting over physical or cognitive effort, termed *effort discounting* (e.g., Mitchell, 2004; Westbrook et al., 2013).

Different mathematical models have been proposed to describe both delay and probability discounting (e.g., exponential, hyperbolic, q-exponential, quasi-hyperbolic; for a review, see Frederick et al., 2002; Green & Myerson, 2004). For example, a hyperboloid function that well describes the discounting of a delayed or probabilistic reward has the form (Green et al., 1994; Green et al., 1999; Myerson & Green, 1995):

$$V = A / (1 + bX)^s, \tag{1}$$

where V is the subjective value of a delayed or probabilistic reward, A is the objective amount of the reward, b is the discounting rate parameter (k for delay discounting and h for probability discounting), X is either the delay until receipt of the reward (for delay discounting) or the odds against receipt of the reward (for probability discounting)[1], and s is a free parameter that for

[1] The odds against receipt of a probabilistic reward equals $(1-p)/p$, where p is the probability of occurrence.

delay discounting represents the nonlinear scaling of amount and/or time perception and is generally equal to or less than 1.0 (McKerchar et al., 2010; Myerson & Green, 1995), and for probability discounting corresponds to a decision weight, which is similar to what Kahneman and Tversky (1979) proposed in prospect theory (McKerchar et al., 2010; Myerson et al., 2011).

Similarities between the discounting of delayed gains and the discounting of probabilistic gains have received considerable attention in the literature (Green & Myerson, 2004; Prelec & Loewenstein, 1991; Rachlin et al., 1991). Both types of discounting relate to behaviors often conceived of as "impulsive," and are well described by the same form of mathematical function (e.g., the hyperboloid; Equation 1; Ostaszewski et al., 1998). As a consequence of these similarities, it has been proposed that delay and probability discounting reflect a single underlying process in which increases in the time to an outcome reflect decreases in the likelihood of obtaining the outcome and/or in which decreases in the probability of receiving an outcome reflect increases in the waiting time to eventual receipt of the outcome (Myerson et al., 2003; Rachlin et al., 1986).

The accumulated evidence in the literature, however, reveals that the processes underlying the discounting of delayed gains are different from those underlying the discounting of probabilistic gains. For example, amount of reward has opposite effects on the degree of delay and probability discounting: Whereas degree of delay discounting decreases with amount, degree of probability discounting increases with amount (Estle et al., 2006; Green et al., 1999; Myerson et al., 2003). Moreover, the parameters of the discounting function behave differently with amount: Whereas amount of delayed reward affects the discounting rate parameter of the hyperboloid discounting function but not its exponent, the opposite is true for the amount of probabilistic reward (Green et al., 2013; Myerson et al., 2011). Age may have different effects on the discounting of delayed and probabilistic rewards: Whereas degree of delay discounting tends to decrease with age, degree of probability discounting does not appear to change with age (Mok et al., 2020; Olson et al., 2007; Scheres et al., 2006). Reward-type also shows different effects on delay and probability discounting: Whereas delayed monetary rewards are discounted less steeply than delayed consumable rewards, probabilistic monetary rewards are discounted at similar rates as probabilistic consumable rewards (Estle et al., 2007). The view that delay and probability discounting reflect different underlying processes is further supported by the finding that the correlation between the two is typically weak (Jarmolowicz et al., 2012; Madden et al., 2009; Ohmura et al., 2006; Shead & Hodgins, 2009; for reviews, see Green & Myerson, 2010; Green et al., 2014) and the patterns of brain activation evoked by risk and intertemporal choices are partially distinct (Peters & Büchel, 2009; Weber & Huettel, 2008).

1.2 Discounting Tasks

Both delay and probability discounting have been studied with different discounting tasks (for reviews, see Green et al., 2014; Madden & Johnson, 2010; Matta et al., 2012) that may be divided into two categories: those that allow for the determination of a discounting curve and those that do not. The former tasks typically are more time consuming but may provide answers to important theoretical questions (e.g., what mathematical models describe discounting; what are the processes that underlie the choice behaviors). Tasks that preclude determining a discounting curve typically require less time on the part of the participant while providing sufficient information to evaluate individual or group differences in degree of discounting.

1.2.1 Measuring Discounting with a Discounting Curve

Discounting curves, which show the change in subjective value of an outcome as a function of its delay or probability of occurrence, can be used to quantify degree of discounting in two distinct ways. The first involves fitting a quantitative discounting model to the data (e.g., the hyperbola) and using the value of the discount rate parameter as a measure of degree of discounting. The second involves calculating the area under the empirically determined discounting curve and is an atheoretical approach for determining the degree of discounting (Myerson et al., 2001). Although several procedures were developed to measure delay discounting, analogous procedures can be used to measure probability discounting.

Delay discounting is commonly measured using a binary choice task, in which individuals are asked to make a series of dichotomous choices between an immediate, smaller amount and a delayed, larger amount. Across choices, the immediate amount (adjusting-amount procedure) or the time to the larger amount (adjusting-delay procedure) is varied to reveal at which point the delayed, larger amount is judged to be subjectively equal to the immediate, smaller amount, referred to as the *indifference point*[2]. The amount of the immediate outcome at the indifference point represents the subjective value of the larger amount when it is delayed for the specified length of time. The procedure to obtain the indifference point is typically repeated across different delays or amounts, thereby allowing for the determination of a discounting curve.

A popular procedure for determining indifference points is to fix the delayed amount while systematically increasing (or decreasing) the immediate amount. A predetermined rule is typically required to establish the indifference point when individuals switch from one alternative to the other in a series of choices. For example, Rachlin et al. (1991) presented participants with pairs of choices between a smaller, immediate reward and a larger, delayed

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[2] Another, although uncommon procedure, is an adjusting-delayed-amount procedure, in which, the amount of the immediate outcome and the delay to the larger outcome are fixed, while the amount of the delayed reward is adjusted until participants are equally likely to choose the immediate and delayed rewards. Unlike the adjusting-amount and the adjusting-delay procedures, however, the adjusting-delayed-amount procedure is not useful for establishing discounting curves (Holt et al., 2012).

reward (e.g., "Would you prefer to receive $10 now or $100 in 1 year?"). While the amount of the delayed reward was fixed across pairs, the amount of the immediate reward was increased from zero to that of the delayed amount (and/or decreased from the delayed amount to zero); the average of the immediate amounts just before and just after a participant switched to the initially dispreferred alternative was taken as an estimate of the present subjective value of the delayed reward (see also Green et al., 1997; Mitchell, 1999). It is to be noted that the order of presentation of immediate amounts may affect the observed indifference points. For example, it has been reported that the ascending sequence produces lower indifference points (i.e., steeper discounting) than the descending sequence (Robles & Vargas, 2008; Robles et al., 2009).

A similar reliable procedure to determine indifference points is to fix the delayed outcome while systematically adjusting the immediate amount based on individuals' previous choices. For example, Du et al. (2002) used an adjusting-amount procedure in which the amount of the immediate, smaller reward in the first choice was equal to one-half the amount of the larger, delayed reward (e.g., $50 now or $100 in 1 year). If the participant chose the immediate reward, then its amount was reduced on the next choice; if the participant chose the delayed reward, then the amount of the immediate reward was increased on the next choice. The size of the adjustment after the first choice was half the amount of the immediate reward, and on each subsequent choice, the adjustment was half the amount of the prior adjustment. This procedure rapidly converges on an estimate of the present subjective value of the delayed reward. Furthermore, research has shown that this procedure produces similar results to the fixed sequence procedure (Rodzon et al., 2011).

There are methods of measuring discounting that do not involve a binary choice task. For example, Chapman (1996) employed a fill-in-the-blank (matching) task in which participants reported the amount of money to be delivered in the future that would be subjectively equal to a fixed amount of money delivered immediately (e.g., "$500 now or $__ 1 year from now; What amount would have to appear in the blank to make both equally attractive?"). The amount reported by the participant was used to calculate the rate of discounting. Smith and Hantula (2008) adopted this task and asked participants to report the amount of money to be delivered immediately that would be subjectively equal to a fixed amount of money delivered in the future. The amount reported by the participant was taken as an estimate of the present subjective value of the delayed reward to determine discounting curves. It is to be noted, however, that they found that their fill-in-the-blank task generated shallower discounting functions than that of the binary choice task. Similarly, Weatherly and Derenne (2011) compared a fill-in-the-blank task with a multiple-choice method, in which participants identified the indifference point from a list of response options that were presented, and reported that the two methods generated dissimilar discounting functions.

1.2.2 Measuring Discounting without a Discounting Curve

While some discounting tasks measure the change in subjective value, thereby allowing for the determination of a discounting curve, others directly estimate degree of discounting by assuming a specific discounting function. For example, Kirby et al. (1999) developed a 27-item monetary choice questionnaire (MCQ) in which each item is a binary choice between a smaller immediate reward and larger delayed reward (e.g., "Do you prefer receiving $33 today or $80 in 14 days?"). The items were created based on nine, logarithmically spaced values of the k parameter in Mazur's (1987) simple hyperbolic discounting model[3], and individual rates of

[3] The simple hyperbolic discounting function in Mazur (1987) has the form: $V = A/ (1 + kD)$, where V is the subjective value of a delayed reward, A is the objective amount of the reward, k is the discounting rate parameter, and D is the time until receipt of the reward. Notice that the simple hyperbolic discounting model is a special case of Equation 1, the hyperboloid discounting function, in which s is equal to 1.0.

discounting were estimated by observing participants' choice patterns. For example, if a participant preferred receiving $33 today over $80 in 14 days and receiving $85 in 7 days over $31 today, her discount rate (i.e., *k* parameter in the hyperbolic discounting model) would be a value greater than 0.10 (determined by the first choice) but less than 0.25 (determined by the second choice). The geometric mean is used to represent the discount rate to avoid underweighting the smaller of the two parameters; the choices in this example yield a discount rate of 0.16.

As an alternative, atheoretical approach to determining degree of discounting with the MCQ, Myerson et al. (2014) proposed a different scoring method for the MCQ. Specifically, they used the proportion of items on which the participant chose the larger delayed reward to represent the rate of discounting. Although this method does not yield a (range of) specific value(s) for an individual's *k* parameter, it has the advantage that it does not require the assumption of a specific theoretical model (i.e., the simple hyperbola) and is easy to calculate. Notably, Myerson et al. showed that the proportion measure was very highly correlated with measures of *k* ($r > .97$). This scoring method has been adopted for the other two analogous questionnaires to the MCQ that measure the discounting of delayed and probabilistic losses and identify potential subgroups (Myerson et al., 2017; Yeh et al., 2020).

Koffarnus and Bickel (2014) developed a five-item discounting task to determine the Effective Delay 50% (ED_{50}) of a reward (i.e., the delay at which present subjective value of a reward becomes half of its nominal value). Each of the five items consists of a binary choice between a smaller, immediate reward of amount .5X and a larger, delayed reward of amount X. The delay used for the first item starts at a fixed value of 3 weeks. Akin to the adjusting-amount procedure of Du et al. (2002), the delay used for the subsequent items is determined by the participant's choice on the previous items. If the participant chooses the immediate reward, then the delay is reduced for the next choice; if the participant chooses the delayed reward, then the delay is increased for the next choice. This iteration continues for five items, with the amount of delay changing by predetermined adjustments ranging from 1 hour to 7 years. This procedure results in 32 potential ED_{50} values (2^5), nearly evenly spaced (on a logarithmic scale) between 1 hour and 25 years. The ED_{50} values can then be converted to a discounting rate given that they are simple inverses based on Mazur's (1987) hyperbolic discounting model (Yoon & Higgins, 2008).

Also based on the same hyperbolic discounting model, Yoon and Chapman (2016) developed a titration procedure for a ternary choice task (the Three-option Adaptive Discounting rate measure) to measure degree of delay discounting. The three options with each choice question represent a discounting rate (*k*), and a resolution (*r*) with an upper boundary ($k + 1.96*r$) and a lower boundary ($k - 1.96*r$), and an individual's discounting rate can be categorized into one of three different ranges according to their response to the question. The delay and the amount for the options are determined by algorithms derived from the hyperbolic discounting model and *k* and *r* values, and thus vary question by question. In their titration procedure, both the responses to the previous and the current questions are used to determine both the direction and the magnitude of the adjustment to *k* and *r* values for the following question. The task produces rapid convergence on an estimate of an individual's discounting rate with high precision.

1.3 Differences Between the Discounting of Gains and Losses

There are several significant similarities in the discounting of gains and losses. For example, like the discounting of delayed and probabilistic gains, both the discounting of delayed and probabilistic losses have been demonstrated empirically (e.g., Estle et al., 2006). Furthermore, the same mathematical function that describes the discounting of gains can be used to describe the discounting of losses (e.g., the hyperboloid; Equation 1; Green, Myerson, Oliveira, et al., 2014). An important phenomenon found in the discounting of delayed gains in which peoples' preferences switch from a larger, later gain to a smaller, sooner gain as time to the smaller, sooner outcome approaches, termed a *preference reversal*, has been observed in the discounting of delayed losses as well (Kirby & Herrnstein, 1995; Holt et al., 2008).

Despite these significant similarities, people evaluate gains and losses in different ways. For example, people are more risk-averse when choosing between probabilistic gains but more risk-taking when choosing between probabilistic losses involving the same amount of money (Kahneman & Tversky, 1979). A recent factor analysis from a study of the discounting of delayed gains, probabilistic gains, delayed losses, and probabilistic losses identified three principal factors: one for delayed gains, one for probabilistic gains, and one for delayed losses and probabilistic losses (Mejía-Cruz et al., 2016). This finding suggests that the underlying processes for the discounting of delayed losses and probabilistic losses may be more similar to each other than they are for those of delayed gains and probabilistic gains.

Despite the far fewer studies of the discounting of losses than that of the discounting of gains, the small body of research has uncovered significant differences between the discounting of gains and losses, consistent with the view that the processes underlying the discounting of gains are different from those that underlie the discounting of losses. The following subsections summarize four major differences between the discounting gains and losses: the sign effect, the magnitude effect, negative discounting, and the presence of subgroups in the discounting of losses.

1.3.1 Sign Effect

Consistently reported in the literature is the finding that gains are discounted at a higher rate than losses of the same magnitude. In delay discounting, this finding is referred to as the sign effect (Benzion et al., 1989; Thaler, 1981). The sign effect is robust and has been replicated in studies using different commodities, such as money (Estle et al., 2006; Furrebøe, 2020; Murphy et al., 2001), cigarettes (Johnson et al., 2007), health outcomes (Baker et al., 2003; Chapman, 1996; MacKeigan et al., 1993), environmental consequences (Hardisty & Weber, 2009), and working time (Abdellaoui et al., 2018). The sign effect also has been reported in probability discounting (Estle et al., 2006; Ohmura et al., 2005), where probabilistic gains are discounted at a higher rate than probabilistic losses of the same magnitude. This latter finding is consistent with the prediction of prospect theory that people are more likely to choose a sure, smaller gain over a probabilistic, larger prospect but risk a probabilistic, larger loss over a sure, smaller expense (Kahneman & Tversky, 1979).

1.3.2 Magnitude Effect

A robust finding in the discounting literature is the magnitude effect, in which large future gains are discounted less steeply than small future gains, whereas large probabilistic gains are discounted more steeply than small probabilistic gains (Estle et al., 2006; Green et al., 1999; Myerson et al., 2003). The effect of amount, however, is minimal if not absent in the discounting of losses. For example, Ostaszewski and Karzel (2002) examined both delay and probability discounting of losing $200, $5,000, and $30,000 hypothetical money. They reported a magnitude effect for the discounting of delayed losses (i.e., larger losses were discounted less steeply than smaller losses) but no effect of amount on the discounting of probabilistic losses. Baker et al. (2003) also found a magnitude effect for delay discounting of losing $10, $100, and $1,000 hypothetical money and for the discounting of equivalent worth of cigarettes, but this effect was much less pronounced when compared with the discounting of delayed gains. Other studies, in fact, have found no systematic effect of amount on the discounting of either delayed losses or probabilistic losses over a wide range of amount from $10 to $500,000 (Estle et al., 2006; Green, Myerson, Oliveira, et al., 2014; McKerchar et al., 2013; Mitchell & Wilson, 2010).

1.3.3 Negative Discounting

Although the subjective value of an outcome typically decreases as the time to its occurrence increases, referred to as *positive temporal discounting*, the opposite pattern (i.e., the subjective value of an outcome increases along with the time to its occurrence), referred to as negative temporal discounting, has been reported (e.g., Loewenstein, 1987; Van der Pol & Cairns, 2000). Negative temporal discounting has received little attention in the literature because most research only focuses on the delay discounting of gains, and most all individuals show positive temporal discounting. With the discounting of delayed losses, however, a large number of individuals appear to show negative temporal discounting (Myerson et al., 2017; Yeh et al., 2020). Furthermore, the likelihood of negative temporal discounting appears to be affected by the types of losses being evaluated. Specifically, Harris (2012) found that when the aversive experiences were monetary and property losses, most participants preferred to postpone the loss; when the aversive experiences were social rejection, embarrassment, and pain, however, although some participants preferred to defer the loss, many others elected to undergo these unpleasant experiences immediately. For example, when asked to pick one of six possible temporal placements to receive a very painful bee sting, about 33% of participants chose the longest delay (i.e., 5 years) while about 35% of participants chose to experience it immediately.

To date, no research has reported negative discounting with probabilistic gains (i.e., the subjective value of an outcome increases along with the odds against its occurrence). Yeh et al. (2020), however, observed a substantial number of participants who showed negative discounting when evaluating probabilistic losses. Although such a finding requires further examination, it suggests that negative discounting might be an important feature shared by the discounting of delayed losses and probabilistic losses.

1.3.4 Subgroups in the Discounting of Losses

The finding of negative discounting with losses calls attention to the importance of evaluating individual differences in choice behavior. Further support for the need to evaluate individual differences comes from recent studies that have identified subgroups of individuals who exhibit distinct choice patterns in their discounting of losses. Gonçalves and Silva (2015) compared the discounting of delayed monetary gains and losses and found that although roughly 95% of the participants discounted delayed gains in the typical manner (i.e., positive discounting), only about 40% of the participants showed the typical delay discounting pattern for losses (i.e., loss becoming less aversive with increasing delay). Among the remaining participants, about 40% showed typical discounting at shorter delays, followed by negative temporal discounting at longer delays (i.e., loss becoming more aversive with increasing delay), and about 20% showed zero discounting (i.e., the aversiveness of a loss did not change with delay).

Consistent with the findings of Gonçalves and Silva (2015), Myerson et al. (2017) identified a three-group classification based on the way individuals chose between smaller, immediate payments and larger, delayed payments in two independent samples. Participants completed a delayed losses discounting task that had the same structure as the MCQ, and the correlation between their choice of the smaller, immediate payment and the logarithm of the *k* parameters for each of the 27 delayed loss questions was calculated. 61% and 55% of the participants in the two samples showed a positive correlation (i.e., the choice of the smaller, immediate payment decreased as the delay to the larger payment increased), indicating typical discounting of delayed losses, and 18% and 23% of the participants in the two samples showed a negative correlation (i.e., the choice of the smaller, immediate payment increased as the delay to the larger payment increased), indicative of negative discounting. There also was a substantial proportion of individuals (21% and 22%) who showed no discounting, always choosing to pay immediately.

Yeh et al. (2020) expanded the investigation of subgroups to the discounting of probabilistic losses. Unlike Myerson et al. (2017), Yeh et al. determined individual choice patterns by mixture model analysis, a principal unsupervised learning method to identify clusters, and one that prevents the arbitrariness involved when the sign of a correlation is used as the basis for classification. Consistent with the finding of subgroups in the discounting of delayed losses reported in Myerson et al., the mixture model analysis also identified three distinct choice patterns that corresponded to typical (46.5%), atypical (i.e., negative discounting; 15.8%), and minimal discounting (37.7%). Furthermore, Yeh et al. identified another three distinct choice patterns based on the way individuals chose between certain, smaller payments and probabilistic, larger payments: 68.3% of the participants showed the typical discounting pattern, being more likely to choose the probabilistic payment as its probability decreased; 15.0% of the participants were less likely to choose the probabilistic payment as its probability decreased; and 16.7% of the participants tended to choose only the certain, smaller payment or were indifferent between the two alternatives and showed minimal discounting. In contrast, 87.1% of the participants showed the typical pattern when discounting delayed gains (i.e., decreasing their choice of a delayed gain as time to its receipt increased).

The existence of subgroups is critical for understanding individual choice behavior over losses; in fact, the presence of these subgroups may help explain some of the inconsistencies noted in the literature on loss discounting. For example, because the discounting of delayed gains and delayed losses correlated differently within the subgroups (Myerson et al., 2017; Yeh et al., 2020), the finding that the correlation between the discounting of delayed gains and delayed losses is sometimes positive (e.g., Mitchell & Wilson, 2010) and sometimes negative (e.g., Hardisty & Webber, 2009) might be explained by different percentages of the subgroups present in each sample. Overrepresentation of certain subgroups also may account for instances of negative discounting (e.g., Loewenstein, 1987). It is worth noting, however, that the finding of subgroups is relatively new and that no study has investigated whether subgroups are present in the discounting of probabilistic gains. Thus, the present work conducted a systematic replication of Yeh et al and extended the investigation to the discounting of probabilistic gains.

1.4 Relations Between Discounting and Everyday Behaviors

The discounting framework has received considerable attention in the literature due, in part, to the association between degree of discounting with various maladaptive behaviors, although the associations reported are largely with the discounting of gains. For example, steep discounting of delayed gains has been linked to substance use (e.g., alcohol use, smoking; Audrain-McGovern et al., 2009; Bickel et al., 1999; Petry, 2001a), drug addiction (Amlung et al., 2017; MacKillop et al., 2011), gambling problems (Dixon et al., 2003), obesity (Weller et al., 2008), and risky sexual behavior (Chesson et al., 2006), and shallow discounting of probabilistic gains has been linked to gambling problems (Holt et al., 2003; Kyonka & Schutte, 2018; Madden et al., 2009; Petry, 2001b). It is worth noting that recent efforts have begun to focus on the development of interventions aimed at reducing degree of discounting, with the assumption that such interventions then will assist in reducing maladaptive behaviors (e.g., DeHart et al., 2016; Rung & Madden, 2018; Scholten et al., 2019; Sze et al., 2017).

Associations between the discounting of losses and maladaptive behaviors have been reported in the literature, although conflicting findings have been obtained. For example, while some studies reported an association between steep delay discounting of losses and smoking (Baker et al., 2003; Odum et al., 2002) and cocaine use (Cox et al., 2019), others failed to identify such a relation (Mejía-Cruz et al., 2016; Ohmura et al., 2005). Although perceived risk seems to relate to the likelihood of substance use (Volkow & Li, 2004; Weinstein et al., 2005), no relation has been found between the rates of discounting probabilistic losses and the use of cigarettes (Yi et al., 2007; Odum et al., 2002; Ohmura et al., 2005), alcohol (Takahashi et al., 2009), cocaine, and marijuana (Mejía-Cruz et al., 2016). On the other hand, research has suggested a link between steep discounting of delayed losses and the use of alcohol and marijuana (Bailey et al., 2018; Gerst et al., 2017; Mejía-Cruz et al., 2016; Takahashi et al., 2009). These conflicting results may be due to the presence of the discounting subgroups, although further investigations are required to test this account. As Yeh et al. (2020) noted, the subgroups in the discounting of losses are likely to show different characteristics, and hence different percentages of the subgroups in the samples may create inconsistent findings.

Other investigations have focused on associations between degree of discounting and general, everyday choice behaviors, thereby demonstrating the relevance of the discounting framework to everyday decision-making. For example, recent meta-analyses showed that shallow discounting of delayed gains was associated with healthier body mass index, healthier diets and greater exercise (Barlow et al., 2016; Sweeney & Culcea, 2017). Steep discounting of delayed gains was associated with an increased likelihood of having credit card debt as well as the amount of such debt even after controlling socioeconomic variables (Meier & Sprenger, 2010). Moreover, participants who took out a payday and/or automobile title loan discounted delayed gains more steeply than those who did not (Mahoney & Lawyer, 2016), and patients who showed greater treatment adherence discounted probabilistic health gains less steeply than those who did not (Bruce et al., 2016). For older adults (> 70 years of age), steep discounting of delayed gains was associated with lower wealth, fewer investment in health, and less planning for end-of-life care (Huffman et al., 2019).

It is to be noted, however, that the associations reported between degree of discounting and everyday behaviors are generally weak at best. Chapman et al. (2001) found weak or no relation between the degree of discounting delayed gains and delayed losses with preventive health behaviors such as influenza vaccination and adherence to cholesterol-lowering medication. Chabris et al. (2008) regressed 15 everyday behaviors on the degree of discounting delayed gains and found that only a few were weakly associated (i.e., BMI, smoking, exercise, prescription drug completion, and credit card bill paid in full), while the association between delay discounting and many other behaviors (i.e., dieting, overeating, healthy food choices, dental check-ups, flossing, late credit-card payment, percentage of income saved, gambling, wealth relative to friends, and wealth relative to siblings) was close to zero. Li et al. (2019) expanded Chabris et al.'s investigation to 28 everyday behaviors and reported that the average of the absolute values of the correlations were .06 with the discounting of delayed gains and .05 with the discounting of delayed losses.

Considering the robust findings on the association between degree of discounting and maladaptive behaviors, perhaps the weak associations between discounting and everyday behaviors are somewhat surprising. It is possible that degree of discounting captures important aspects of impulsiveness, a key feature shared by various maladaptive behaviors (e.g., drug abuse; Bickel & Marsch, 2001), which leads to stronger associations than that with everyday behaviors, in which impulsiveness plays a relatively less significant role. It also is possible that degree of discounting has limited contributions to decision-making underlying everyday choice behaviors, thereby leading to the weak associations. It is worth noting, however, that only a few studies to date have investigated everyday behaviors that involved delayed and/or probabilistic consequences with the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses (e.g., Mejía-Cruz et al., 2016; Ohmura et al., 2005; Takahashi et al., 2009). Moreover, those studies were all focused on the maladaptive behaviors, making it difficult to determine to what extent delay and probability discounting could account for everyday choice behaviors in general. Thus, the present work created a list of behaviors that involve delayed and/or probabilistic consequences and are not limited to maladaptive behaviors, and then examined their associations with the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses.

1.5 The Current Study

Two experiments were conducted in the current study to answer two important research questions: (1) Are there subgroups in the discounting of probabilistic gains, and (2) What is the degree to which delay and probability discounting are associated with everyday behaviors that have delayed and/or probabilistic consequences?

Experiment 1 is a systematic replication of Yeh et al. (2020). The Yeh et al. study was the first to identify subgroups in both the discounting of delayed losses and the discounting of probabilistic losses. The same methodological and analytic approach is used in Experiment 1 to evaluate participants' performance on a newly developed probabilistic gains questionnaire that shares the same structure with that of the MCQ to determine whether there also are subgroups in the discounting of probabilistic gains. The findings would provide further information regarding similarities and differences between the discounting of gains and losses.

Experiment 2 uses a newly developed field behavior questionnaire to determine the extent to which the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses is related everyday behaviors that involve delayed and/or probabilistic consequences. Because the same discounting measures (i.e., monetary choice questionnaires) are used, Experiment 2 also serves as a replication of Experiment 1. The findings would provide information regarding the relation of delay and probability discounting to our everyday choice behaviors in general.

Chapter 2: Experiment 1

A probabilistic gains questionnaire whose structure is similar to the three previously developed monetary choice questionnaires (i.e., delayed gains, delayed losses, and probabilistic losses questionnaires) was developed. In addition, the experiment provided a systematic replication of Yeh et al. (2020) by modifying the probabilistic losses questionnaire used in that study. Participants completed the delayed gains, delayed losses, probabilistic losses, and the newly developed probabilistic gains questionnaires to evaluate similarities and differences among these four discounting tasks.

2.1 Method

2.1.1 Participants

All participants for the experiment were recruited from the pool of workers maintained by Amazon's Mechanical Turk (MTurk) and had to have an IP address inside the United States and a previous MTurk approval HIT rate greater than or equal to 85%. In total, 958 Mturk workers completed the survey. Although all completers provided a consent for participation at the beginning of the survey, 83 indicated that they wanted to preclude their data from analysis when being probed at the end of the survey. Follow-up inspections of the remaining data excluded additional 441 completers due to: (1) Duplicate GPS locations (*n* = 171); (2) Duplicate MTurk Worker IDs (*n* = 14); and (3) A completion time less than 10.8 minutes (the average amount of time needed for skilled readers to read through the survey; *n* = 256; Rayner, 1998). The final sample was comprised of 434 individuals who were between the ages of 18 and 77 (218 females, 216 males; mean age = 39.6, *SD* = 11.3; mean education = 15.5 years, *SD* = 2.5; mean individual annual income = $44,290, *SD* = 54,915; mean household annual income = $76,620, *SD* = 149,020). Most participants answered all the demographic questions; however, 9 participants did not report explicit individual annual income, 8 did not report explicit household annual income, and 11 provided questionable income information (i.e., the individual annual income was greater than the household annual income). All questionable data were re-coded as missing values. Each participant was compensated $0.50 for completing the experiment.

2.1.2 Materials and Procedure

Delayed Gains Questionnaire: The 27-item questionnaire developed by Kirby et al. (1999) was used to evaluate the discounting of delayed gains. For each item, participants were asked to choose between an immediate, smaller gain and a delayed, larger gain (i.e., they were asked, "Which would you prefer to receive?"). As may be seen in the left columns of Table 1, the items are divided into three sets of 9 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). Moreover, the items in each set correspond to nine *k* values, which represent different discounting rates in a simple hyperbolic discounting function (Mazur, 1987). Based on their choice between receiving an immediate, smaller reward or a delayed, larger reward, an individual's discounting rate can be inferred to be greater or lesser than the corresponding *k* value.

We used the proportion of choice of the delayed reward to represent the degree to which an individual discounted delayed gains, instead of the inferred *k* value.

Delayed Losses Questionnaire: A 27-item questionnaire analogous to the delayed gains questionnaire to evaluate discounting of delayed losses was developed by Myerson et al. (2017). 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?"). As may be seen in the right columns of Table 1, the items are divided into three sets of 9 questions each, based on whether the delayed amount is small ($75, $90, or $105), medium ($150, $165, or $180), or large ($225, $240, or $255). 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 lower rate than gains; e.g., Frederick, Loewenstein, & O'Donoghue, 2002).

It is to be noted, the values of each item in both the delayed gains and delayed losses questionnaires were determined by the simple hyperbolic discounting function to maintain the same spacing between logarithmic k parameters across the three sets of amount. To refine such spacing, a few items were adjusted from the ones used in Myerson et al. (noted in Table 1). The proportion of choices of the immediate payment was used to represent the degree to which an individual discounted delayed losses.

Table 1

Questions in the Delayed Gains and the Delayed Losses Questionnaires

Gains					Losses				
Q	V_i($)	A_d($)	*D*(days)	*k*	Q	V_i($)	A_d($)	*D*(mos)	*k*
				Small Delayed Outcomes					
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[a]	66	105	22	0.00088
5	14	25	19	0.041	23	41	75	12	0.0023
7	15	35	13	0.10	21[a]	47	105	7	0.0058
11	11	30	7	0.25	17	33	90	4	0.014
				Medium Delayed Outcomes					
1	54	55	117	0.00016	27[a]	161	165	91	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 Outcomes					
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[a]	114	225	14	0.0023
19	33	80	14	0.10	9[a]	100	240	8	0.0058
4	31	85	7	0.25	24	93	255	4	0.014

Note. Q = question order; V_i = immediate amount; A_d = delayed amount; *D* = duration of the delay. The *k* values for both questionnaires are given in days (i.e., 365/12 per month) even though the delays for the loss questions seen by participants were given in months.

[a]The item in the current experiment was different from the one used in Myerson et al. (2017).

Probabilistic Losses Questionnaire: A 27-item questionnaire analogous to the delayed gains and the delayed losses questionnaires to evaluate discounting of probabilistic losses was first developed by Yeh et al. (2020). Although their questionnaire had been shown to be reliable and to assess an appropriate range of the discounting of probabilistic losses, a practical concern with it was that the difference in amount between a smaller, certain and a larger, probabilistic loss varied little along with the discounting parameter (i.e., the *h* parameter in the simple hyperbolic model of probability discounting)[4]. For example, the numbers used in the items with the *lowest* and the *highest h* values at the small amount level were $21 vs. $70 and $17 vs. $60, at the medium amount level were $33 vs. $110 and $32 vs. $110, and at the large amount level were $48 vs. $160 and $46 vs. $170. It is likely that participants' responses in Yeh et al. were driven largely by the probability of each item, and it remains to be examined whether there would be subgroups of people that still show qualitatively different choice patterns when both amount and probability each play significant roles in the decision-making.

To resolve the issue and minimize differences between the probabilistic losses and the other choice questionnaires, the amounts of each item were re-determined while maintaining their basic structure. Specifically, as may be seen in the right columns of Table 2, the items are divided into three sets of 9 questions each, based on whether the probabilistic amount is small ($150, $180, or $210), medium ($300, $330, or $360), or large ($450, $480, or $510), and the items correspond to nine logarithmically spaced values of the *h* parameter. For each item, participants were asked to choose between a certain, smaller loss and a larger, probabilistic loss in which the probabilities of both paying and not paying were explicitly stated in the question. For example, participants were asked, "Which would you prefer? Paying $166 for sure or 5%

[4] The simple hyperbolic discounting function in Rachlin et al. (1991) has the form: $V = A/(1 + h\Theta)$, where V is the subjective value of a probabilistic reward, A is the objective amount of the reward, h is the discounting rate parameter, and Θ is the odds against receipt of the probabilistic reward, $\Theta = (1 - p)/p$.

chance of having to pay $210 (95% chance of paying nothing)." The proportion of choices of the certain payment was used to represent the degree to which an individual discounted probabilistic losses.

Probabilistic Gains Questionnaire: Following our previous efforts, a 27-item questionnaire directly analogous to the other choice questionnaires to evaluate discounting of probabilistic gains was developed in this study. As may be seen in the left columns of Table 2, the items are divided into three sets of 9 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. The amounts were determined to be within the ranges of the other choice questionnaires with minimum repetition, and the probabilities were biased toward high values as compared with those used in the probabilistic losses questionnaire because of risk aversion (i.e., people are less willingly to make a risky choice when outcomes involve gains; e.g., Kahneman & Tversky, 1979). For each item, participants were asked to choose between a certain, smaller gain and a larger, probabilistic gain in which the probabilities of both receiving and not receiving were explicitly stated in the question. For example, participants were asked, "Which would you prefer? Receiving $64 for sure or 7% chance of receiving $70 (93% chance of receiving nothing)." The proportion of choices of the probabilistic gain was used to represent the degree to which an individual discounted probabilistic gains.

After reading information about the study and agreeing to participate, participants completed the four choice questionnaires in different orders. The order of the questionnaires was counterbalanced such that each of 24 permutations was used for about equal numbers of participants. Before the start of each choice questionnaire, a brief illustration of the type of choices involved was presented, followed by a forced-choice question in which the participant was asked what choice task was involved. Participants needed to answer the forced-choice question correctly in order to proceed, which ensured they were aware of the main attributes of each choice questionnaire (i.e., delayed or probabilistic; gain or loss). For example, before the start of the delayed gains questionnaire, participants were asked, “To be certain you understand the instructions, please select the one option from the following choices that best describes what you are being asked to do:”, and they needed to select “You will be asked to make a choice between receiving an amount of money now and receiving an amount later.” in order to proceed. Following the completion of all four questionnaires, participants answered a series of demographic questions and were given a password to arrange for compensation. All data were collected using the Qualtrics internet survey platform.

2.1.3 Analyses

For each of the four choice questionnaires, a generalizability coefficient in Generalizability (G) theory was calculated to estimate the reliability of the measurement (Shavelson et al., 1989). Unlike classical test theory in which the measurement error is undifferentiated, G theory pinpoints the sources of systematic and unsystematic error variation. Specifically, it estimates the variation in scores due to each person, each facet (e.g., item), and their interactions. With these variance component estimates, the reliability of a person’s observed score on a measurement to the expected value of his or her observed scores over all observations in the universe of generalization (analogous to a person’s “true score” in classical test theory) can be obtained (i.e., generalizability coefficient).

Table 2

Questions in the Probabilistic Gains and the Probabilistic Losses Questionnaires

Gains					Losses				
Q	V_c($)	A_p($)	*P*	*h*	Q	V_c($)	A_p($)	*P*	*h*
Small Probabilistic Outcomes									
13	64	70	.07	0.0071	15	166	210	.05	0.0140
20	56	60	.25	0.0238	8	128	180	.08	0.0353
26	45	50	.41	0.0772	25	91	150	.12	0.0884
22	50	60	.55	0.2444	6	86	180	.17	0.2239
7	36	50	.67	0.7896	2	54	150	.24	0.5614
18	40	70	.77	2.5109	10	54	210	.33	1.4229
5	21	50	.85	7.8254	23	27	150	.44	3.5794
3	20	70	.91	25.2778	21	26	210	.56	9.0070
11	11	60	.95	84.6364	17	16	180	.69	22.8145
Medium Probabilistic Outcomes									
1	100	110	.07	0.0075	27	261	330	.05	0.0139
6	93	100	.25	0.0251	22	213	300	.08	0.0355
24	108	120	.41	0.0772	4	218	360	.12	0.0888
16	100	120	.55	0.2444	12	172	360	.17	0.2239
10	79	110	.67	0.7967	18	119	330	.24	0.5599
21	57	100	.77	2.5256	7	77	300	.33	1.4264
14	42	100	.85	7.8254	14	54	300	.44	3.5794
8	34	120	.91	25.5752	20	45	360	.56	8.9091
27	20	110	.95	85.5000	1	29	330	.69	23.1023
Large Probabilistic Outcomes									
9	146	160	.07	0.0072	19	380	480	.05	0.0139
15	159	170	.25	0.0231	11	362	510	.08	0.0356
12	135	150	.41	0.0772	16	273	450	.12	0.0884
4	142	170	.55	0.2410	13	244	510	.17	0.2233
2	108	150	.67	0.7896	26	162	450	.24	0.5614
25	91	160	.77	2.5385	3	123	480	.33	1.4296
23	63	150	.85	7.8254	5	81	450	.44	3.5794
19	46	160	.91	25.0580	9	60	480	.56	8.9091
17	31	170	.95	85.1935	24	45	510	.69	23.0000

Note. Q = question order; V_c = certain amount; A_p = probabilistic amount; *P* = probability associated with the probabilistic amount. The *h* values were calculated using odds against.

The proportion of participants who chose the alternative that was used to measure discounting (i.e., the delayed gain, the immediate loss, the probabilistic gain, and the certain loss) on each of the 27 items was plotted as a function of the log k or log h for each choice questionnaire to reveal whether the items adequately assessed preferences over the range of possible subjective values of the delayed or probabilistic outcome (Myerson et al., 2017). Moreover, to evaluate the magnitude effect, these proportions were fitted with a logistic growth function:

$$P = 1 \,/\, [1 + e^{-(x - x_0 - x_1 * A_{\text{Medium}} - x_2 * A_{\text{Large}})\, r}], \tag{2}$$

where P, the dependent variable, is the proportion of choices; x is the logarithm of the discounting parameter values corresponding to the various items; 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 significance of x_1 and x_2 was tested to evaluate whether the proportion of choices changed as a function of amount.

Following Yeh et al. (2020), mixture model analyses were conducted to identify potential negative discounting subgroups. A mixed effects logistic regression was first built to model the data for each questionnaire. For individual j responding to item i, using log k or log h as a predictor, and letting γ denote a fixed effect and μ denote a random effect,

$$\text{logit}\big[P(\text{response})_{ij}\big] = \gamma_{00} + \gamma_{10}\log(k \text{ or } h) + \mu_{0j} + \mu_{1j}\log(k \text{ or } h) + \epsilon_{ij}, \tag{3}$$

where $P(\text{response})_{ij}$ is the probability of choosing a specific option (e.g., the delayed gain), γ_{00}

and γ_{10} are the fixed effects of the intercept and slope, μ_{0j} and μ_{1j} are the random effects of the intercept and slope, and ϵ is a residual. Mixture model allows for the joint estimation of the probabilities that the observations in a sample belong to each latent class and for the fitting of a logistic regression to the choice of a specific option (e.g., the delayed gain) on the latent classes.

Although an assumption that the observations were from multimodal distributions (i.e., subgroups) was made, the numbers of individual distributions (latent classes or mixture components) which were combined to form the mixture distribution were unclear. Thus, different numbers of latent classes were specified to obtain all possible solutions, and the results were evaluated by Bayesian Information Criterion (BIC) and entropy measures. In general, the model with the lowest BIC is preferred. The entropy measure ranges from 0.0 to 1.0, and values closer to 1.0 indicate more accurate classification as well as greater separation between classes (Celeux & Soromenho, 1996).

Finally, Pearson correlation coefficients among choice tasks were calculated to determine the relations among the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses. Furthermore, a multiple regression model was built for each choice questionnaire to evaluate the relations between demographics and degree of discounting. Specifically, the outcome variable was the performance on a choice questionnaire, and the predictors were gender, age, years of education, and household income. Multiple imputation using predictive mean matching was performed to handle missing data, and the estimates obtained from the multiple regression models on all the imputed datasets were combined to generate the final output. All *p*-values reported were corrected for multiple comparisons according to the false discovery rate method proposed by Benjamini and Hochberg (1995).

It is to be noted, before the analyses, all missing values in the data were imputed with group means and a squared Mahalanobis distance was calculated for each case to identify potential multivariate outliers. No case was identified under this screening.

All analyses were conducted using R Version 3.5.0 (R Core Team, 2018); the VCA package (Version 1.4.2) was used to conduct variance component analysis for calculating the generalizability coefficients; the FlexMix package (Version 2.3-15; Leisch, 2004) was used to conduct mixture model analyses and to derive entropy measures; and the mice package (Version 3.6.0; Buuren & Groothuis-Oudshoorn, 2011) was used to impute incomplete multivariate data and to combine estimates across imputed datasets.

2.2 Results

2.2.1 Reliability of Choice Questionnaires

For each of the four choice questionnaires, the responses to the 27 items represent a partially nested design in which items are nested within amount and crossed with participants: Participant × (Item: Amount). This gives rise to 5 variance components: Participant, Amount, an interaction of Participant and Amount, Item within Amount (a combination of Item and an interaction of Item and Amount), and a residual (a combination of an interaction of Participant and Item, an interaction of Participant, Amount, and Item, and a residual error). Assuming Amount is a random facet, the generalizability coefficient can be derived with the equation:

$$E\rho^2 = \frac{\sigma^2_{Participant}}{\sigma^2_{Participant} + \frac{\sigma^2_{Participant \times Amount}}{n'_{Amount}} + \frac{\sigma^2_{Participant \times (Item:Amount)}}{n'_{Amount} n'_{Item}}}, \quad (4)$$

where $E\rho^2$ is the generalizability coefficient, n'_{Amount} is the number of amount, and n'_{Item} is the number of items within an amount level.

Table 3 summarizes the estimated variance components for each of the four choice questionnaires. Using these estimated variance components with Equation 4, the obtained generalizability coefficients for the delayed gains, delayed losses, probabilistic gains, and probabilistic losses questionnaires were .91, .94, .84, and .87, respectively. These results attest to the satisfactory reliability of our measures of individuals' degree of discounting on all four choice questionnaires.

Table 3

Estimated Variance Components of Choice Questionnaires

Source of Variance Component	Delayed Gains	Delayed Losses	Probabilistic Gains	Probabilistic Losses
P	.04	.07	.02	.03
A	.00	.00	.00	.00
P × A	.00	.00	.00	.00
I, I × A	.11	.05	.14	.11
P × I, P × A × I, e	.11	.13	.10	.13

Note. P = participant; A = amount; I = item; e = residual error.

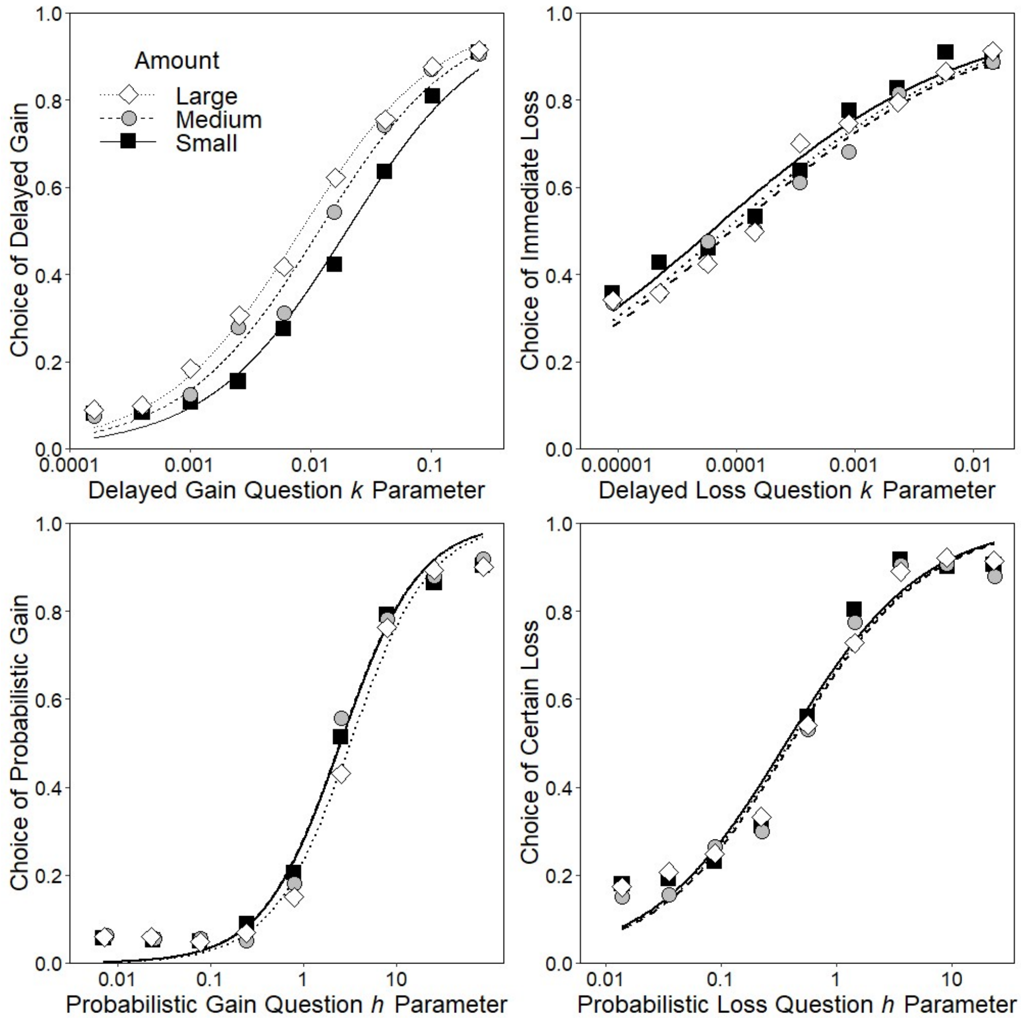
2.2.2 Proportion of Choices and Effect of Amount

Figure 1 shows the proportion of participants who chose the alternative that measured individuals' discounting (i.e., the delayed gain, the immediate loss, the probabilistic gain, and the certain loss) on each item of the four choice questionnaires plotted as a function of the discounting parameter (i.e., *k* or *h*). As may be seen, all four choice questionnaires included items that covered a wide range of choices (e.g., from only a few individuals choosing the delayed gain to most of the participants choosing the delayed gain). Moreover, choices systematically changed as a function of the discounting parameters.

The curves in Figure 1 show the results of fitting Equation 2 to the data. The R^2 for the delayed gains, delayed losses, probabilistic gains, and probabilistic losses questionnaires were .99, .97, .99, and .97, respectively. The behavioral data were well fitted, providing further confirmation that choice changed systematically with the discounting parameters. With regard to the magnitude effect, the parameters of x_1 (i.e., the difference between small and medium amounts) and x_2 (i.e., the difference between small and large amounts) were significant for the delayed gains questionnaire (for x_1, t [23] = -4.38, $p < .001$; for x_2, t [23] = -7.25, $p < .001$); increases in amount increased the likelihood of participants choosing the delayed gain. Consistent with these results, when compared with 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, Equation 2 provided a significantly better fit to the data only for the delayed gains, F (2, 25) = 26.60, $p < .001$, and not for the delayed losses, F (2, 25) = 1.80, $p = .19$, the probabilistic gains, F (2, 25) = 1.46, $p = .25$, or the probabilistic losses, F (2, 25) = .10, $p = .91$, questionnaires.

Figure 1

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



Note. Proportion of participants who chose the delayed gain on each question of the delayed gains questionnaire (top-left panel), the immediate loss on each question of the delayed losses questionnaire (top-right panel), the probabilistic gain on each question of the probabilistic gains questionnaire (bottom-left panel), and the certain loss on each question of the probabilistic losses questionnaire (bottom-right panel), for the small, medium, and large amounts, plotted as a function of the discounting parameter associated with that question by amount . Note the logarithmic scaling of the discounting parameter in all four panels.

2.2.3 Mixture Model Analyses

For each of the four choice questionnaires, the mixture model analyses showed a monotonic improvement in BIC with the number of latent classes specified (see Table 4). Although the entropy measures varied along with the number of latent classes specified in each questionnaire, all values were quite high. To visualize whether the increase in numbers of latent classes was meaningful and whether there were negative discounting subgroups, logistic growth functions for different numbers of latent classes, ranging from three to six, are plotted in Figure 2[5]. Noticeably, inconsistent with Yeh et al. (2020) in which a negative discounting subgroup on the delayed losses questionnaire was apparent beginning with the 3-class solution, no negative discounting subgroup was identified in the current analyses even with the 6-class solution. Although a negative discounting subgroup on the probabilistic losses questionnaire was identified across solutions, the revealed choice patterns (i.e., the logistic growth functions) were different from the ones reported in Yeh et al. in that *P*(response) = .50 was outside the range of log(*h*) (-1.86 to 1.36) covered by the questionnaire. In Yeh et al., *P*(response) = .50 was at log(h) ≈ .30 across different solutions.

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[5] The logistic growth function for plotting Figure 2 has the form $P(x) = 1/[1 + \left(\frac{1}{y0} - 1\right) e^{-rx}]$, where *P* is the probability of a response to a specific question (choosing the delayed gain, immediate loss, probabilistic gain, or certain loss based on the questionnaire), *x* is the logarithm of *k* or *h* for that question, y0 is the intercept of the logistic growth function (i.e., the probability of a response when *x* = 0), and *r* is the parameter governing the rate of growth in *P*. For a specific latent class, the intercept, y0, and the rate parameter, *r*, equal to $e^{\gamma_{00}}/(1 + e^{\gamma_{00}})$ and γ_{10}, respectively, where γ_{00} and γ_{10} are the fixed effects of intercept and slope in Equation 3 for that latent class.

To gain insight into why the current analyses failed to replicate the findings of negative subgroups in the losses questionnaires, individual intercepts plotted as a function of individual slopes derived from Equation 3 are shown in Figure 3. As may be seen, there are far more individuals with negative slopes on both losses questionnaires (*n* = 34 for delayed losses; *n* = 39 for probabilistic losses) than on either of the gains questionnaires (*n* = 7 for delayed gains; *n* = 17 for probabilistic gains), supporting the presence of negative discounting subgroups in the losses questionnaires. However, individuals with positive slopes showed greater clustering than those with negative slopes, and the absolute values of the positive slopes were generally greater than those of the negative slopes. Since classification in the current mixture model analyses was based on individual intercepts and slopes, the negative discounting subgroups failed to emerge on the delayed losses questionnaire and showed different choice patterns on the probabilistic losses questionnaire.

Table 4

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

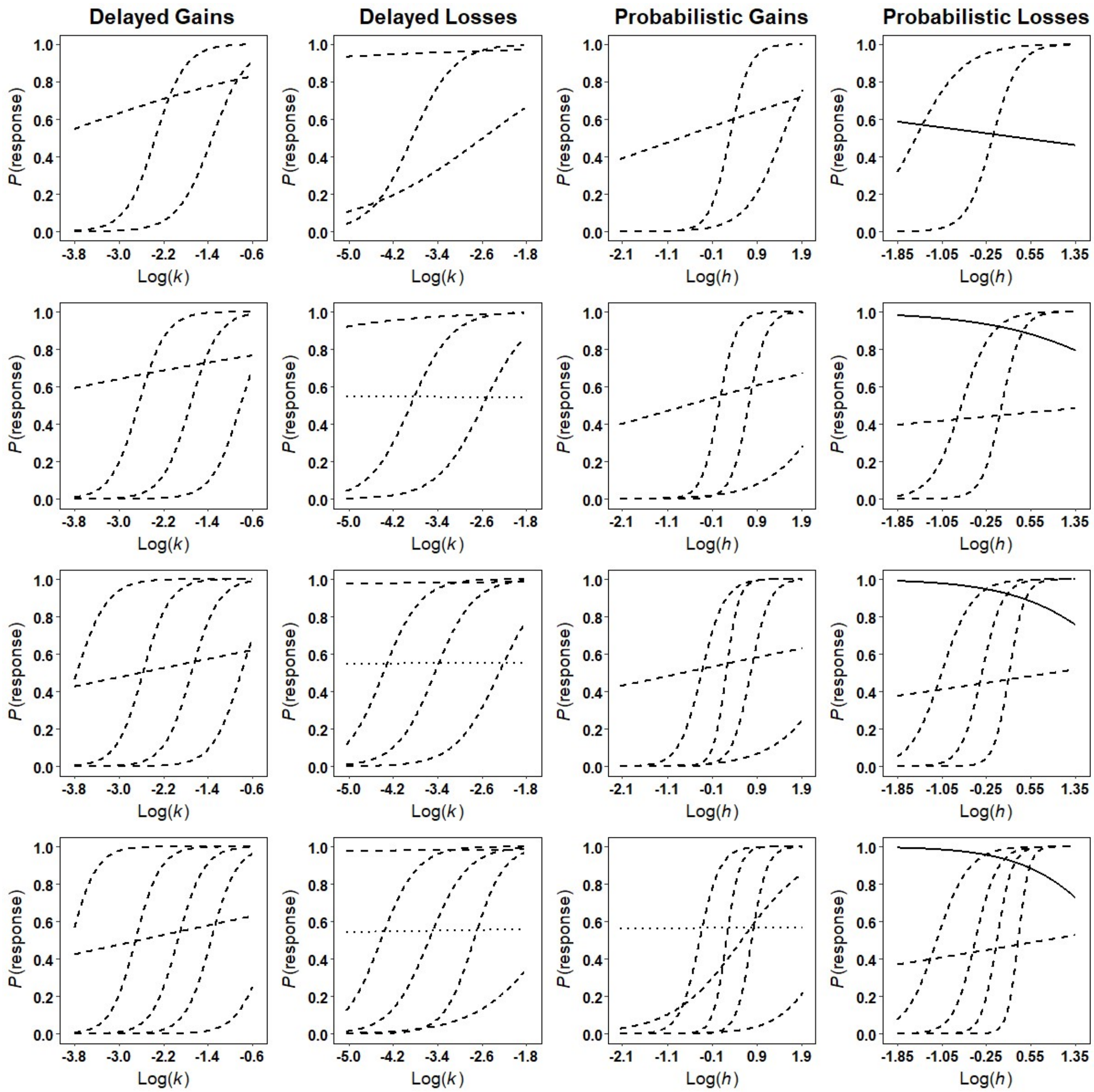
Latent classes	Delayed Gains		Delayed Losses		Probabilistic Gains		Probabilistic Losses	
	BIC	Entropy	BIC	Entropy	BIC	Entropy	BIC	Entropy
1	11026	--	13336	--	8910	--	11436	--
2	8937	.92	10380	.95	7034	.96	8712	.96
3	8105	.93	9420	.93	6365	.95	7926	.97
4	7505	.94	8750	.95	5940	.91	7390	.93
5	7170	.94	8385	.94	5795	.88	7129	.90
6	7028	.91	8262	.93	5729	.89	7078	.89
7	7021	.89	8226	.92	5670	.87	7015	.88

2.2.4 Intercorrelations Among Choice Questionnaires

Table 5 presents the intercorrelations among the four choice questionnaires. Participants who chose more delayed gains were significantly more likely to also choose more immediate losses, probabilistic gains, and probabilistic losses; participants who chose more immediate losses were significantly more likely to also choose more certain losses; and those who chose more probabilistic gains were also more likely to choose more probabilistic losses.

Figure 2

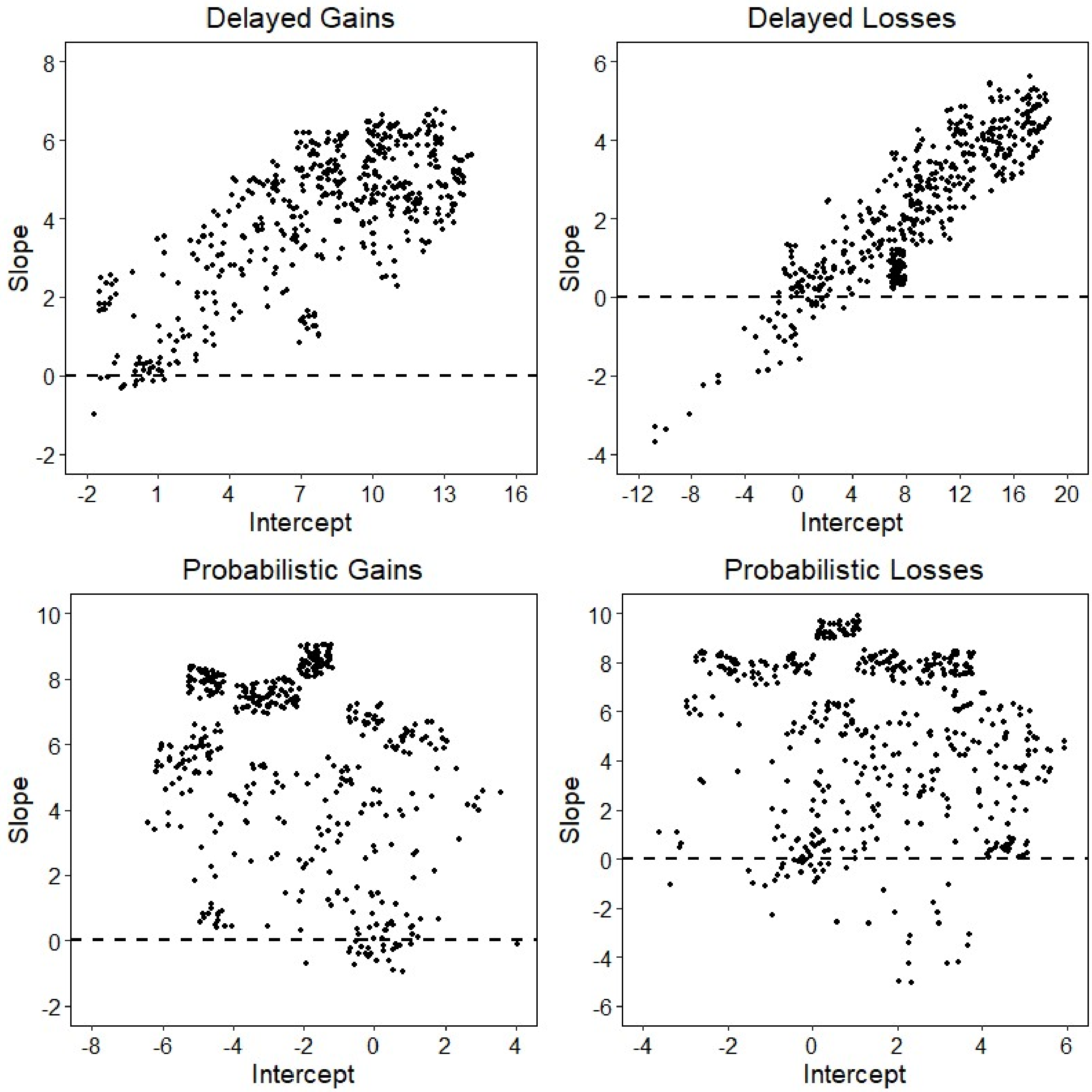
Logistic Growth Functions for Different Numbers of Latent Classes



Note. Logistic growth functions for the delayed gains (first column), the delayed losses (second column), the probabilistic gains (third column), and the probabilistic losses (fourth column) questionnaires were identified by the mixture model analyses with different numbers of latent classes specified, ranging from three in the top row to six in the bottom row. The y-axes for the delayed gains are the probability of choosing the delayed gain, for the delayed losses are the probability of choosing the immediate loss, for the probabilistic gains are the probability of choosing the probabilistic gain, and for the probabilistic losses are the probability of choosing the certain loss. The line type of each latent class corresponds to the fitted slope (i.e., γ_{10} in Equation 3 for a specific latent class) in which a dashed line represents a slope greater than .1, a solid line represents a slope less than -.1, and a dotted line represents a slope within the range of .1 and -.1.

Figure 3

Scatterplot of Individual Intercepts and Slopes



Note. The scatterplot was created with jitter to provide a clear view of the clustered data points.

Table 5

Intercorrelations Among Choice Questionnaires

Questionnaire	1	2	3	4
1. Delayed Gains	–	.14**	.27***	-.20***
2. Delayed Losses		–	-.07	.19***
3. Probabilistic Gains			–	-.48***
4. Probabilistic Losses				–

*p < .05. **p < .01. ***p < .001.

2.2.5 Relations Between Demographics and Degree of Discounting

Table 6 summarizes the multiple regression models predicting performance on the delayed gains, delayed losses, probabilistic gains, and probabilistic losses questionnaires with gender, age, years of education, and household income. As may be seen, the demographic variables explained only a small proportion of the total variance in degree of discounting (all adjusted R^2 were less than .05). Nonetheless, both age and household income were significant predictors of degree of discounting delayed gains. All other regression coefficients failed to reach significance after the associated p-values were corrected by the false discovery rate method.

Table 6

Summary of Multiple Regression for Demographics Predicting the Degree of Discounting

Variable	b	b 95% CI	β	t	F	df^{d}	p	adjusted R^2
Delayed Gains					5.24	4, 425.05	<.01	.04
(Intercept)	-2.61	[-10.39, 5.18]		-.66		365.17	.77	
Gender[a]	.90	[-.20, 1.99]	.08	1.60		426.40	.32	
Age[b]	.07	[.02, .12]	.14	2.82		426.97	.02	
Years of education	.17	[-.05, .39]	.08	1.56		426.85	.32	
Household income[c]	1.03	[.31, 1.74]	.14	2.82		360.54	.02	
Delayed Losses					.49	4, 426.95	.87	.01
(Intercept)	15.72	[5.91, 25.54]		3.15		423.41	.01	
Gender[a]	-.75	[-2.16, .65]	-.05	-1.05		426.97	.54	
Age[b]	.03	[-.04, .09]	.04	.86		426.97	.63	
Years of education	.04	[-.23, .32]	.02	.31		426.86	.87	
Household income[c]	.09	[-.81, .99]	.01	.19		422.18	.89	
Probabilistic Gains					.62	4, 425.93	.82	.01
(Intercept)	10.93	[5.68, 16.18]		4.09		396.63	<.01	
Gender[a]	.20	[-.54, .95]	.03	.54		426.97	.79	
Age[b]	-.02	[-.05, .01]	-.06	-1.18		426.97	.48	
Years of education	-.07	[-.21, .08]	-.04	-.88		426.36	.63	
Household income[c]	.04	[-.44, .52]	.01	.17		385.32	.89	
Probabilistic Losses					1.70	4, 426.25	.34	.01
(Intercept)	22.45	[15.62, 29.28]		6.46		406.99	<.01	
Gender[a]	-.29	[-1.26, .69]	-.03	-.58		426.75	.79	
Age[b]	.03	[-.01, .07]	.07	1.43		426.95	.34	
Years of education	-.01	[-.21, .18]	-.01	-.14		425.96	.89	
Household income[c]	-.67	[-1.30, -.04]	-.10	-2.09		398.66	.13	

Note. [a]Female = 0; Male = 1. [b]Age was mean-centered. [c]Due to a highly skewed distribution, a natural logarithm transformation was applied to the household income for the analysis. [d]The degrees of freedom in multiple imputation was calculated based on the proportion of the variation attributable to the missing data.

2.3 Discussion

Everyday choices often involve outcomes that are delayed and/or probabilistic, and that involve gains and/or losses. The effects of type of outcome (gain or loss) and whether it is delayed or probabilistic can be studied within the discounting framework. The current experiment developed a new probabilistic gains questionnaire and conducted a systematic replication of Yeh et al. (2020). Consistent with previous findings, the four choice questionnaires (delayed gains, delayed losses, probabilistic gains, probabilistic losses) showed good reliability (i.e., the generalizability coefficients for all four choice questionnaires were greater than .83). Furthermore, participants' choices on these questionnaires systematically varied with the discounting parameters, validating the basic assumption that the objective value of an outcome is subjectively discounted as the time until its occurrence increases or as the likelihood of its occurrence decreases.

The different effects of amount on degree of discounting (i.e., magnitude effects) is a robust benchmark and suggests that the discounting of delayed and probabilistic gains involves different underlying processes, and the absence of an effect of amount on degree of discounting with delayed and probabilistic losses suggests that different processes are involved in the discounting of losses. Consistent with these findings, previous research that examined the discounting of delayed gains, delayed losses, and probabilistic losses with the current type of questionnaire found that participants' choices of delayed gains increased with amount (i.e., larger delayed gains were discounted less steeply than smaller delayed gains), whereas their choices of delayed and probabilistic losses were not affected by amount (Kirby et al., 1999; Myerson et al., 2017; Yeh et al., 2020).

Participants' performance on the delayed gains, delayed losses, and probabilistic losses questionnaire was replicated in the current experiment, but their choices on the new probabilistic gains questionnaire did not differ significantly across amounts. It is possible that the amounts used in the current probabilistic gains questionnaire were too small to show the typical reverse magnitude effect (larger probabilistic gains discounted more steeply than smaller probabilistic gains). However, given that Myerson et al. (2011) found that the degree of discounting increased continuously with the amount of probabilistic reward ranging from \$20 to \$10,000,000, the amounts used in the current experiment would seem to be sufficient to observe an effect of amount. Another possibility is that the resolution of the probabilistic gains questionnaire limited a finding of a reverse magnitude effect. Specifically, the degree of discounting probabilistic gains was measured by 9 binary questions for each amount level, and thus a score could only be a whole number between 0 and 9. Moreover, these 9 questions were associated with different h values that significantly influenced participants' choices (see the sigmoidal curves in Fig. 1). The null finding may reflect that the effect of amount was not large enough to bias participants' choices. Combined with the significant effect of amount observed with the delayed gains questionnaire, the current findings suggest that the weighting of amount for delayed gains was greater than that for probabilistic gains.

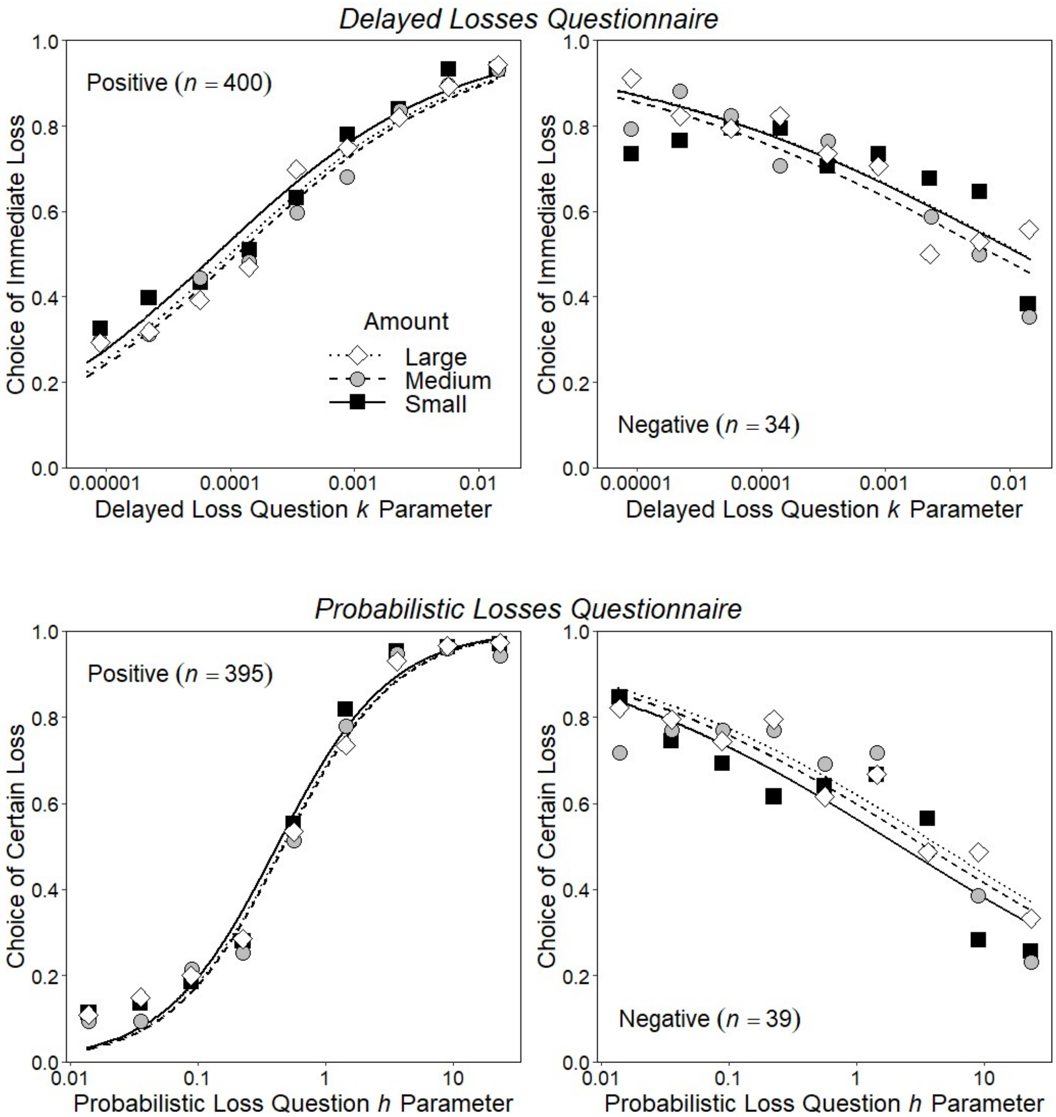
A systematic replication of Yeh et al. (2020) was conducted in this experiment by modifying the probabilistic losses questionnaire and conducting mixture model analyses. Although a negative discounting subgroup was identified on the probabilistic losses questionnaire, the observed choice patterns (i.e., the relation between responses and the logarithm of h values) deviated from the ones reported in Yeh et al. More surprisingly, even though the presence of a negative discounting subgroup on the delayed losses questionnaire has been observed in three independent samples in two different studies (Myerson et al., 2017; Yeh et al., 2020), no negative discounting subgroup was identified in this experiment. Nonetheless, a follow-up analysis of individual-fitting parameters revealed that there were far more individuals with negative slopes on the questionnaires for losses than for the questionnaires with gains.

When the performance on the choice questionnaires by individuals with positive and negative slopes was investigated further, evidence supporting the existence of negative discounting subgroups in the losses questionnaires was apparent. As may be seen in Figure 4, in which the proportion of participants who chose the immediate loss and the certain loss on each item of the losses questionnaires is plotted as a function of the discounting parameter (i.e., k or h), choice systematically changes with the discounting parameter both for individuals with a positive and a negative slopes. In contrast, as may be seen in Figure 5, in which the proportion of participants who chose the delayed gain and the probabilistic gain on each item of the gains questionnaires is plotted, choice systematically increases with the discounting parameter for the individuals with a positive slope; choice did not change systematically with the discounting parameter for individuals with a negative slope.

Yeh et al. (2020) also reported that the correlations of participants' choices on delayed losses and delayed gains questionnaires were different between the positive (i.e., $r = .22$; $n = 286$) and negative (i.e., $r = -.45$; $n = 63$) discounting subgroups on the probabilistic losses questionnaire. When the same correlations were calculated for the individuals with a positive or a negative slope in the current experiment, a similar finding was obtained. Specifically, the correlation for the positive discounting subgroup was .17 ($n = 395$) and for the negative discounting subgroup was -.29 ($n = 39$). Thus, the failure of replication was likely due to the different proportions of individuals showing typical and atypical choice patterns between samples. To be noted, the difference in the mixture model solutions between Yeh et al. and the current study suggests that one of the two samples was a misrepresentation of the population. An additional sample with an even larger sample size will be needed to establish the true proportions of individuals who show positive and negative discounting in the population.

Figure 4

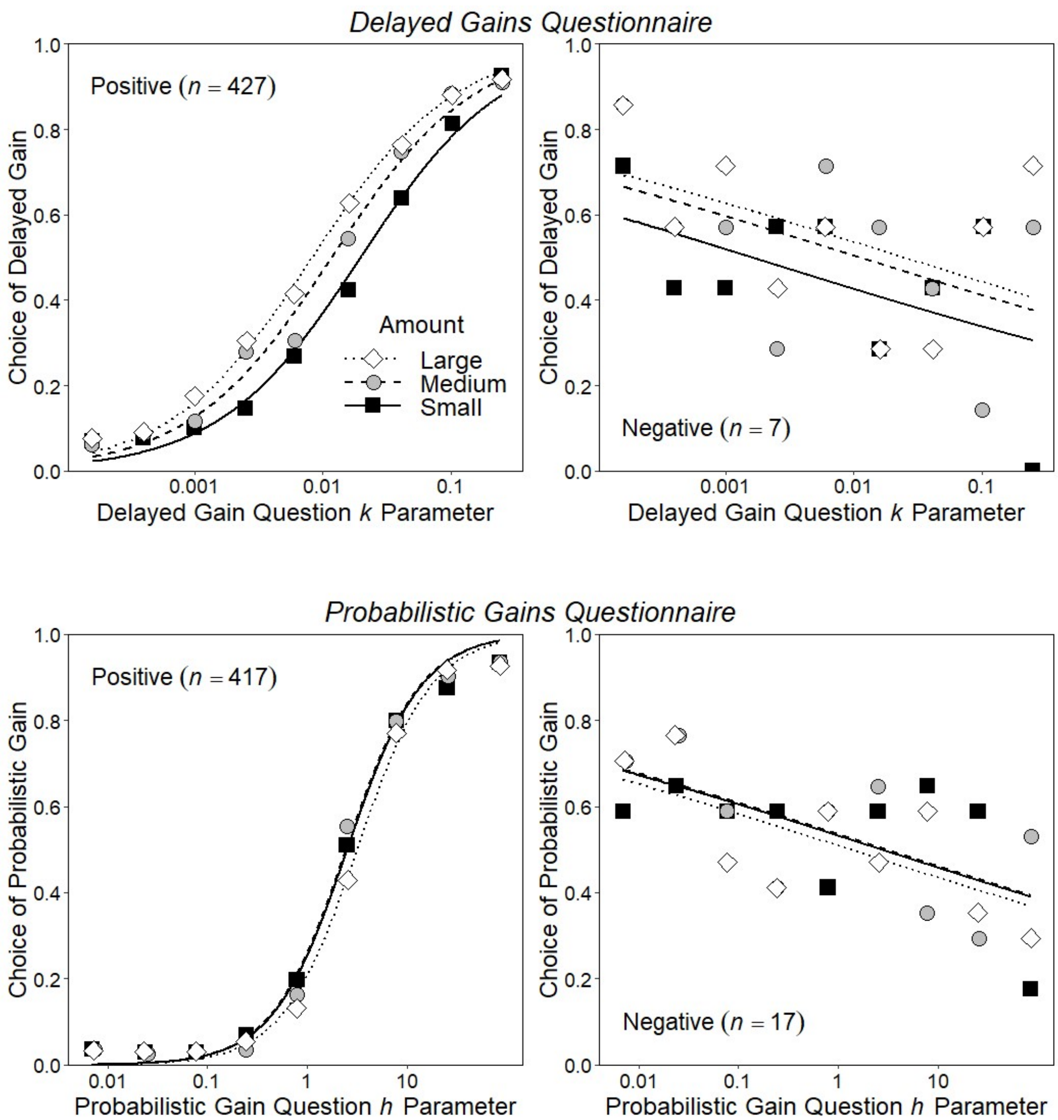
Participants with a Positive or a Negative Slope Choosing the Immediate Loss and the Certain Loss



Note. Proportion of participants with a positive or a negative slope who chose the immediate loss on each question of the delayed losses questionnaire (top panels), and proportion of participants with a positive or a negative slope 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.

Figure 5

Participants with a Positive or a Negative Slope Choosing the Delayed Gain and the Probabilistic Gain



Note. Proportion of participants with a positive or a negative slope who chose the delayed gain on each question of the delayed gains questionnaire (top panels), and proportion of participants with a positive or a negative slope who chose the probabilistic gain on each question of the probabilistic gains questionnaire (bottom panels), plotted as a function of the discounting parameter associated with that question.

The relations among the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses were investigated through the correlations among the choice questionnaires. Consistent with the literature, a weak positive correlation between the delayed and probabilistic gains questionnaires was observed (for a summary, see Green & Myerson, 2004). Although there is disagreement in the literature as to the correlations between the discounting of delayed and probabilistic losses and between the discounting of gains and losses, delayed or probabilistic, in most cases the directions of the correlations (i.e., positive or negative) identified in the current experiment were consistent with the significant findings reported previously (Chapman, 1996; Mejía-Cruz et al., 2016; Shead & Hodgins, 2009; Yeh et al., 2020). Thus, the overall findings support the use of the current choice questionnaires.

Finally, the relations between the demographic variables and the degree of discounting were investigated in the current experiment. Consistent with the literature, both greater age and household income were related to higher scores on the delayed gains questionnaire, which represents a lower rate of discounting delayed gains (Green et al., 1996, Whelan & McHugh, 2009). Previous research also had found that the degree of discounting delayed gains decreases with years of education (de Wit et al., 2007). The null finding in the current experiment suggests that the relation between the degree of discounting delayed gains and years of education might be confounded with other demographic variables. Indeed, a follow-up analysis showed that when both age and household income were removed from the regression model, years of education became a significant predictor of performance on the delayed gains questionnaire (p = .02). Thus, our finding suggests that years of education does not account for variability in the discounting of delayed gains above and beyond the variability accounted for by age and household income. It is to be noted, none of the demographic variables was significantly related to the discounting of delayed losses, probabilistic gains, and probabilistic losses. These findings are consistent with the view that the decision-making processes underlying the discounting of delayed gains are different from those for the discounting of delayed losses, probabilistic gains, and probabilistic losses.

Chapter 3: Experiment 2

Experiment 1 validated the use of the newly developed probabilistic gains questionnaire and the modified probabilistic losses questionnaire. Experiment 2 used these two discounting questionnaires as well as the delayed gains and delayed losses questionnaires to investigate associations between degree of discounting and everyday behaviors. In addition, Experiment 2 examined the replicability of the findings in Experiment 1. Because the participants in Experiments 1 and 2 were recruited from different subject pools (i.e., MTurk and Qualtrics panels), and in Experiment 2, the recruitment was stratified to have equal numbers of participants in the different age groups, the replication also tested the generalizability of the previous findings.

3.1 Method

3.1.1 Participants

Because the frequency of many everyday behaviors varies with age, it was necessary that individuals over a wide age range be studied. A stratified sampling was conducted to ensure similar numbers of participants in four pre-determined age groups. Participants were between the ages of 18-34 in the first age group, 35-49 in the second age group, 50-64 in the third age group, and 65-80 in the fourth age group.

Multiple exclusion criteria were implemented by Qualtrics project managers to ensure the quality of data. These exclusion criteria were: (1) A completion time less than one-half the median completion time of the entire sample; (2) Failing any of the three attentional check items; (3) Providing contradictory personal information (e.g., personal income greater than household income); (4) Providing irrelevant or nonsensical responses to questions with a text box; (5) Straightlining (i.e., identical answers to items in a battery of questions using the same response scale); (6) Submitted surveys likely from the same participant. In total, 191 out of 703 participants were excluded, and the final sample was comprised of 512 individuals, in which 3 participants later were identified as multivariate outliers and were removed from the analyses (see 3.1.3 Analyses for details). Table 7 summarizes the demographics of the final sample by age group. Among the groups, there were significant differences in the proportions of female, individual income, and household income before and after removing outliers. The compensation for each participant was between $3.00-$5.00 per completion, which depended on the reward they chose to receive (e.g., SkyMiles, cash, gift cards).

Table 7

Summary of Demographics by Age Groups

Variables	Age group 18-34 [a]	35-49	50-64	65-80	χ^2/F	*df*	*p*
Age							
n	127	128	128	129			
Mean ± SD	27.5 ± 4.7	40.5 ± 4.0	56.6 ± 4.1	69.2 ± 3.5			
Gender					66	3	<.01
Female (*n*)	76	73	27	87			
Male (*n*)	51	55	101	42			
Education					.23	3, 489	.87
n (*n* of missing)	120 (7)	122 (6)	123 (5)	128 (1)			
Mean ± *SD*	13.7 ± 2.6	13.9 ± 3.5	13.8 ± 2.8	14.0 ± 2.4			
Individual income					3.42	3, 347	.02
n (*n* of missing)	81 (46)	92 (36)	92 (36)	91 (38)			
Mean ± *SD*	77694 ± 150198	78201 ± 74067	67925 ± 100771	44015 ± 31886			
Household income					2.92	3, 337	.03
n (*n* of missing)	78 (49)	92 (36)	85 (43)	87 (42)			
Mean ± *SD*	241650 ± 965347	112423 ± 106957	78728 ± 74542	63769 ± 37737			

Note. [a]Three cases (1 female, 2 males) in this age group later were identified as multivariate outliers and were removed from the analyses (see 3.1.3 Analyses for details). After removing these outliers, the Mean ± *SD* for individual income and household income became 69272 ± 132180 and 90782 ± 151164, respectively.

3.1.2 Materials and Procedure

Field Behavior Questionnaire: A collection of field behavioral questions was created to assess everyday behaviors in eight categories: procrastination, healthy habits, novel-seeking purchasing, impulsive purchasing, risk-taking behaviors, risky financial decisions, future-oriented financial decisions, and financial-loss deferment[6]. These behaviors were selected due to their relevance to the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses. For each of the 51 questions, participants were asked to indicate the frequency of the stated behavior on a 0-100 slider (0 = Never; 100 = Always) based on their experience in the past year. To ensure that participants understood how to perform the task, a practice question, "In the past year, I walked across the Atlantic Ocean", was given at the beginning of the questionnaire and the correct response (i.e., moving the slider to the 0 position) had to be provided in order to proceed. Throughout the questionnaire, participants could use a checkbox next to each stated behavior to indicate questions that were not applicable, which were coded as non-responding. Table 8 lists the 51 behavioral questions with the numbers of non-responding due to inapplicability, and the sample mean and *SD*.

To recruit the sample, the experimenters contracted with Qualtrics and built a survey using its internet survey platform. Qualtrics project managers then distributed the survey by leveraging Qualtrics's industry contacts to solicit participants. After reading information about the study and agreeing to participate, participants first completed the four choice questionnaires used in Experiment 2, presented in a randomized order. At the beginning of each of the choice questionnaires, participants needed to pass a forced-choice question indicating their

[6] Multiple existing instruments were consulted to create the questions. These instruments were the procrastination scale (Lay, 1986), the pure procrastination scale (Steel, 2010), the Melbourne decision making questionnaire (Mann et al., 1997), the exploratory buying behavior tendencies scale (Baumgartner & Steenkamp, 1996), the impulsive buying tendency scale (Badgaiyan et al., 2016), the reckless behavior questionnaire (Shaw et al., 1992), and the financial management behavior scale (Dew & Xiao, 2011).

comprehension of the instruction in order to proceed. Following completion of the four choice questionnaires, participants completed the Field Behavior Questionnaire, with the order of the eight categories randomized. Participants completed all behavioral questions from one category in a randomized order before completing the questions of another category. After completion of the Field Behavior Questionnaire, participants answered a series of demographic questions (age, gender, years of education, individual and household income).

Table 8

Field Behavior Questionnaire

Behavioral question	*N of non-responding*	*M*	*SD*
Procrastination			
P1. Left dirty dishes overnight.	19	46.6	34.5
P2. Found myself saying, “I’ll do it tomorrow”.	14	53.8	30.8
P3. Left jobs that required very little effort unfinished for days.	56	36.6	32.8
P4. Wasted time by doing other things in preparing for some deadline.	44	42.9	32.4
P5. Put things off so long that my well-being or efficiency unnecessarily suffered.	28	39.3	33.0
P6. Delayed tasks beyond what was reasonable.	25	42.0	32.8
P7. Wasted a lot of time on trivial matters before getting to the final decisions.	33	40.2	32.2
Healthy habits			
HH1. Monitored my diet in terms of caloric, fat, carbohydrate, cholesterol, and/or sodium intake.	20	51.2	33.8
HH2. Used sunscreen to prevent damage from harsh sunlight.	28	47.7	36.4
HH3. Exercised regularly.	17	54.2	33.8
HH4. Flossed my teeth regularly.	23	55.6	35.1
HH5. Ate fruits, vegetables, and whole grains regularly.	9	68.3	28.2
HH6. Drank plenty of water each day.	7	69.6	28.9
HH7. Stood or walked as much as possible each day.	15	62.6	30.4
Novel-seeking purchasing			
NS1. Tended to buy the same flavor of food items even though different flavors were available.[a]	11	34.2	26.7
NS2. Stuck with a brand I usually buy rather than try something I was not very sure of.[a]	9	35.5	27.8
NS3. Was a brand-loyal consumer.[a]	10	36.7	28.8
NS4. Ordered dishes I am familiar with when I went to a restaurant.[a]	16	29.8	26.9
NS5. Was cautious in trying new or different products.[a]	16	41.8	29.5
NS6. Ate the same kinds of foods on a regular basis.[a]	4	29.9	25.7
Impulsive purchasing			
IP1. Put items in my shopping cart that were not on my shopping list.	10	63.1	29.7
IP2. Regretted purchases I made.	16	41.8	32.9
IP3. Bought items I was not planning to buy and that I didn’t really need.	13	52.2	31.6
IP4. Bought snacks on impulse.	9	62.6	29.3
IP5. Bought things because I like buying things, rather than because I needed them.	17	46.8	32.4
IP6. Bought what I liked without thinking about consequences.	15	50.5	32.9
IP7. Bought products and services according to how I felt at that moment.	19	51.5	31.6
Risk-taking behaviors			
RT1. Drove in a way that a driver’s education teacher would consider “reckless”.	49	25.6	32.4

Behavioral question	*N of non-responding*	*M*	*SD*
RT2. Drove while under the influence of alcohol.	58	15.2	28.1
RT3. Had unprotected sex with someone I didn't know well.	67	19.0	32.2
RT4. Drove more than 20 miles per hour over the speed limit.	44	27.0	32.9
RT5. Drove without caring about the speed.	47	23.6	30.7
RT6. Engaged in activities that were high-risk (e.g., bungee jumping, racing, rock-climbing, paragliding).	57	19.3	30.6
RT7. Drove without wearing a seat belt.	40	24.3	33.9
Risky financial decisions			
RF1. Had high-risk investments in my investment portfolio.	93	26.1	32.7
RF2. Put money into the stock market when I had money left over.	93	29.6	34.9
RF3. Enjoyed gambling.	61	33.9	36.3
RF4. Made risky financial decisions.	66	32.1	33.7
RF5. Took risks to maximize my profits (e.g., using borrowed money to invest).	83	27.2	34.0
Future-oriented financial decisions			
FO1. Made financial decisions to maximize my retirement savings.	65	45.3	36.1
FO2. Saved for a long-term goal such as a car, education, home, etc.	39	50.3	35.1
FO3. Contributed money to a retirement account.	73	43.0	37.4
FO4. Saved for the future.	28	53.5	35.2
FO5. Spent extra money to buy an energy-saving product.	61	40.7	33.7
Financial-loss deferment			
FL1. Paid only the minimum amount due each month on my credit cards.	62	40.4	37.1
FL2. Used my credit cards for a cash advance when I needed money to spend.	72	27.8	34.6
FL3. Used an installment plan service (i.e., paid off purchases over time) when the option was available.	60	41.1	36.2
FL4. Did not pay my credit card balance in full even when I was able to do so.	81	31.8	35.1
FL5. Delayed a payment knowing I would still need to pay it later.	40	37.5	36.2
FL6. Used my credit cards without thinking how much I would owe at the end of the billing cycle.	69	36.9	35.4
FL7. Preferred to delay a payment instead of resolving it immediately.	48	34.3	34.7

Note. [a]Reverse-scored question.

3.1.3 Analyses

The data analyses conducted for Experiment 1 were repeated for Experiment 2. These analyses evaluated the generalizability coefficients, the effects of amount, the presence of discounting subgroups, the intercorrelations among choice questionnaires, and the relations between demographics and degree of discounting.

Separate structural equation modeling was performed to investigate the association between degree of discounting and everyday behaviors for each of the eight categories of the Field Behavior Questionnaire, and whether the association depended on the age group. In each model, a latent variable representing shared features of the everyday behaviors in the same category was regressed on the degree of discounting the delayed gains, the delayed losses, the probabilistic gains, and the probabilistic losses measured by the four choice questionnaires. The error variances of the choice questionnaires were predetermined based on the generalizability coefficients obtained in Experiment 1, and the error variances of the field behavior questions were freely estimated.

The correlations among the choice questionnaires were freely estimated except ones between the delayed gains and probabilistic losses questionnaires and between the delayed losses and probabilistic gains questionnaires. Specifically, the correlations between the discounting of delayed gains and probabilistic losses and between the discounting of delayed losses and probabilistic gains were restricted to 0 due to disjoint attributes.

A data-driven approach was used to determine the associations among the residuals of the field behavior questions. Three goodness-of-fit indices, Tucker-Lewis index (TLI), the comparative fit index (CFI), and the root mean squared error of approximation (RMSEA), were evaluated throughout the iterations to identify parsimonious models that well fitted the data. To examine whether the association between degree of discounting and everyday behaviors for each category depended on the age groups, two steps of analyses were conducted. First, to ensure that the latent variables reflected the same construct across age groups, measurement invariance in factor loadings was tested for everyday behaviors of each category. Specifically, a baseline model in which the same factor structure is imposed on all age groups was compared with a more restricted model in which the factor loadings are constrained to be equal across groups.

When the measurement invariance condition was met (i.e., the two models did not significantly differ), a chi-squared test was conducted to determine whether a model with equal regression coefficients across groups significantly differed from one without such equality constraint (for both models, the factor loadings and the residual covariances of the observed variables as well as the residual variances and the residual covariances of the latent variables were fixed across groups). An insignificant result would suggest that the association between the degree of discounting and everyday behaviors of a category did not depend on the age groups and hence the regression coefficients of the model with the equality constraint would be evaluated. Otherwise, the regression coefficients were evaluated separately by age group. It is to be noted that all missing values in this analysis were imputed by case-wise maximum likelihood estimations along with the model fittings.

To further investigate associations between degree of discounting and different everyday behaviors, separate multiple regression models were built for each field behavior question. Specifically, the outcome variable was the frequency of a field behavior, and the predictors were the performance on the four choice questionnaires, gender, age, years of education, and household income. For each field behavior, the R^2s of the models with and without including the performance on the four choice questionnaires were compared to determine the proportion of unique variance that was explained by degrees of delay and probability discounting. Multiple imputation using predictive mean matching was performed to handle missing data, and the estimates obtained from the multiple regression models on all the imputed datasets were combined to generate the final output. Although the correlations among the predictors (i.e., collinearity) could increase the type II error rate (i.e., a failure to reject a false null hypothesis when the regression coefficient is not equal to zero), the issue was ameliorated by the sample size of the current experiment (Mason & Perreault, 1991). To control the type I error rate (i.e., rejecting a true null hypothesis when the regression coefficient is no different from zero, due to numerous evaluations), all *p*-values reported were corrected according to the false discovery rate method proposed by Benjamini and Hochberg (1995).

It is to be noted that before conducting the above analyses, inspection of the dataset identified two cases in which none of the field behavioral questions was answered. These responses were excluded from the analyses that involved field behavioral questions but were included in all other analyses. In an attempt to identify potential multivariate outliers, all missing values in the data were imputed with group means, and a squared Mahalanobis distance was calculated for each case. Three cases with the greatest distance from the centroid and that appeared to be separate from others were excluded from the analyses. A follow-up inspection revealed that all three cases belonged to the same age group (i.e., ages of 18-34): Two cases had the highest individual and household income in the sample, and all three cases showed a tendency to use the highest and lowest frequency ratings of the Field Behavior Questionnaire.

The analyses were conducted using R Version 3.5.0 (R Core Team, 2018); the VCA package (Version 1.4.2) was used to conduct variance component analysis for calculating the generalizability coefficients; the FlexMix package (Version 2.3-15; Leisch, 2004) was used to conduct mixture model analyses and to derive entropy measures; the mice package (Version 3.6.0; Buuren & Groothuis-Oudshoorn, 2011) was used to impute incomplete multivariate data and to combine estimates across imputed datasets; and the lavaan package (Version 0.6-6; Rosseel, 2012) was used to conduct structural equation modeling.

3.2 Results

3.2.1 Reliability of Choice Questionnaires

Table 9 summarizes the estimated variance components for each of the four choice questionnaires in Experiment 2. Using these estimated variance components with Equation 4, the obtained generalizability coefficients for the delayed gains, delayed losses, probabilistic gains, and probabilistic losses questionnaires were .90, .94, .89, and .91, respectively. Consistent with the findings in Experiment 1, these results attest to the good reliability of the measures of individuals' degree of discounting on all four choice questionnaires.

Table 9

Estimated Variance Components of Choice Questionnaires in Experiment 2

Source of Variance Component	Delayed Gains	Delayed Losses	Probabilistic Gains	Probabilistic Losses
P	.04	.07	.04	.05
A	.00	.00	.00	.00
P × A	.00	.00	.00	.00
I, I × A	.08	.02	.08	.05
P × I, P × A × I, e	.13	.13	.12	.14

Note. P = participant; A = amount; I = item; e = residual error.

3.2.2 Proportion of Choices and Effect of Amount

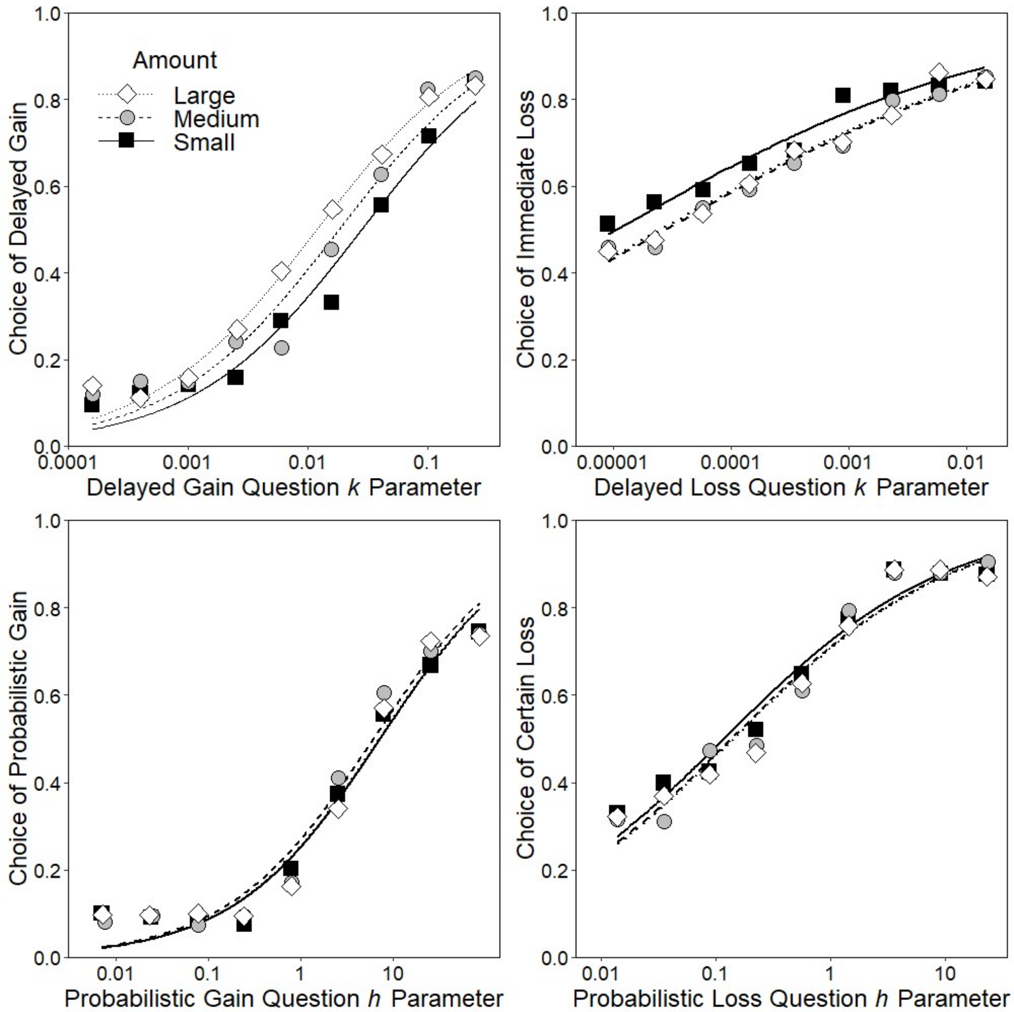
Figure 6 shows the proportion of participants who chose the alternative that measured individuals' discounting (i.e., choice of the delayed gain, the immediate loss, the probabilistic gain, and the certain loss) on each item of the four choice questionnaires plotted as a function of the discounting parameter (i.e., k or h). The curves show the results of fitting Equation 2 to the data. The R^2 for the delayed gains, delayed losses, probabilistic gains, and probabilistic losses questionnaires were .97, .97, .96, and .96, respectively.

Consistent with the findings in Experiment 1, for the delayed gains questionnaire, the parameter x_1 (i.e., the difference between small and medium amounts) was very close to significant, $t(23) = -2.07$, $p = .05$, and the parameter x_2 (i.e., the difference between small and large amounts) was significant, $t(23) = -4.07$, $p < .001$. That is, increases in amount increased the likelihood of participants' choosing the delayed gain. In contrast, the parameters x_1 and x_2 for the probabilistic gains and for the probabilistic losses questionnaires were insignificant (all ps >. 45). For the delayed losses questionnaire, however, both parameters x_1 and x_2 were significant (for x_1, t [23] = 4.46, $p < .001$; for x_2, t [23] = 4.01, $p < .001$), reflecting the fact that small delayed payments were discounted more steeply than both medium and large delayed payments. Consistent with these findings, when compared with 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, Equation 2 provided a significantly better fit to the data for both the delayed gains, $F(2, 25) = 8.22$, $p < .01$, and the delayed losses, $F(2, 25) = 12.30$, $p < .001$, but not for the probabilistic gains, $F(2, 25) = .20$, $p = .82$, or the probabilistic losses, $F(2, 25) = .31$, $p = .74$, questionnaires.

To investigate further the effect of amount on the delayed gains and delayed losses questionnaires, the dichotomous variables in Equation 2 were modified to test for a difference between medium and large amounts. The intercept parameter reflecting such difference was close to significant for the delayed gains, $t(23) = -2.01$, $p = .06$, and insignificant for the delayed losses, $t(23) = -.47$, $p = .64$, questionnaires.

Figure 6

Proportions of Participants Choosing the Delayed Gain, the Immediate Loss, the Probabilistic Gain, and the Certain Loss in Experiment 2



Note. Proportion of participants who chose the delayed gain on each question of the delayed gains questionnaire (top-left panel), the immediate loss on each question of the delayed losses questionnaire (top-right panel), the probabilistic gain on each question of the probabilistic gains questionnaire (bottom-left panel), and the certain loss on each question of the probabilistic losses questionnaire (bottom-right panel), for the small, medium, and large amounts, plotted as a function of the discounting parameter associated with that question by amount. Note the logarithmic scaling of the discounting parameter in all four panels.

3.2.3 Mixture Model Analyses

Consistent with the findings in Experiment 1, for each of the four choice questionnaires, the mixture model analyses showed a monotonic improvement in BIC with the number of latent classes specified (see Table 10). Although the entropy measures varied along with the number of latent classes specified in each questionnaire, all entropy values were quite high. To visualize whether the increase in numbers of latent classes was meaningful and whether there were negative discounting subgroups, logistic growth functions for different numbers of latent classes, ranging from three to six, are plotted in Figure 7. Noticeably, no negative discounting subgroup was identified on either the delayed losses questionnaire or the probabilistic losses questionnaire.

To gain insight into why the current analyses failed to reveal the presence of a negative discounting subgroup in the losses questionnaires, individual intercepts plotted as a function of individual slopes derived from Equation 3 are presented in Figure 8. As may be seen, there are more individuals with negative slopes on both losses questionnaires (n = 46 for delayed losses; n = 43 for probabilistic losses) than on either of the gains questionnaires (n = 29 for delayed gains; n = 36 for probabilistic gains), suggesting the presence of negative discounting subgroups in the losses questionnaires. However, individuals with positive slopes showed greater clustering than those with negative slopes, and the absolute values of the positive slopes were generally greater than those of the negative slopes. Thus, no negative discounting subgroup emerged on the questionnaires for losses in the mixture model analysis.

Consistent with the findings in Experiment 1, when the performance on the choice questionnaires by individuals with a positive or a negative slope was further investigated, evidence supporting the existence of negative discounting subgroups in the losses questionnaires was observed. As may be seen in Figure 9 in which the proportion of participants who chose the immediate loss and the certain loss on each item of the losses questionnaires is plotted as a function of the discounting parameter (i.e., k or h), choice systematically changes with the discounting parameter both for individuals with positive and negative slopes. In contrast, as may be seen in Figure 10 in which the proportion of participants who chose the delayed gain and the probabilistic gain on each item of the gains questionnaires is plotted, choice systematically changes with the discounting parameter only for the individuals with a positive slope but not for those with a negative slope.

Table 10

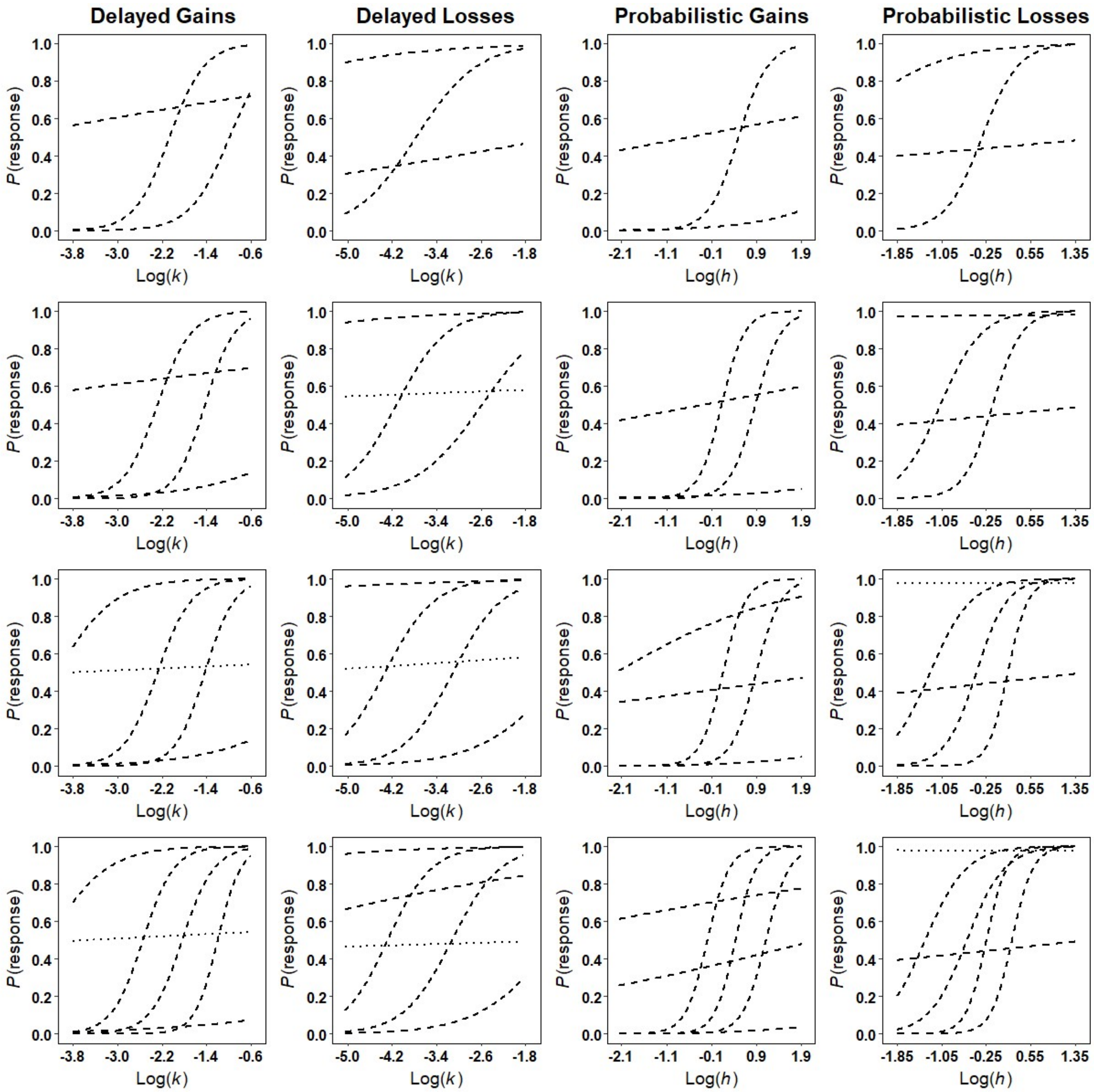
Bayesian Information Criterion (BIC) and Entropy Fit Statistics for Mixture Models with Different Numbers of Latent Classes in Experiment 2

Latent classes	Delayed Gains		Delayed Losses		Probabilistic Gains		Probabilistic Losses	
	BIC	Entropy	BIC	Entropy	BIC	Entropy	BIC	Entropy
1	14275	--	16304	--	13199	--	15235	--
2	12040	.90	12865	.96	10766	.95	12205	.96
3	10694	.93	12060	.93	9193	.96	10639	.97
4	10119	.93	11439	.93	8732	.91	10054	.95
5	9728	.94	11084	.94	8593	.91	9882	.92
6	9533	.92	11022	.91	8499	.89	9873	.87
7					8425	.88		

Note. The mixture model analysis identified only six unique subgroups for the delayed gains, delayed losses, and probabilistic losses questionnaires when seven latent classes were specified.

Figure 7

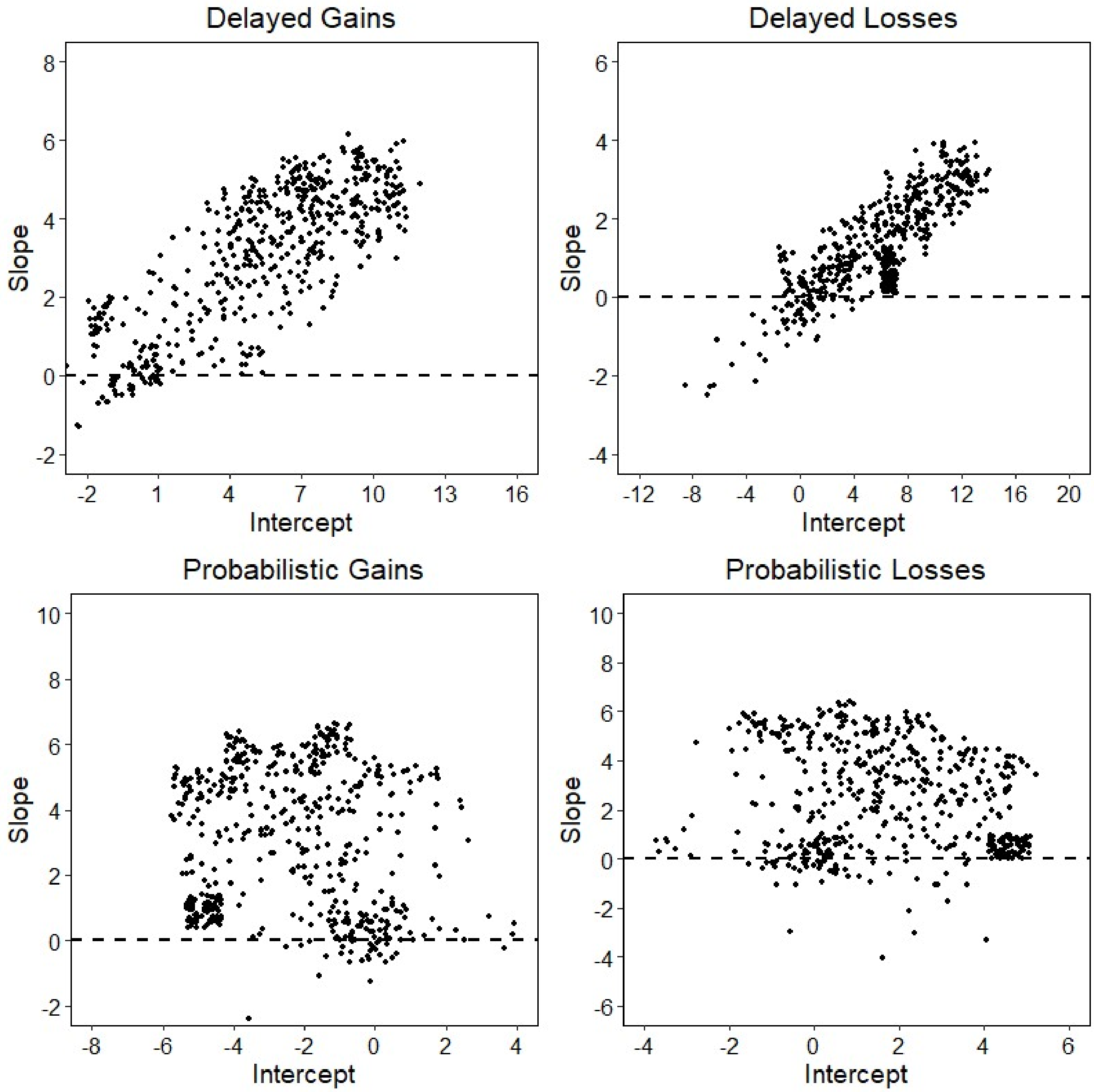
Logistic Growth Functions for Different Numbers of Latent Classes in Experiment 2



Note. Logistic growth functions for the delayed gains (first column), the delayed losses (second column), the probabilistic gains (third column), and the probabilistic losses (fourth column) questionnaires were identified by the mixture model analyses with different numbers of latent classes specified, ranging from three, in the top row, to six, in the bottom row. The y-axes for the delayed gains are the probability of choosing the delayed gain, for the delayed losses are the probability of choosing the immediate loss, for the probabilistic gains are the probability of choosing the probabilistic gain, and for the probabilistic losses are the probability of choosing the certain loss. The line type of each latent class corresponds to the fitted slope (i.e., γ_{10} in Equation 3 for a specific latent class) in which a dashed line represents a slope greater than .1, and a dotted line represents a slope within the range of .1 and -.1. No latent class had a slope less than -.1.

Figure 8

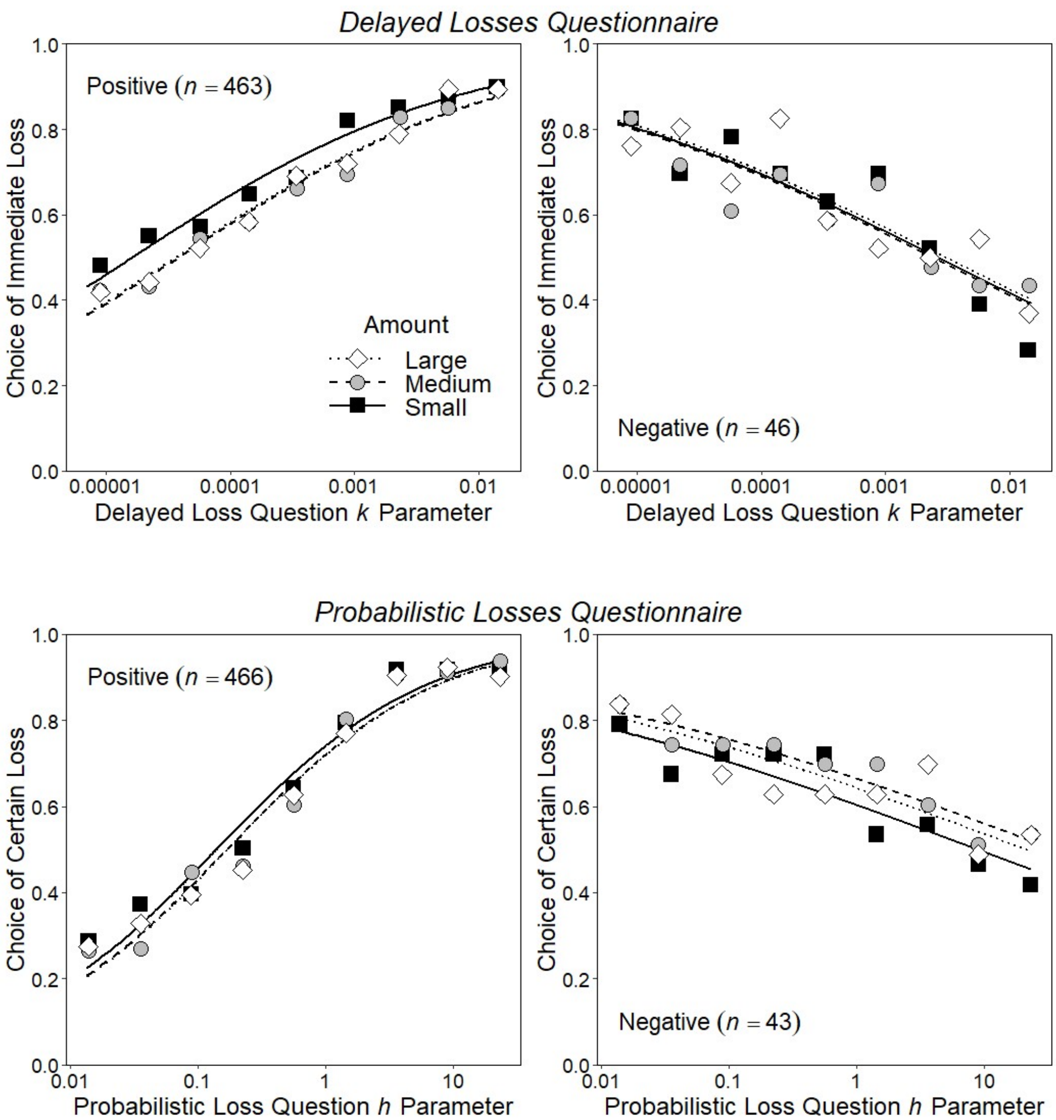
Scatterplot of Individual Intercepts and Slopes in Experiment 2



Note. The scatterplot was created with jitter to provide a clear view of the clustered data points.

Figure 9

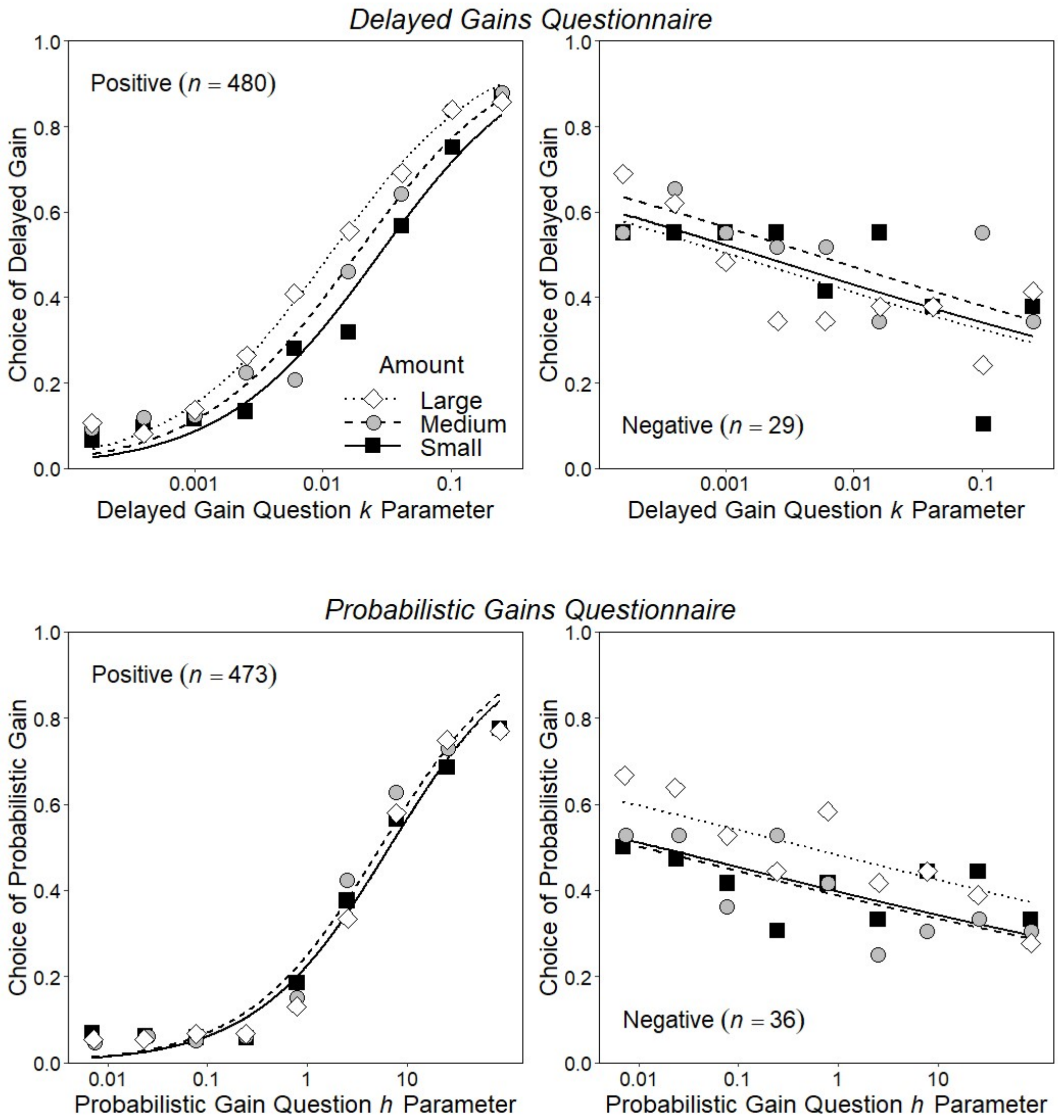
Participants with a Positive or a Negative Slope Choosing the Immediate Loss and the Certain Loss in Experiment 2



Note. Proportion of participants with a positive or a negative slope who chose the immediate loss on each question of the delayed losses questionnaire (top panels), and proportion of participants with a positive or a negative slope 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.

Figure 10

Participants with a Positive or a Negative Slope Choosing the Delayed Gain and the Probabilistic Gain in Experiment 2



Note. Proportion of participants with a positive or a negative slope who chose the delayed gain on each question of the delayed gains questionnaire (top panels), and proportion of participants with a positive or a negative slope who chose the probabilistic gain on each question of the probabilistic gains questionnaire (bottom panels), plotted as a function of the discounting parameter associated with that question.

3.2.4 Intercorrelations Among Choice Questionnaires

Table 11 presents the intercorrelations among the four choice questionnaires. Consistent with Experiment 1, participants who chose more delayed gains were significantly more likely to also choose more probabilistic gains; participants who chose more immediate losses were significantly more likely to also choose more certain losses; and those who chose more probabilistic gains were also more likely to choose more probabilistic losses. However, the correlations between delayed gains and delayed losses and between delayed gains and probabilistic losses were significant in Experiment 1 but not in Experiment 2; the correlation between delayed losses and probabilistic gains was insignificant in Experiment 1 but significant in Experiment 2.

Table 11

Intercorrelations Among Choice Questionnaires in Experiment 2

Questionnaire	1	2	3	4
1. Delayed Gains	–	.08	.21***	-.00
2. Delayed Losses		–	-.18***	.42***
3. Probabilistic Gains			–	-.42***
4. Probabilistic Losses				–

*$p < .05$. **$p < .01$. ***$p < .001$.

3.2.5 Relations Between Demographics and Degree of Discounting

Table 12 summarizes the multiple regression models predicting performance on the delayed gains, delayed losses, probabilistic gains, and probabilistic losses questionnaires with gender, age, years of education, and household income. As was found in Experiment 1, the demographic variables explained only a small proportion of the total variance in degree of discounting (all adjusted R^2 were less than .07). However, years of education but not age or household income was a significant predictor of degree of discounting delayed gains; both gender and age were significant predictors of degree of discounting delayed losses, probabilistic gains, and probabilistic losses; household income was a significant predictor of degree of discounting probabilistic gains. All other regression coefficients failed to reach significance after the corresponding *p*-values were corrected for multiple comparisons.

Table 12

Summary of Multiple Regression for Demographics Predicting the Degree of Discounting in Experiment 2

Variable	b	b 95% CI	β	t	F	df[d]	p	adjusted R^2
Delayed Gains					3.70	4, 259.34	.01	.03
(Intercept)	.71	[-8.39, 9.80]		.16		45.34	.89	
Gender[a]	-1.11	[-2.17, -.05]	-.09	-2.06		436.35	.06	
Age[b]	.01	[-.03, .04]	.01	.33		490.94	.81	
Years of education	.29	[.10, .47]	.14	2.99		282.63	.01	
Household income[c]	.61	[-.27, 1.49]	.08	1.40		32.54	.24	
Delayed Losses					4.84	4, 428.91	<.01	.05
(Intercept)	32.28	[20.27, 44.28]		5.48		31.75	<.01	
Gender[a]	-1.93	[-3.27, -.60]	-.13	-2.84		392.85	.01	
Age[b]	.05	[.01, .09]	.12	2.67		500.18	.02	
Years of education	-.02	[-.25, .21]	-.01	-.14		406.28	.89	
Household income[c]	-1.18	[-2.34, -.03]	-.12	-2.10		25.18	.69	
Probabilistic Gains					6.86	4, 440.99	<.01	.06
(Intercept)	-2.88	[-9.82, 4.07]		-.81		291.88	.48	
Gender[a]	1.83	[.90, 2.76]	.17	3.85		486.26	.00	
Age[b]	-.03	[-.06, .00]	-.10	-2.23		483.13	.04	
Years of education	.07	[-.09, .24]	.04	.88		328.52	.45	
Household income[c]	.88	[.23, 1.54]	.13	2.66		191.01	.02	
Probabilistic Losses					4.53	4, 453.14	.01	.04
(Intercept)	26.58	[15.62, 37.54]		4.99		25.52	<.01	
Gender[a]	-1.79	[-2.95, -.64]	-.14	-3.05		464.07	.01	
Age[b]	.05	[.01, .08]	.12	2.71		497.57	.01	
Years of education	-.13	[-.33, .07]	-.06	-1.25		379.90	.27	
Household income[c]	-.63	[-1.64, .38]	-.07	-1.28		25.71	.27	

Note. [a]Female = 0; Male = 1. [b]Age was mean-centered. [c]Due to a highly skewed distribution, a natural logarithm transformation was applied to household income for the analysis. [d]The degrees of freedom in multiple imputation were calculated based on the proportion of the variation attributable to the missing data.

3.2.6 Association Between Degree of Discounting and Everyday Behaviors in Each Behavioral Category by Age Group

All models with imposed factor structure fitted the data well when the residuals of field behavior questions were allowed to covary. Specifically, all TLIs were greater than .91, all CFIs were greater than .91, and all RMSEAs were less than .08.

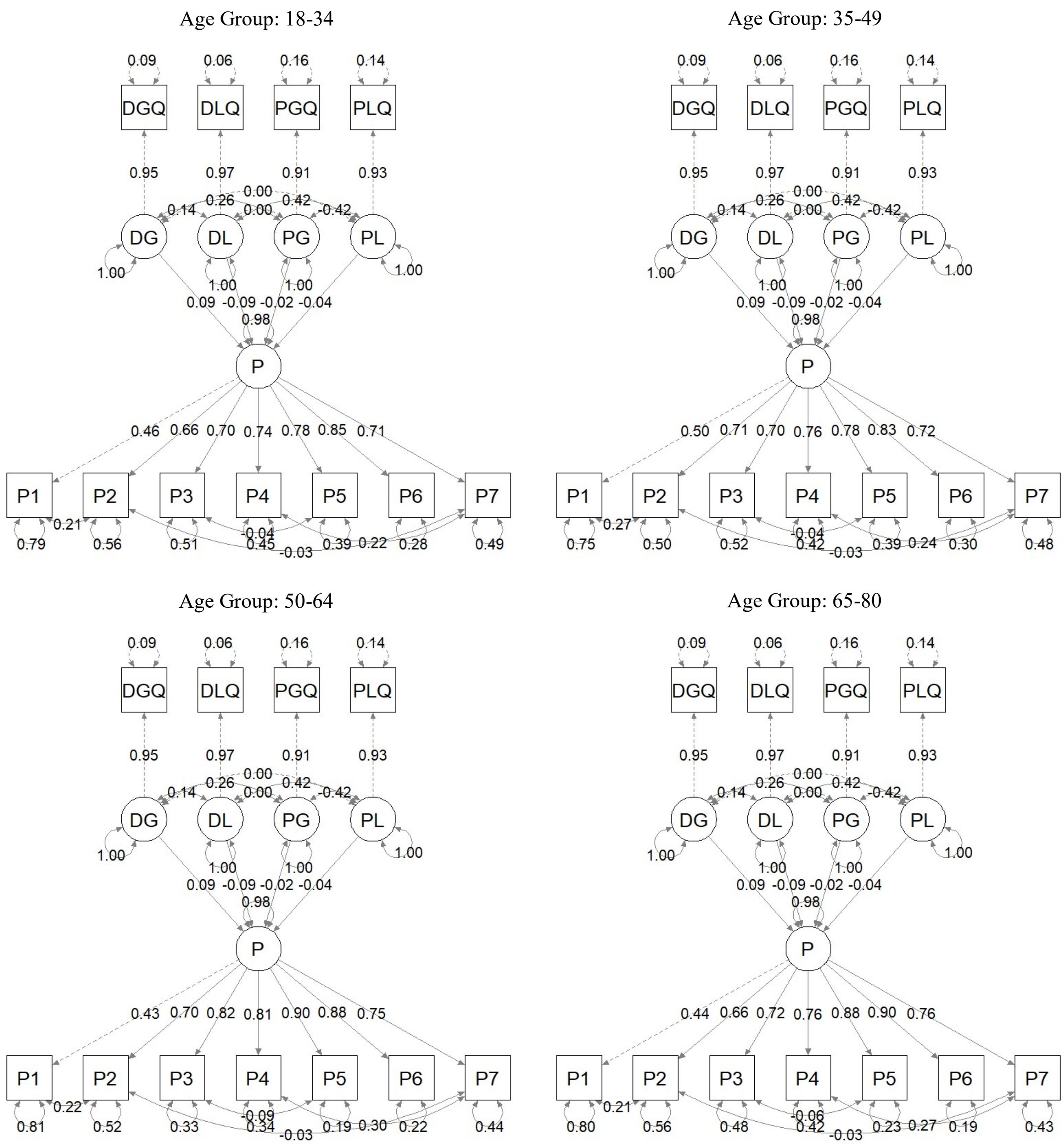
Measurement invariance in factor loadings was met for all behavioral categories except for risky financial decisions and financial loss deferment. For these two categories, the latent variable did not represent the same construct across age groups, thus the regression coefficients could not be meaningfully compared between groups. For five of the other categories, the subsequent chi-square test showed that the association in procrastination, healthy habits, novel-seeking purchasing, risk-taking behaviors, and future-oriented financial decisions did not depend on the age groups (all *p*s > .41). Only for impulsive purchasing did the association differ significantly across the age groups ($p = .04$), thus the regression coefficients were evaluated separately by age group.

Figure 11 summarizes the fitting estimates in SEM for each of the eight categories by age group, noting that the estimates cannot be meaningfully compared between age groups for risky financial decisions and financial loss deferment. To facilitate interpretation of the regression coefficients and the residual variances, all values reported were standardized to have a variance of 1.0 and indicated units of change in standard deviation when there was a one standard deviation increase in the linked variable. Overall, the standardized regression coefficients (i.e., correlations) were weak, and only a few reached statistical significance. Specifically, the degree of discounting delayed gains correlated significantly only with impulsive purchasing in the 18-34 year-old group ($r = -.28$; $p = .02$; see panel d in Fig. 11; steep discounting of delayed gains was associated with higher frequencies of impulsive purchasing behaviors); the degree of discounting delayed losses significantly correlated only with risk-taking behaviors ($r = -.18$; $p < .01$; see panel e in Fig. 11; steep discounting of delayed losses was associated with higher frequencies of risk-taking behaviors); the degree of discounting probabilistic gains significantly correlated only with future-oriented financial decisions ($r = .14$; $p = .03$; see panel g in Fig. 11; steep discounting of probabilistic gains was associated with lower frequencies of future-oriented financial decisions); the degree of discounting probabilistic losses significantly correlated only with impulsive purchasing in the 35-49 year-old group ($r = -.29$; $p = .03$; see panel d in Fig. 11; steep discounting of probabilistic losses was associated with higher frequencies of impulsive purchasing behaviors).

Figure 11

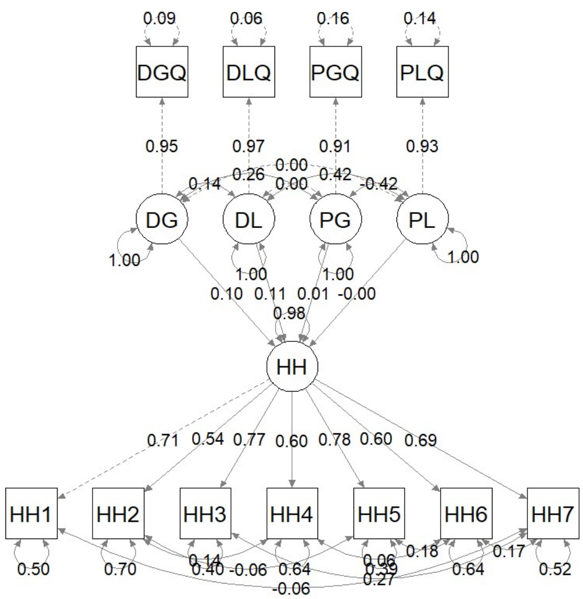
Path Diagrams of Association Between Degree of Discounting and Everyday Behaviors of Each Category by Age Group

a. Procrastination

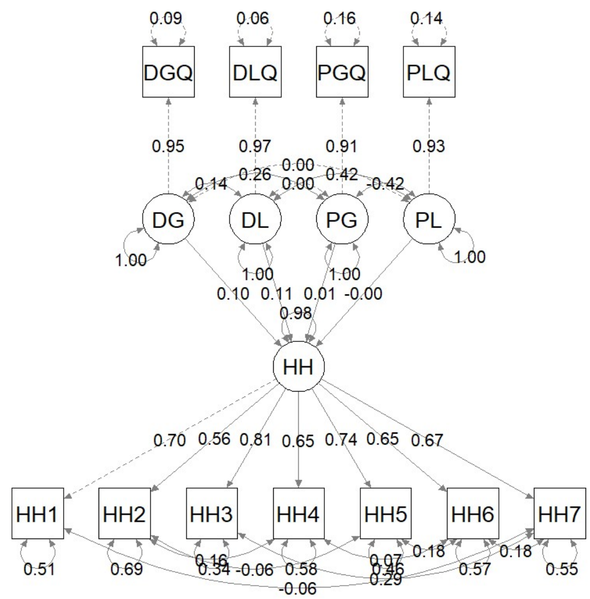


b. Healthy Habits

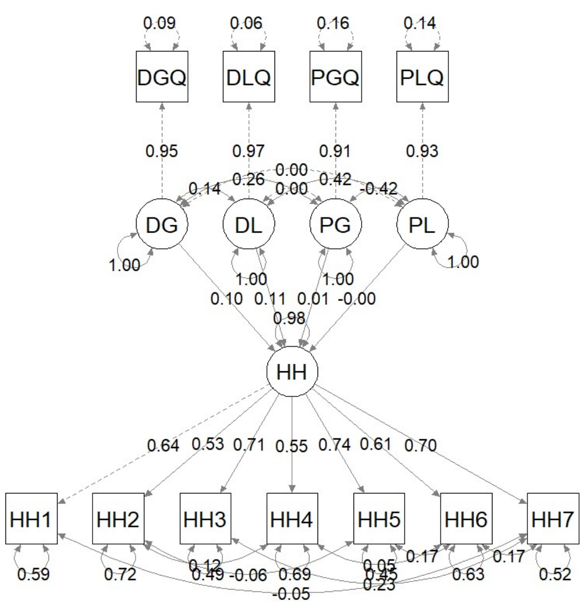
Age Group: 18-34



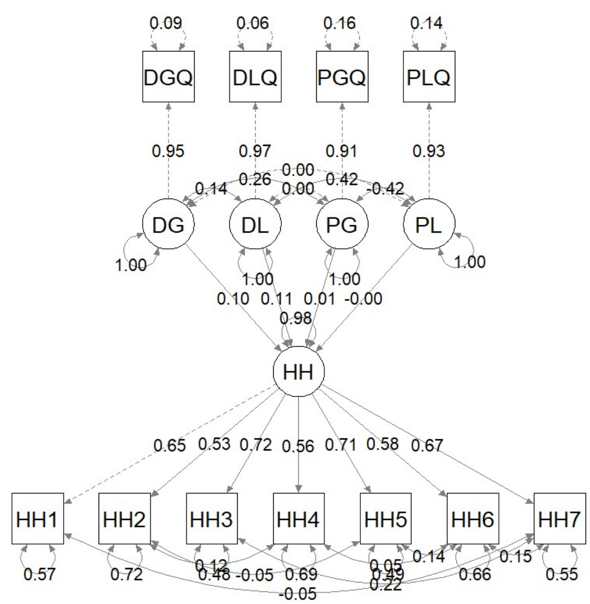
Age Group: 35-49



Age Group: 50-64

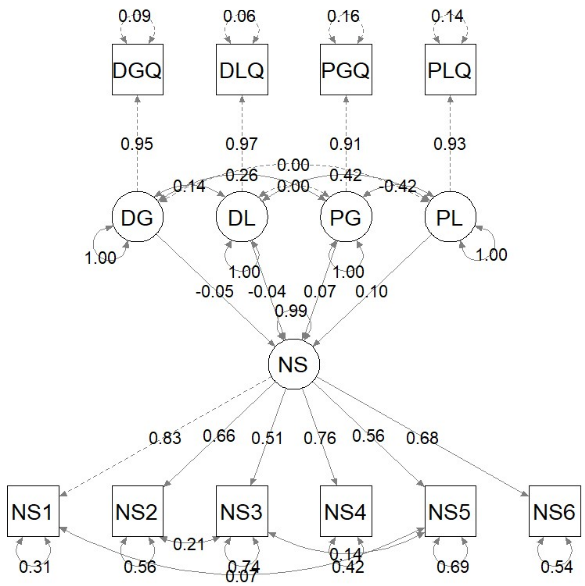


Age Group: 65-80

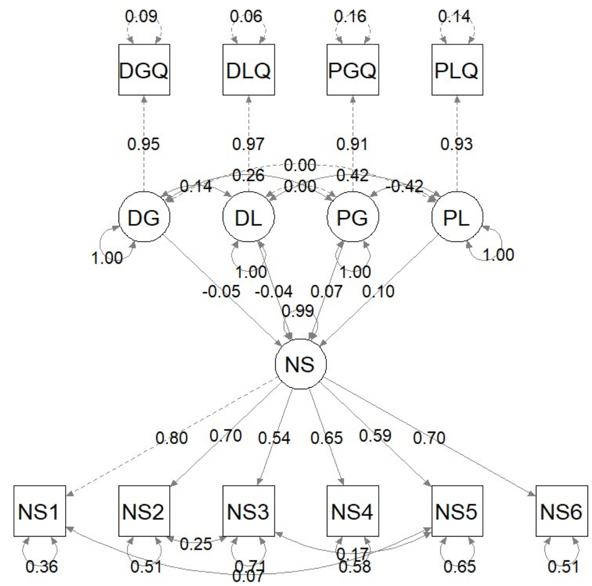


c. Novel-seeking Purchasing

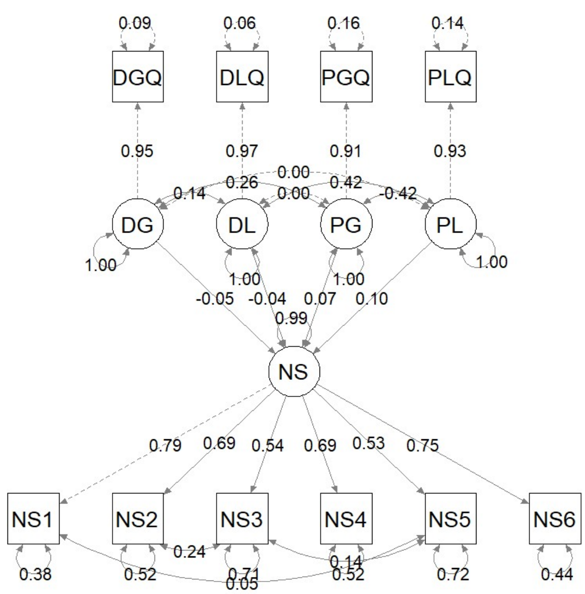
Age Group: 18-34



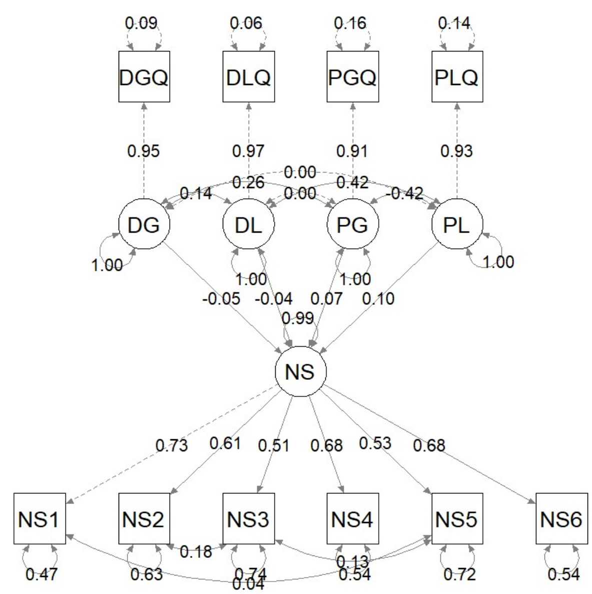
Age Group: 35-49



Age Group: 50-64

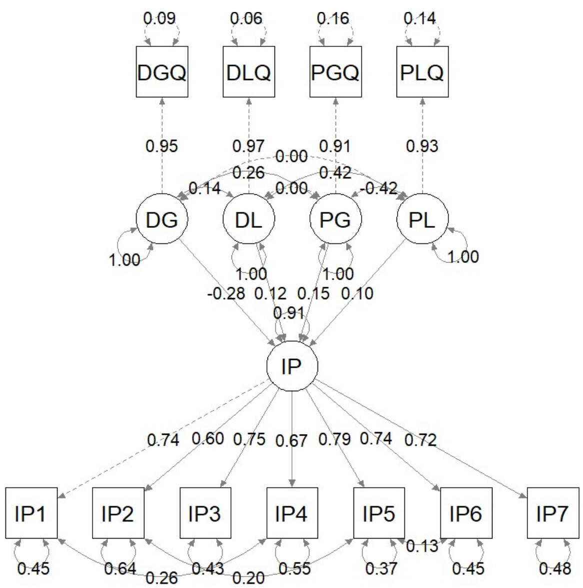


Age Group: 65-80

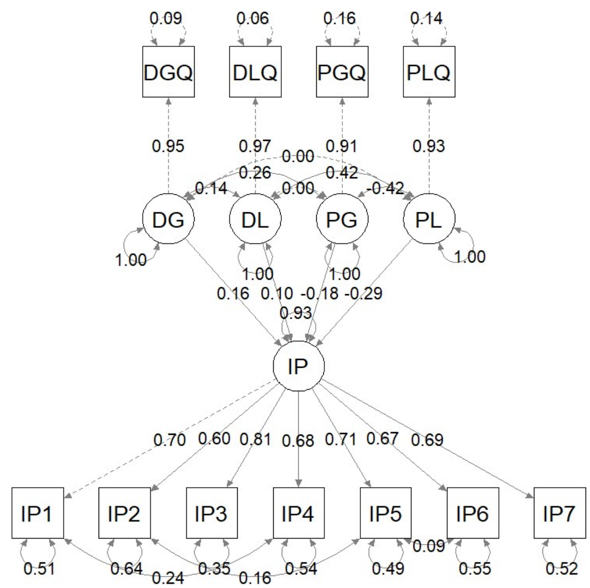


d. Impulsive Purchasing

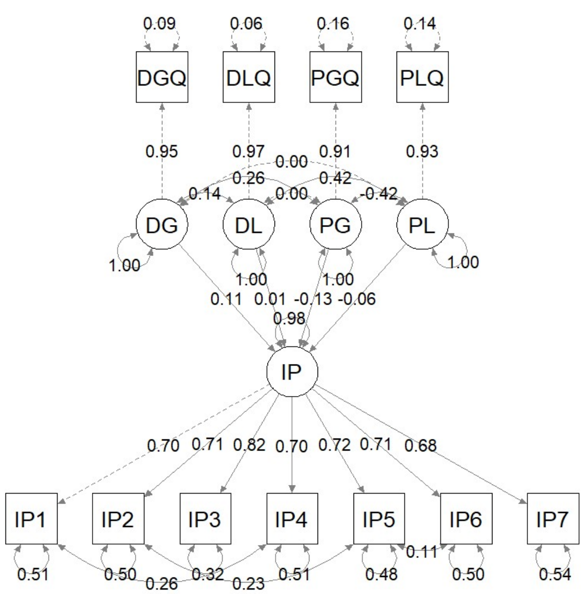
Age Group: 18-34



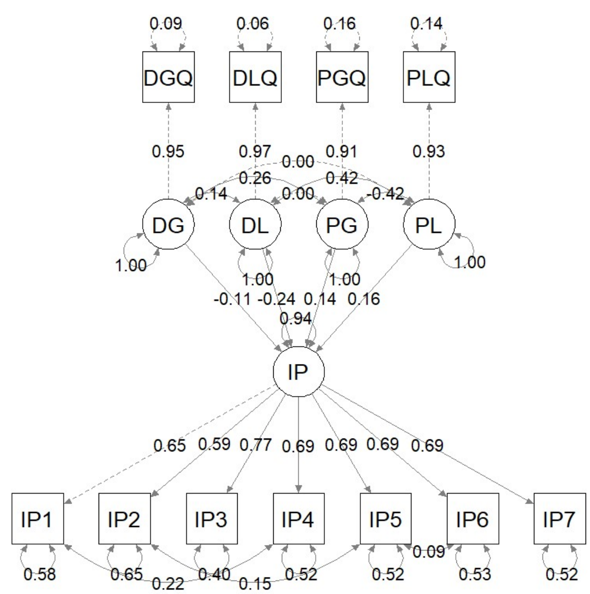
Age Group: 35-49



Age Group: 50-64

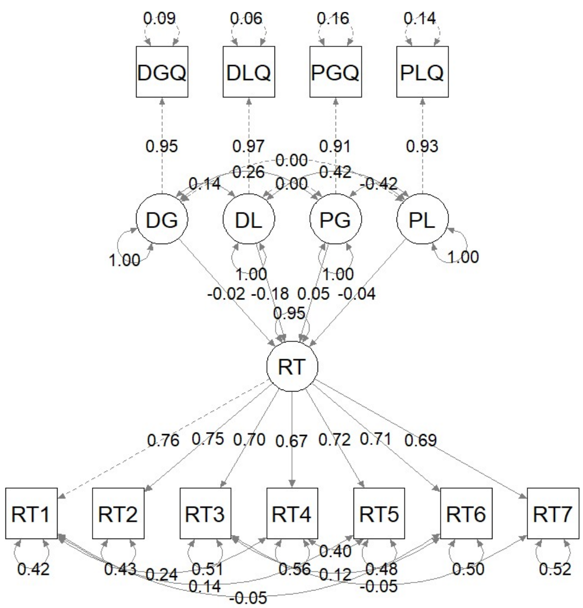


Age Group: 65-80

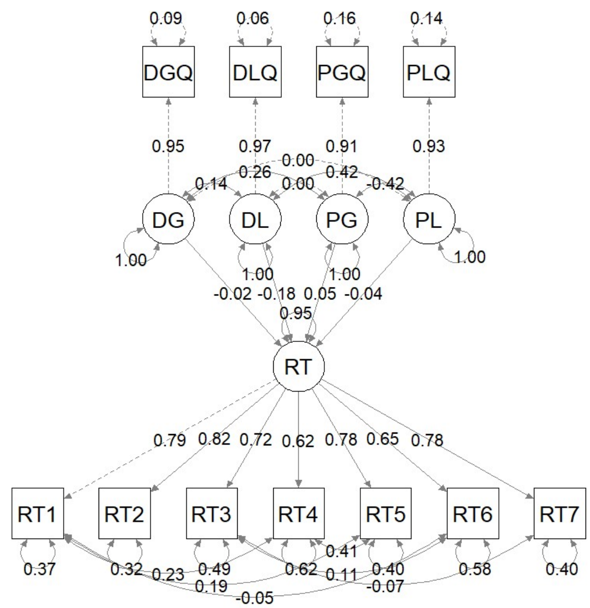


e. Risk-taking Behaviors

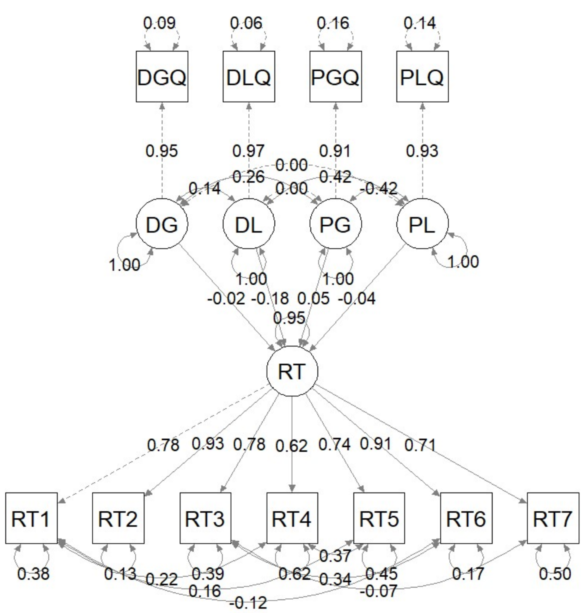
Age Group: 18-34



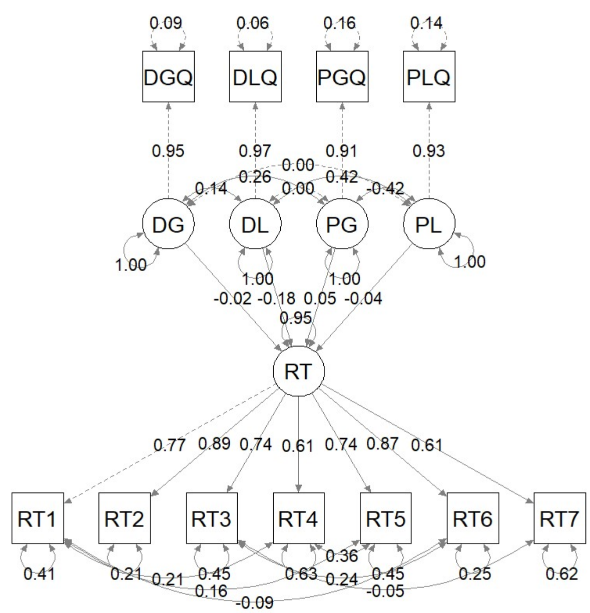
Age Group: 35-49



Age Group: 50-64

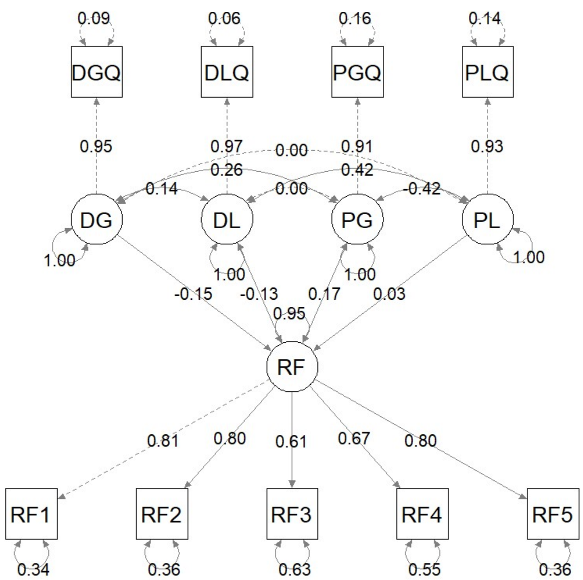


Age Group: 65-80

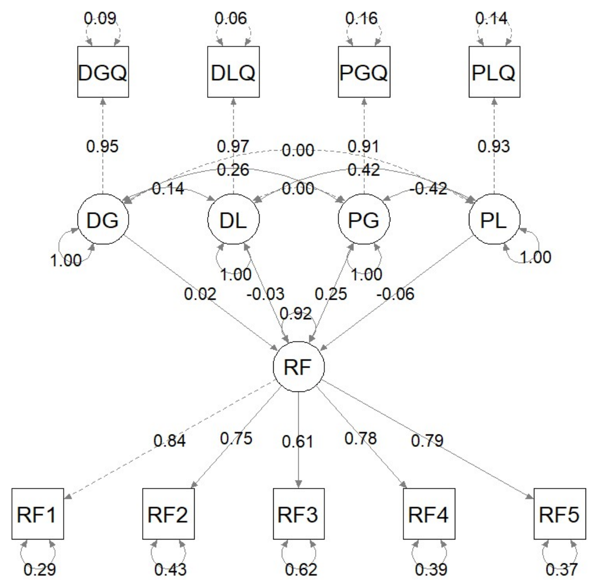


f. Risky Financial Decisions

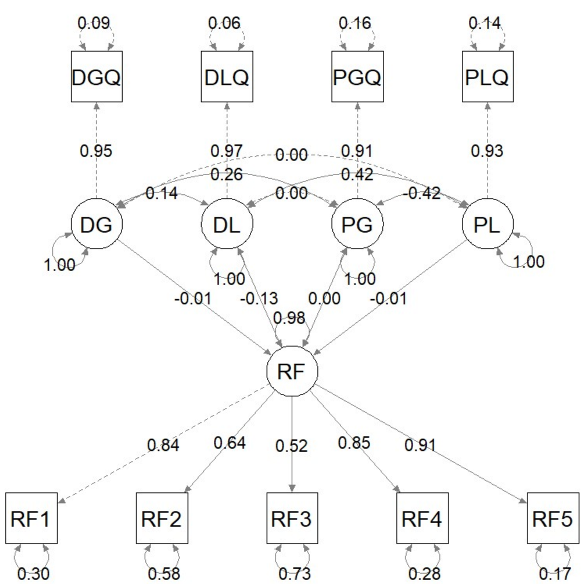
Age Group: 18-34



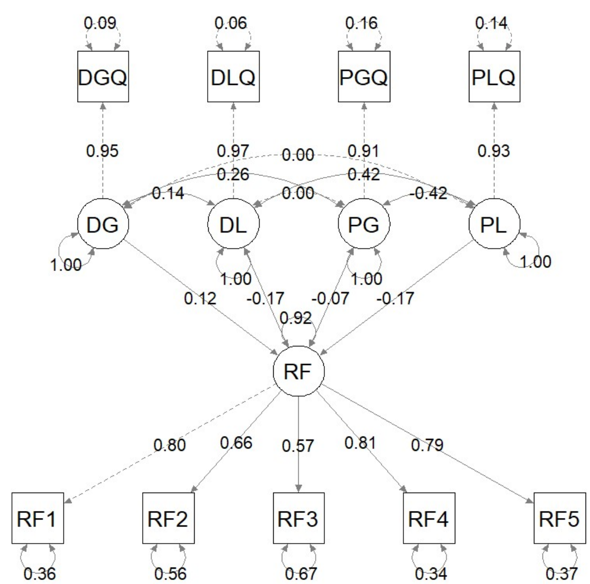
Age Group: 35-49



Age Group: 50-64

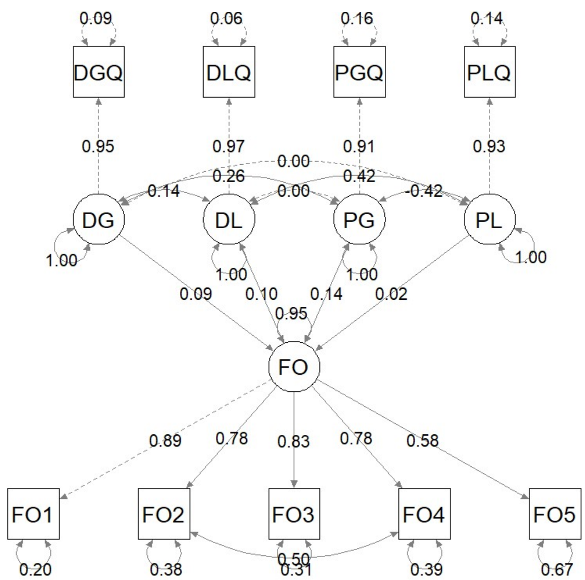


Age Group: 65-80

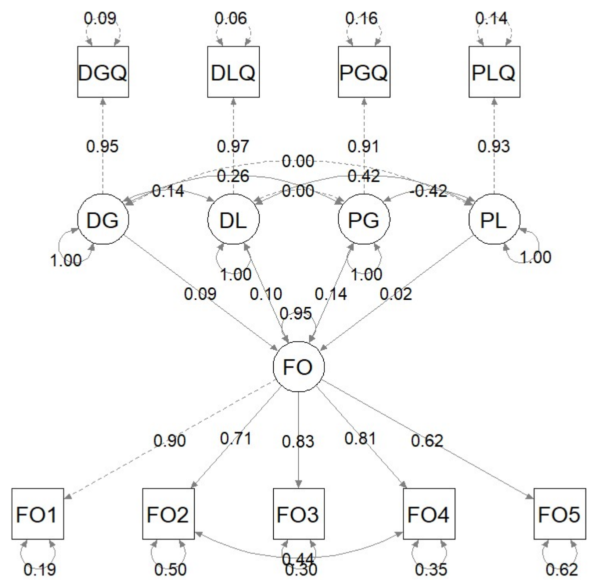


g. Future-oriented Financial Decisions

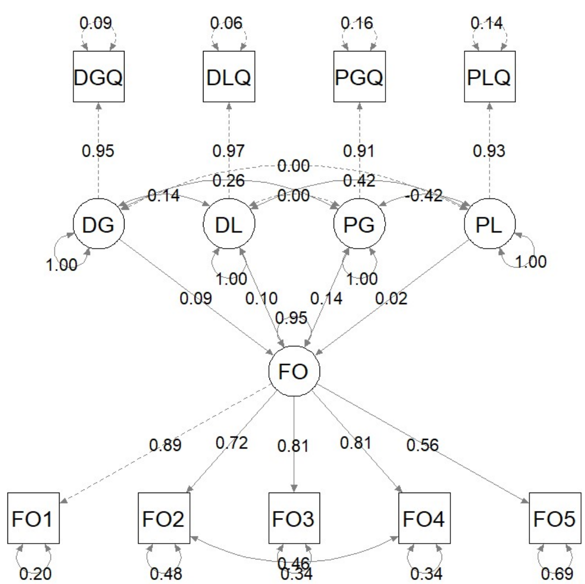
Age Group: 18-34



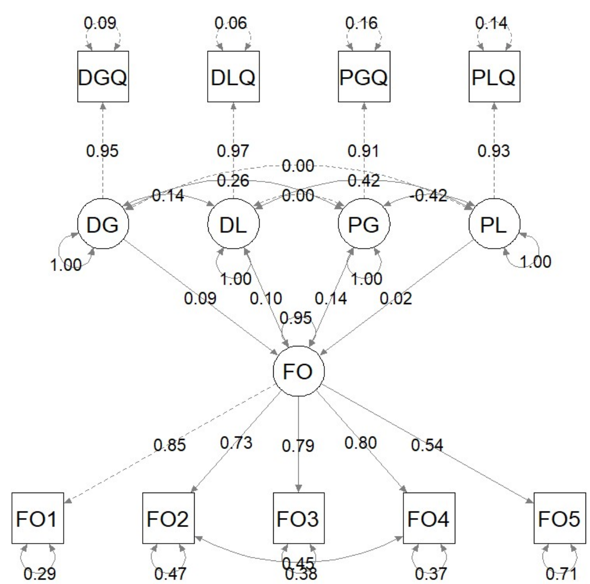
Age Group: 35-49



Age Group: 50-64

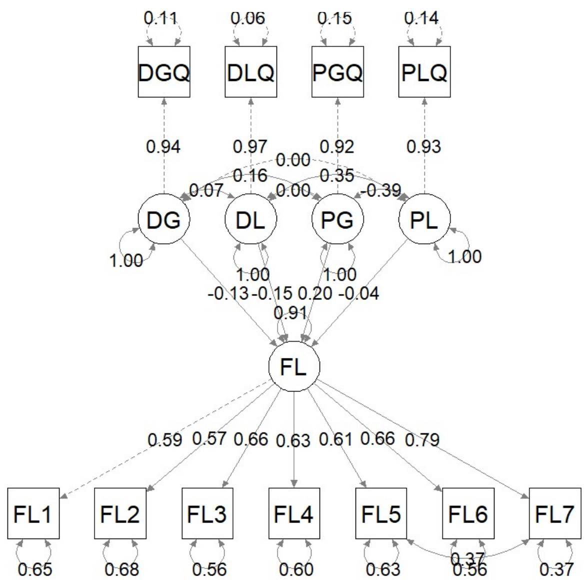


Age Group: 65-80

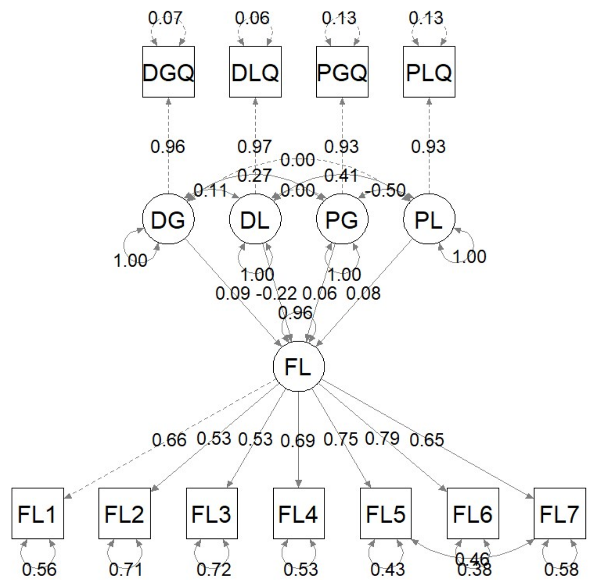


h. Financial Loss Deferment

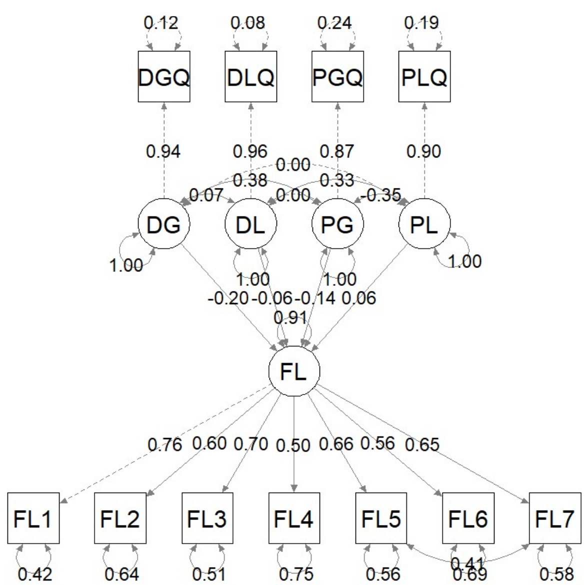
Age Group: 18-34



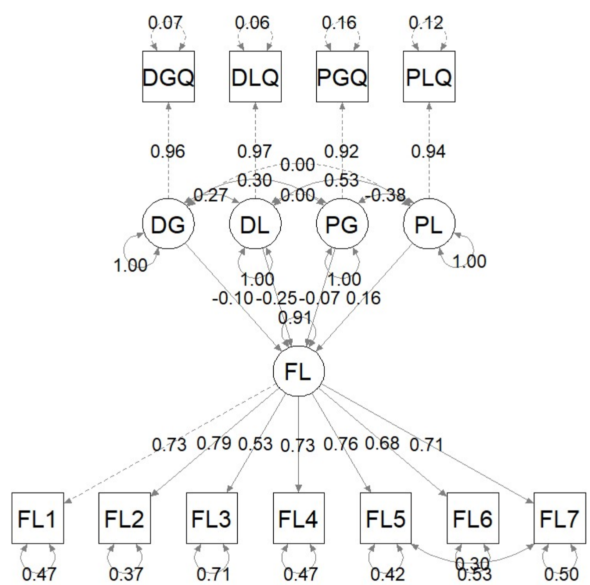
Age Group: 35-49



Age Group: 50-64



Age Group: 65-80



Note. DGQ: Delayed Gains Questionnaire; DLQ: Delayed Losses Questionnaire; PGQ: Probabilistic Gains Questionnaire; PLQ: Probabilistic Losses Questionnaire; P: procrastination; HH: healthy habits; NS: novel-seeking purchasing; IP: impulsive purchasing; RT: risk-taking behaviors; RF: risky financial decisions; FO: future-oriented financial decisions; FL: financial loss deferment. All values reported in the models were standardized to have a variance of 1.0.

3.2.7 Relations Between Degree of Discounting and Everyday Behaviors After Controlling for Demographic Variables

Table 13 presents the results of the regression models. As may be seen, only two regression coefficients of the degree of discounting reached significance after correcting *p*-values for multiple comparisons. Specifically, steep discounting of probabilistic gains was associated with higher frequencies of HH6, “Drank plenty of water each day”, and steep discounting of delayed losses was associated with higher frequencies of RT7, “Drove without wearing a seat belt”.

Degree of discounting and the demographic variables (i.e., gender, age, years of education, and household income) accounted for only small proportions of variance in everyday behaviors as indicated by the R^2s in Table 13. Moreover, degree of discounting accounted for only limited proportions of variance in everyday behaviors beyond the demographic variables as indicated by ΔR^2. The models with and without the degree of discounting as a predictor differed significantly only on HH6.

Table 13

Summary of Multiple Regression for the Degree of Discounting Predicting Everyday Behaviors

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
				Procrastination				
P4					.10 (.02)	2.31	4, 472.17	.20
(Intercept)	19.71	[-30.76, 70.18]	0	.78			56.50	.65
Delayed gains	.46	[-.03, .96]	.08	1.84			407.80	.22
Delayed losses	-.51	[-.93, -.10]	-.12	-2.42			474.68	.08
Probabilistic gains	.06	[-.54, .66]	.01	.19			426.29	.92
Probabilistic losses	-.03	[-.55, .48]	-.01	-.13			409.18	.95
Gender[a]	-3.06	[-90, 2.88]	-.05	-1.01			321.56	.54
Age[b]	-.48	[-.65, -.31]	-.24	-5.50			426.98	<.01
Years of education	.29	[-.77, 1.35]	.03	.54			159.24	.79
Household income[c]	2.17	[-2.48, 6.81]	.05	.94			38.75	.57
P2					.12 (.02)	1.72	4, 444.07	.37
(Intercept)	60.89	[11.68, 110.09]	0	2.50			43.10	.08
Delayed gains	.50	[.04, .97]	.1	2.12			396.55	.14
Delayed losses	-.29	[-.69, .10]	-.07	-1.45			417.82	.38
Probabilistic gains	.11	[-.48, .69]	.02	.36			240.54	.86
Probabilistic losses	-.12	[-.60, .36]	-.03	-.49			459.68	.80
Gender[a]	-13.64	[-19.14, -8.13]	-.22	-4.87			423.51	<.01
Age[b]	-.40	[-.56, -.24]	-.21	-4.91			495.12	<.01
Years of education	.47	[-.48, 1.42]	.04	.97			379.36	.56
Household income[c]	-.59	[-5.18, 3.99]	-.01	-.26			29.26	.90
P5					.07 (.01)	1.68	4, 463.65	.38
(Intercept)	61.55	[-1.90, 124.99]	0	2.03			18.40	.20
Delayed gains	.24	[-.28, .76]	.04	.92			298.20	.58
Delayed losses	-.52	[-.95, -.09]	-.12	-2.39			454.47	.09
Probabilistic gains	.12	[-.50, .74]	.02	.38			399.14	.86
Probabilistic losses	.05	[-.47, .57]	.01	.19			484.08	.92
Gender[a]	-.06	[-6.14, 6.02]	0	-.02			322.77	.99
Age[b]	-.45	[-.63, -.28]	-.22	-5.11			492.90	<.01
Years of education	.65	[-.38, 1.68]	.06	1.24			391.49	.46
Household income[c]	-2.44	[-8.38, 3.51]	-.06	-.87			14.78	.61
P6					.06 (.01)	1.40	4, 461.51	.47
(Intercept)	74.24	[17.79, 130.69]	0	2.68			31.60	.06
Delayed gains	.42	[-.09, .93]	.08	1.61			340.40	.31
Delayed losses	-.22	[-.66, .21]	-.05	-1.00			376.38	.54
Probabilistic gains	-.10	[-.72, .52]	-.02	-.31			410.05	.88
Probabilistic losses	-.37	[-.89, .15]	-.07	-1.38			487.33	.40
Gender[a]	-.55	[-6.70, 5.61]	-.01	-.17			284.55	.93
Age[b]	-.38	[-.56, -.20]	-.19	-4.19			405.55	<.01
Years of education	.20	[-.82, 1.22]	.02	.38			471.88	.85
Household income[c]	-2.59	[-7.68, 2.05]	-.06	-1.04			26.95	.54

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
P7					.08 (.01)	.92	4, 452.68	.66
(Intercept)	-3.84	[-66.1, 58.42]	0	-.13			17.95	.95
Delayed gains	.1	[-.39, .60]	.02	.41			423.21	.84
Delayed losses	-.33	[-.75, .09]	-.08	-1.53			406.79	.34
Probabilistic gains	.32	[-.30, .94]	.05	1.02			253.79	.54
Probabilistic losses	.08	[-.43, .59]	.02	.31			480.63	.88
Gender[a]	-4.25	[-1.35, 1.84]	-.07	-1.38			192.45	.40
Age[b]	-.41	[-.58, -.24]	-.21	-4.77			488.74	<.01
Years of education	1.14	[.08, 2.20]	.1	2.13			160.80	.14
Household income[c]	2.76	[-3.03, 8.55]	.07	1.02			14.81	.55
P3					.03 (.01)	.69	4, 400.00	.79
(Intercept)	42.24	[-25.51, 110.00]	0	1.32			16.04	.45
Delayed gains	.19	[-.35, .72]	.03	.68			207.26	.71
Delayed losses	-.23	[-.67, .21]	-.05	-1.02			384.81	.54
Probabilistic gains	-.05	[-.70, .60]	-.01	-.16			292.20	.94
Probabilistic losses	-.31	[-.85, .23]	-.06	-1.13			356.71	.50
Gender[a]	-5.14	[-11.48, 1.20]	-.08	-1.60			233.31	.31
Age[b]	-.24	[-.41, -.06]	-.12	-2.59			482.29	.06
Years of education	.15	[-.92, 1.22]	.01	.27			324.87	.90
Household income[c]	.22	[-5.61, 6.06]	.01	.08			16.87	.97
P1					.07 (.01)	.47	4, 465.35	.88
(Intercept)	70.52	[9.24, 131.80]	0	2.36			27.01	.11
Delayed gains	.10	[-.44, .64]	.02	.35			338.01	.86
Delayed losses	.13	[-.33, .58]	.03	.55			419.64	.79
Probabilistic gains	.29	[-.36, .95]	.05	.88			418.78	.59
Probabilistic losses	-.23	[-.78, .32]	-.04	-.83			478.16	.62
Gender[a]	-6.11	[-12.39, .18]	-.09	-1.91			471.08	.20
Age[b]	-.45	[-.64, -.26]	-.21	-4.69			321.91	<.01
Years of education	.68	[-.45, 1.81]	.06	1.18			213.06	.48
Household income[c]	-2.92	[-8.53, 2.70]	-.06	-1.08			21.89	.52
			Healthy Habits					
HH6					.04 (.03)	4.05	4, 488.68	.02
(Intercept)	41.93	[-2.33, 86.19]	0	1.88			84.88	.22
Delayed gains	.01	[-.44, .46]	0	.06			447.88	.98
Delayed losses	.40	[.02, .78]	.1	2.07			471.06	.15
Probabilistic gains	-.86	[-1.40, -.32]	-.16	-3.11			488.73	.02
Probabilistic losses	-.36	[-.83, .10]	-.08	-1.54			472.02	.33
Gender[a]	4.56	[-.70, 9.82]	.08	1.70			491.80	.27
Age[b]	.13	[-.03, .28]	.07	1.64			495.12	.30
Years of education	.58	[-.34, 1.51]	.06	1.24			358.78	.46
Household income[c]	2.16	[-1.73, 6.05]	.06	1.10			80.86	.51
HH2					.10 (.02)	2.71	4, 314.05	.13
(Intercept)	-83.46	[-139.52, -27.39]	0	-2.98			60.51	.03
Delayed gains	.71	[.09, 1.33]	.12	2.30			72.98	.11

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Delayed losses	.38	[-.10, .86]	.08	1.57			261.75	.33
Probabilistic gains	-.36	[-1.06, .34]	-.05	-1.01			205.69	.54
Probabilistic losses	-.37	[-.93, .20]	-.07	-1.28			492.55	.45
Gender[a]	-8.66	[-15.31, -2.02]	-.12	-2.56			320.40	.06
Age[b]	-.14	[-.34, .06]	-.06	-1.35			165.15	.41
Years of education	1.86	[.73, 2.99]	.14	3.23			373.97	.01
Household income[c]	9.43	[4.47, 14.39]	.2	3.81			54.85	.01
HH5					.05 (.02)	2.15	4, 490.90	.24
(Intercept)	30.11	[-18.60, 78.81]	0	1.26			31.31	.46
Delayed gains	.42	[-.02, .85]	.09	1.89			450.54	.21
Delayed losses	.19	[-.18, .56]	.05	1.03			488.87	.54
Probabilistic gains	.32	[-.21, .85]	.06	1.17			471.93	.48
Probabilistic losses	.37	[-.08, .81]	.08	1.60			490.11	.31
Gender[a]	2.22	[-2.92, 7.36]	.04	.85			470.00	.61
Age[b]	.15	[.00, .30]	.09	1.99			492.28	.17
Years of education	1.03	[.15, 1.92]	.1	2.29			452.69	.11
Household income[c]	.53	[-3.81, 4.88]	.02	.25			28.11	.90
HH7					.02 (.01)	1.32	4, 485.77	.50
(Intercept)	16.09	[-32.04, 64.22]	0	.67			70.05	.71
Delayed gains	.31	[-.18, .79]	.06	1.25			407.36	.46
Delayed losses	.39	[-.02, .79]	.09	1.87			485.48	.22
Probabilistic gains	-.06	[-.64, .52]	-.01	-.20			492.09	.92
Probabilistic losses	-.11	[-.61, .38]	-.02	-.45			446.43	.82
Gender[a]	-.36	[-6.01, 5.29]	-.01	-.13			474.15	.95
Age[b]	-.06	[-.22, .11]	-.03	-.65			400.47	.73
Years of education	-.02	[-1.02, .98]	0	-.04			278.22	.98
Household income[c]	3.55	[-.60, 7.70]	.09	1.70			81.64	.28
HH3					.06 (.01)	1.14	4, 452.51	.56
(Intercept)	-52.80	[-114.28, 8.67]	0	-1.77			24.20	.27
Delayed gains	.13	[-.39, .66]	.02	.50			433.81	.80
Delayed losses	.34	[-.12, .80]	.07	1.46			266.52	.37
Probabilistic gains	-.47	[-1.11, .17]	-.07	-1.43			403.53	.38
Probabilistic losses	.07	[-.47, .61]	.01	.25			462.94	.90
Gender[a]	3.69	[-2.49, 9.88]	.05	1.17			449.02	.48
Age[b]	-.11	[-.30, .07]	-.05	-1.23			450.67	.46
Years of education	1.17	[.10, 2.23]	.1	2.15			429.41	.13
Household income[c]	7.65	[2.30, 12.99]	.17	2.95			24.91	.04
HH1					.05 (.01)	1.10	4, 450.32	.58
(Intercept)	-39.43	[-96.16, 17.29]	0	-1.41			38.16	.40
Delayed gains	.07	[-.46, .60]	.01	.26			420.13	.90
Delayed losses	.27	[-.19, .72]	.06	1.16			304.78	.48
Probabilistic gains	.44	[-.20, 1.09]	.07	1.35			417.73	.41
Probabilistic losses	.30	[-.25, .85]	.06	1.07			405.70	.52
Gender[a]	-3.59	[-9.75, 2.57]	-.05	-1.14			484.19	.49
Age[b]	.01	[-.17, .20]	.01	.16			461.15	.94

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Years of education	1.98	[.92, 3.04]	.17	3.65			455.50	<.01
Household income[c]	4.59	[-.42, 9.59]	.1	1.86			36.29	.24
HH4					.06 (.01)	1.07	4, 377.87	.59
(Intercept)	-44.07	[-96.49, 8.35]	0	-1.67			110.14	.29
Delayed gains	.36	[-.19, .92]	.06	1.29			336.17	.45
Delayed losses	.31	[-.19, .81]	.07	1.23			108.60	.46
Probabilistic gains	-.32	[-.98, .34]	-.05	-.94			465.86	.57
Probabilistic losses	-.11	[-.68, .47]	-.02	-.37			348.73	.86
Gender[a]	-3.20	[-9.73, 3.33]	-.05	-.96			350.53	.56
Age[b]	.03	[-.17, .22]	.01	.26			320.74	.90
Years of education	1.96	[.82, 3.11]	.16	3.39			251.28	.01
Household income[c]	6.27	[1.66, 10.88]	.14	2.70			103.06	.05
		Novel-seeking Purchasing						
NS3					.05 (.03)	3.22	4, 466.60	.07
(Intercept)	84.56	[33.17, 135.95]	0	3.37			27.28	.02
Delayed gains	-.11	[-.55, .34]	-.02	-.47			447.87	.81
Delayed losses	-.45	[-.83, -.07]	-.12	-2.33			436.55	.10
Probabilistic gains	-.23	[-.79, .33]	-.04	-.80			303.41	.64
Probabilistic losses	.61	[.15, 1.07]	.14	2.59			477.69	.06
Gender[a]	1.08	[-4.22, 6.38]	.02	.40			447.52	.85
Age[b]	-.07	[-.22, .09]	-.04	-.83			494.10	.62
Years of education	-1.16	[-2.07, -.24]	-.11	-2.48			400.78	.07
Household income[c]	-2.82	[-7.57, 1.94]	-.07	-1.23			21.27	.47
NS5					.04 (.01)	1.05	4, 421.83	.59
(Intercept)	111.08	[68.24, 153.91]	0	5.11			193.82	<.01
Delayed gains	-.23	[-.72, .26]	-.05	-.94			157.89	.57
Delayed losses	-.24	[-.63, .15]	-.06	-1.22			461.88	.46
Probabilistic gains	.22	[-.34, .79]	.04	.78			425.36	.65
Probabilistic losses	.28	[-.21, .76]	.06	1.12			387.78	.50
Gender[a]	2.96	[-2.49, 8.42]	.05	1.07			447.30	.52
Age[b]	-.11	[-.27, .04]	-.06	-1.41			486.31	.39
Years of education	-.76	[-1.73, .20]	-.07	-1.56			250.08	.33
Household income[c]	-5.41	[-9.34, -1.48]	-.14	-2.73			97.32	.05
NS6					.04 (.01)	1.00	4, 495.14	.62
(Intercept)	20.71	[-16.32, 57.75]	0	1.10			242.71	.51
Delayed gains	.06	[-.33, .46]	.01	.32			494.59	.88
Delayed losses	.01	[-.33, .35]	0	.07			493.18	.97
Probabilistic gains	.41	[-.08, .90]	.08	1.65			486.43	.30
Probabilistic losses	.23	[-.19, .64]	.06	1.07			489.10	.51
Gender[a]	1.42	[-3.32, 6.16]	.03	.59			482.98	.76
Age[b]	-.08	[-.22, .06]	-.05	-1.14			488.39	.49
Years of education	-1.43	[-2.25, -.61]	-.16	-3.43			442.03	.01
Household income[c]	1.83	[-1.42, 5.08]	.05	1.11			234.92	.51
NS1					.02 (.00)	.73	4, 492.96	.78

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
(Intercept)	68.25	[30.47, 106.04]	0	3.55			378.64	.01
Delayed gains	-.05	[-.47, .37]	-.01	-.25			468.89	.90
Delayed losses	-.08	[-.44, .27]	-.02	-.45			487.06	.82
Probabilistic gains	.33	[-.18, .84]	.07	1.28			492.20	.45
Probabilistic losses	.22	[-.21, .66]	.05	1.00			482.91	.54
Gender[a]	3.52	[-1.43, 8.48]	.07	1.40			480.19	.39
Age[b]	-.11	[-.26, .04]	-.07	-1.49			490.50	.36
Years of education	-.73	[-1.59, .12]	-.08	-1.68			456.12	.28
Household income[c]	-2.75	[-6.08, .57]	-.08	-1.63			335.77	.30
NS2					.03 (.00)	.69	4, 475.24	.79
(Intercept)	45.66	[3.43, 87.90]	0	2.14			103.47	.14
Delayed gains	.02	[-.42, .46]	0	.09			381.77	.96
Delayed losses	-.06	[-.43, .31]	-.02	-.33			427.89	.88
Probabilistic gains	.18	[-.35, .71]	.03	.67			488.90	.71
Probabilistic losses	.34	[-.11, .80]	.08	1.49			436.12	.36
Gender[a]	1.40	[-3.74, 6.55]	.03	.54			459.44	.79
Age[b]	-.21	[-.36, -.06]	-.13	-2.81			494.40	.03
Years of education	-.74	[-1.68, .20]	-.08	-1.55			158.94	.33
Household income[c]	-.64	[-4.34, 3.05]	-.02	-.35			103.73	.87
NS4					.05 (.00)	.49	4, 451.09	.88
(Intercept)	20.82	[-16.29, 57.93]	0	1.10			445.41	.51
Delayed gains	.01	[-.43, .45]	0	.04			189.81	.99
Delayed losses	-.11	[-.47, .24]	-.03	-.62			449.69	.74
Probabilistic gains	-.33	[-.84, .19]	-.06	-1.25			433.94	.46
Probabilistic losses	.04	[-.39, .47]	.01	.18			494.96	.92
Gender[a]	3.40	[-1.64, 8.44]	.06	1.33			333.50	.42
Age[b]	-.18	[-.33, -.04]	-.11	-2.45			475.45	.08
Years of education	-1.50	[-2.35, -.64]	-.16	-3.45			440.84	.01
Household income[c]	2.92	[-.36, 6.20]	.08	1.75			391.82	.26
Impulsive Purchasing								
IP6					.04 (.01)	1.41	4, 484.77	.46
(Intercept)	17.30	[-37.62, 72.21]	0	.64			41.96	.73
Delayed gains	-.60	[-1.12, -.08]	-.11	-2.26			381.24	.11
Delayed losses	-.13	[-.56, .31]	-.03	-.58			481.49	.77
Probabilistic gains	.05	[-.57, .68]	.01	.16			473.00	.94
Probabilistic losses	.05	[-.48, .58]	.01	.19			486.63	.92
Gender[a]	1.48	[-4.64, 7.61]	.02	.48			422.99	.80
Age[b]	-.27	[-.45, -.09]	-.14	-2.98			417.84	.02
Years of education	.42	[-.62, 1.47]	.04	.79			458.30	.64
Household income[c]	3.08	[-1.97, 8.12]	.07	1.24			31.03	.46
IP7					.03 (.01)	.86	4, 458.11	.69
(Intercept)	44.30	[-16.54, 105.14]	0	1.52			20.47	.37
Delayed gains	-.08	[-.60, .44]	-.02	-.31			206.24	.88
Delayed losses	.05	[-.37, .47]	.01	.22			474.86	.91
Probabilistic gains	.57	[-.04, 1.17]	.09	1.85			484.28	.22

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Probabilistic losses	.01	[-.51, .52]	0	.03			451.86	.99
Gender[a]	-3.02	[-8.93, 2.90]	-.05	-1.00			418.11	.54
Age[b]	-.24	[-.41, -.06]	-.12	-2.69			437.86	.05
Years of education	.71	[-.40, 1.83]	.06	1.27			88.41	.45
Household income[c]	-.59	[-5.96, 4.79]	-.01	-.23			19.71	.91
IP2					.05 (.01)	.65	4, 464.23	.80
(Intercept)	21.42	[-29.49, 72.32]	0	.84			71.46	.62
Delayed gains	-.09	[-.6,0 .43]	-.02	-.34			368.46	.87
Delayed losses	-.31	[-.74, .12]	-.07	-1.40			413.80	.39
Probabilistic gains	.22	[-.40, .85]	.04	.70			420.47	.69
Probabilistic losses	.03	[-.50, .55]	.01	.10			451.22	.96
Gender[a]	-6.21	[-12.17, -.26]	-.09	-2.05			492.91	.16
Age[b]	-.36	[-.53, -.18]	-.18	-3.99			477.94	<.01
Years of education	.41	[-.64, 1.45]	.04	.76			351.59	.66
Household income[c]	2.00	[-2.43, 6.42]	.05	.90			76.57	.59
IP4					.02 (.00)	.62	4, 492.41	.82
(Intercept)	39.40	[-3.17, 81.97]	0	1.82			243.69	.23
Delayed gains	-.22	[-.69, .24]	-.04	-.94			435.83	.57
Delayed losses	.22	[-.17, .61]	.05	1.09			490.29	.51
Probabilistic gains	.17	[-.39, .73]	.03	.61			494.67	.75
Probabilistic losses	.01	[-.46, .49]	0	.06			488.19	.98
Gender[a]	-5.98	[-11.41, -.55]	-.1	-2.16			490.70	.13
Age[b]	-.10	[-.26, .06]	-.06	-1.24			492.31	.46
Years of education	.01	[-.97, .99]	0	.03			223.82	.99
Household income[c]	2.04	[-1.68, 5.76]	.05	1.08			249.12	.51
IP1					.03 (.01)	.45	4, 475.93	.89
(Intercept)	35.68	[-17.57, 88.94]	0	1.37			28.49	.41
Delayed gains	-.03	[-.51, .44]	-.01	-.14			321.16	.95
Delayed losses	.06	[-.34, .46]	.02	.30			432.04	.88
Probabilistic gains	.35	[-.22, .92]	.06	1.21			482.89	.46
Probabilistic losses	-.12	[-.60, .36]	-.03	-.49			490.12	.80
Gender[a]	-9.49	[-15.03, -3.95]	-.16	-3.37			455.37	.01
Age[b]	-.03	[-.19, .13]	-.02	-.36			486.54	.86
Years of education	.43	[-.57, 1.44]	.04	.85			164.23	.61
Household income[c]	2.18	[-2.8, 7.16]	.06	.91			21.09	.59
IP5					.08 (.00)	.44	4, 457.01	.89
(Intercept)	-20.95	[-67.03, 25.13]	0	-.90			192.33	.59
Delayed gains	-.29	[-.78, .20]	-.05	-1.17			484.61	.48
Delayed losses	-.11	[-.54, .33]	-.02	-.48			235.37	.80
Probabilistic gains	-.14	[-.75, .47]	-.02	-.45			402.29	.82
Probabilistic losses	.03	[-.49, .54]	.01	.10			471.98	.96
Gender[a]	-5.19	[-11.04, .67]	-.08	-1.74			457.74	.26
Age[b]	-.40	[-.57, -.23]	-.2	-4.55			472.96	<.01
Years of education	.95	[-.09, 20]	.08	1.80			240.35	.24
Household income[c]	5.66	[1.66, 9.66]	.13	2.79			226.40	.04

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
IP3					.05 (.00)	.43	4, 484.2	.90
(Intercept)	33.41	[-13.4, 80.21]	0	1.41			136.28	.39
Delayed gains	-.27	[-.76, .22]	-.05	-1.08			477.49	.51
Delayed losses	-.11	[-.53, .30]	-.03	-.53			484.79	.79
Probabilistic gains	.00	[-.60, .60]	0	.00			449.45	1.00
Probabilistic losses	-.14	[-.66, .37]	-.03	-.55			414.94	.79
Gender[a]	-9.57	[-15.39, -3.74]	-.15	-3.23			456.74	.01
Age[b]	-.26	[-.43, -.09]	-.13	-2.99			477.02	.02
Years of education	.95	[-.10, 20]	.08	1.78			185.97	.25
Household income[c]	1.59	[-2.72, 5.90]	.04	.73			72.49	.67
		Risk-taking Behaviors						
RT7					.08 (.02)	2.11	4, 385.17	.25
(Intercept)	-24.29	[-93.56, 44.98]	0	-.75			15.19	.67
Delayed gains	.09	[-.44, .62]	.02	.33			312.75	.88
Delayed losses	-.64	[-1.08, -.20]	-.14	-2.86			429.76	.03
Probabilistic gains	-.18	[-.85, .50]	-.03	-.51			144.85	.80
Probabilistic losses	.14	[-.41, .69]	.03	.51			331.41	.80
Gender[a]	4.77	[-1.81, 11.35]	.07	1.43			133.20	.38
Age[b]	-.34	[-.53, -.16]	-.16	-3.62			290.84	<.01
Years of education	-.36	[-1.55, .82]	-.03	-.61			73.50	.75
Household income[c]	5.53	[-1.24, 12.30]	.12	1.79			11.49	.30
RT1					.13 (.02)	1.86	4, 484.73	.32
(Intercept)	-31.7	[-83.32, 19.91]	0	-1.24			40.75	.46
Delayed gains	.01	[-.50, .52]	0	.03			174.40	.99
Delayed losses	-.57	[-1.01, -.14]	-.13	-2.62			173.03	.06
Probabilistic gains	-.01	[-.61, .58]	0	-.04			352.38	.98
Probabilistic losses	-.24	[-.82, .34]	-.05	-.82			54.60	.63
Gender[a]	4.50	[-1.68, 10.68]	.07	1.44			118.06	.38
Age[b]	-.43	[-.60, -.26]	-.22	-4.97			368.86	<.01
Years of education	-.05	[-1.13, 1.03]	0	-.09			92.76	.96
Household income[c]	6.35	[1.82, 10.87]	.15	2.84			40.52	.04
RT3					.17 (.02)	1.63	4, 295.94	.40
(Intercept)	-52.61	[-100.21, -5.02]	0	-2.22			48.72	.13
Delayed gains	-.14	[-.61, .32]	-.03	-.60			330.33	.75
Delayed losses	-.24	[-.68, .20]	-.06	-1.08			62.24	.51
Probabilistic gains	-.17	[-.76, .42]	-.03	-.57			172.53	.78
Probabilistic losses	-.54	[-1.01, -.06]	-.11	-2.24			468.70	.11
Gender[a]	7.43	[1.66, 13.19]	.12	2.55			141.32	.07
Age[b]	-.50	[-.66, -.33]	-.26	-5.89			209.40	<.01
Years of education	-.48	[-1.46, .50]	-.04	-.96			161.05	.56
Household income[c]	8.18	[3.90, 12.46]	.2	3.87			40.03	.01
RT6					.21 (.02)	1.50	4, 307.55	.45
(Intercept)	-84.66	[-137.9, -31.43]	0	-3.33			19.21	.03
Delayed gains	-.16	[-.62, .30]	-.03	-.68			124.00	.71

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Delayed losses	-.40	[-.80, .00]	-.1	-2.01			96.07	.18
Probabilistic gains	.30	[-.24, .83]	.05	1.09			296.14	.51
Probabilistic losses	-.04	[-.48, .41]	-.01	-.16			465.15	.94
Gender[a]	5.58	[.49, 10.67]	.09	2.16			413.73	.13
Age[b]	-.55	[-.70, -.39]	-.3	-6.98			236.41	<.01
Years of education	.53	[-.42, 1.49]	.05	1.11			96.76	.51
Household income[c]	9.11	[4.54, 13.68]	.23	4.15			20.70	.01
RT5					.12 (.01)	1.23	4, 455.87	.53
(Intercept)	-22.04	[-68.3, 24.21]	0	-.95			60.27	.57
Delayed gains	.18	[-.27, .63]	.03	.79			485.37	.65
Delayed losses	-.32	[-.70, .07]	-.08	-1.61			444.59	.31
Probabilistic gains	-.06	[-.61, .50]	-.01	-.20			460.59	.92
Probabilistic losses	-.32	[-.81, .17]	-.07	-1.28			210.85	.45
Gender[a]	5.59	[.18, 10.99]	.09	2.03			412.41	.16
Age[b]	-.46	[-.62, -.30]	-.25	-5.67			389.74	<.01
Years of education	.37	[-.60, 1.35]	.03	.75			171.43	.66
Household income[c]	4.29	[.32, 8.25]	.11	2.16			74.09	.14
RT2					.14 (.01)	1.22	4, 335.24	.53
(Intercept)	-73.56	[-121.18, -25.94]	0	-3.18			24.76	.03
Delayed gains	.02	[-.39, .43]	0	.09			430.29	.96
Delayed losses	-.40	[-.75, -.05]	-.11	-2.22			356.86	.12
Probabilistic gains	-.07	[-.62, .49]	-.01	-.24			81.13	.90
Probabilistic losses	.08	[-.36, .52]	.02	.36			252.33	.86
Gender[a]	4.87	[-.42, 10.16]	.09	1.83			97.04	.24
Age[b]	-.37	[-.52, -.21]	-.22	-4.77			143.31	<.01
Years of education	.03	[-.87, .93]	0	.06			112.63	.98
Household income[c]	8.32	[4.14, 12.50]	.23	4.10			24.42	.01
RT4					.14 (.01)	.89	4, 404.37	.67
(Intercept)	-77.58	[-130.06, -25.09]	0	-2.99			37.96	.03
Delayed gains	.16	[-.32, .65]	.03	.66			414.80	.71
Delayed losses	-.35	[-.78, .08]	-.08	-1.61			232.25	.31
Probabilistic gains	-.22	[-.82, .39]	-.04	-.71			331.26	.69
Probabilistic losses	.00	[-.52, .52]	0	.00			279.20	1.00
Gender[a]	1.09	[4.02, 16.16]	.15	3.28			169.83	.01
Age[b]	-.34	[-.52, -.15]	-.17	-3.63			112.62	.01
Years of education	-.27	[-1.34, .79]	-.02	-.51			115.92	.80
Household income[c]	9.97	[5.19, 14.75]	.23	4.26			29.80	<.01
		Risky Financial Decisions						
RF5					.21 (.01)	1.78	4, 276.33	.35
(Intercept)	-91.04	[-152.50, -29.58]	0	-3.13			16.72	.04
Delayed gains	.11	[-.38, .60]	.02	.44			220.09	.83
Delayed losses	-.53	[-.96, -.09]	-.12	-2.38			111.07	.09
Probabilistic gains	-.30	[-.90, .30]	-.05	-.99			252.99	.54
Probabilistic losses	.06	[-.47, .59]	.01	.24			124.41	.90
Gender[a]	11.02	[4.34, 17.70]	.16	3.32			45.22	.01

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Age[b]	-.54	[-.72, -.37]	-.27	-6.07			135.21	<.01
Years of education	.18	[-.87, 1.22]	.01	.34			115.71	.88
Household income[c]	10.81	[5.29, 16.33]	.25	4.17			15.44	.01
RF1					.20 (.01)	.73	4, 279.70	.78
(Intercept)	-106.27	[-164.46, -48.08]	0	-3.83			18.31	.01
Delayed gains	.34	[-.12, .80]	.06	1.44			444.94	.38
Delayed losses	-.20	[-.66, .27]	-.05	-.85			45.16	.61
Probabilistic gains	.02	[-.64, .67]	0	.06			55.81	.98
Probabilistic losses	-.17	[-.68, .35]	-.03	-.63			120.23	.73
Gender[a]	13.54	[7.46, 19.62]	.21	4.43			84.06	<.01
Age[b]	-.34	[-.50, -.17]	-.17	-4.01			261.25	<.01
Years of education	.63	[-.49, 1.74]	.05	1.12			44.16	.51
Household income[c]	10.81	[5.51, 16.10]	.25	4.33			16.09	.01
RF2					.19 (.00)	.52	4, 361.04	.86
(Intercept)	-141.08	[-210.26, -71.90]	0	-4.40			13.25	.01
Delayed gains	.35	[-.21, .90]	.06	1.25			71.33	.46
Delayed losses	-.09	[-.53, .35]	-.02	-.40			159.38	.85
Probabilistic gains	.03	[-.65, .71]	.01	.10			71.71	.96
Probabilistic losses	.14	[-.39, .67]	.03	.54			237.86	.79
Gender[a]	16.17	[9.82, 22.51]	.24	5.05			109.21	<.01
Age[b]	-.09	[-.28, .09]	-.04	-.98			123.61	.55
Years of education	1.07	[.01, 2.12]	.09	1.99			172.44	.18
Household income[c]	12.90	[6.31, 19.48]	.28	4.31			10.92	.01
RF4					.18 (.01)	.45	4, 167.93	.89
(Intercept)	-61.36	[-113.88, -8.83]	0	-2.37			36.26	.11
Delayed gains	-.23	[-.75, .29]	-.04	-.86			119.50	.61
Delayed losses	-.06	[-.57, .46]	-.01	-.22			31.07	.91
Probabilistic gains	.10	[-.61, .81]	.02	.29			42.64	.89
Probabilistic losses	-.29	[-.83, .25]	-.06	-1.05			110.93	.52
Gender[a]	1.17	[3.71, 16.62]	.15	3.14			70.27	.02
Age[b]	-.58	[-.77, -.39]	-.28	-6.04			69.61	<.01
Years of education	.14	[-.89, 1.17]	.01	.27			182.17	.90
Household income[c]	8.45	[3.93, 12.97]	.19	3.78			40.56	.01
RF3					.04 (.01)	.28	4, 276.82	.95
(Intercept)	-23.24	[-82.78, 36.31]	0	-.78			47.87	.65
Delayed gains	.00	[-.69, .69]	0	.00			41.05	1.00
Delayed losses	-.27	[-.81, .27]	-.06	-1.01			80.69	.54
Probabilistic gains	.09	[-.62, .79]	.01	.24			372.58	.90
Probabilistic losses	-.08	[-.73, .57]	-.01	-.25			96.89	.90
Gender[a]	7.63	[-.23, 15.49]	.1	1.95			52.51	.20
Age[b]	-.10	[-.31, .11]	-.04	-.93			161.77	.57
Years of education	.29	[-.94, 1.51]	.02	.46			167.12	.81
Household income[c]	5.01	[-.67, 1.69]	.1	1.81			27.91	.26

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
FO3					.14 (.03)	3.23	4, 336.90	.07
(Intercept)	-132.61	[-213.73, -51.50]	0	-3.57			11.73	.03
Delayed gains	.30	[-.26, .86]	.05	1.06			324.46	.52
Delayed losses	.76	[.29, 1.22]	.15	3.22			482.99	.01
Probabilistic gains	.51	[-.23, 1.24]	.07	1.37			100.43	.41
Probabilistic losses	.17	[-.43, .77]	.03	.55			170.57	.78
Gender[a]	5.13	[-1.93, 12.20]	.07	1.44			109.31	.38
Age[b]	.05	[-.14, .25]	.02	.54			233.96	.79
Years of education	2.69	[1.51, 3.87]	.21	4.51			163.58	<.01
Household income[c]	10.12	[2.42, 17.82]	.21	2.93			9.95	.08
FO1					.18 (.02)	2.51	4, 340.27	.16
(Intercept)	-156.56	[-210.24, -102.89]	0	-5.86			49.83	<.01
Delayed gains	.28	[-.28, .85]	.05	1.00			96.16	.54
Delayed losses	.55	[.10, .99]	.11	2.43			376.89	.08
Probabilistic gains	.48	[-.18, 1.15]	.07	1.43			158.71	.38
Probabilistic losses	.31	[-.22, .84]	.06	1.16			492.71	.48
Gender[a]	6.91	[.26, 13.56]	.1	2.06			106.34	.16
Age[b]	.16	[-.03, .35]	.07	1.65			136.85	.30
Years of education	2.55	[1.47, 3.63]	.2	4.64			248.97	<.01
Household income[c]	12.69	[7.93, 17.45]	.27	5.37			45.04	<.01
FO4					.10 (.02)	2.00	4, 360.86	.28
(Intercept)	-93.86	[-149.36, -38.36]	0	-3.40			48.40	.01
Delayed gains	.38	[-.17, .92]	.06	1.37			317.00	.40
Delayed losses	.55	[.09, 1.01]	.12	2.37			312.01	.09
Probabilistic gains	-.24	[-.92, .44]	-.04	-.70			192.73	.69
Probabilistic losses	-.13	[-.70, .45]	-.02	-.44			208.31	.83
Gender[a]	1.33	[-5.33, 7.98]	.02	.39			163.24	.85
Age[b]	-.10	[-.29, .09]	-.05	-1.01			263.57	.54
Years of education	2.23	[1.14, 3.32]	.18	4.02			371.11	<.01
Household income[c]	9.62	[4.48, 14.75]	.21	3.81			33.32	.01
FO2					.11 (.02)	1.81	4, 279.37	.34
(Intercept)	-93.20	[-145.82, -40.58]	0	-3.53			73.17	.01
Delayed gains	.39	[-.21, .99]	.07	1.29			62.16	.45
Delayed losses	.55	[.07, 1.02]	.12	2.29			165.31	.11
Probabilistic gains	-.10	[-.76, .55]	-.02	-.31			302.87	.88
Probabilistic losses	-.03	[-.58, .52]	-.01	-.10			383.99	.96
Gender[a]	2.50	[-3.97, 8.97]	.04	.76			233.68	.66
Age[b]	-.36	[-.54, -.17]	-.17	-3.71			296.26	<.01
Years of education	1.70	[.63, 2.77]	.14	3.13			458.80	.02
Household income[c]	9.63	[4.97, 14.29]	.21	4.13			65.26	<.01
FO5					.09 (.02)	1.44	4, 324.15	.46
(Intercept)	-102.42	[-161.1, -43.73]	0	-3.58			27.16	.01
Delayed gains	.33	[-.23, .89]	.06	1.17			103.48	.48
Delayed losses	.40	[-.05, .84]	.09	1.76			306.18	.25
Probabilistic gains	.37	[-.26, 1.01]	.06	1.16			332.01	.48

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Probabilistic losses	-.02	[-.57, .54]	0	-.06			209.94	.98
Gender[a]	.35	[-6.31, 7.01]	.01	.10			95.70	.96
Age[b]	.03	[-.16, .23]	.02	.35			111.54	.86
Years of education	1.29	[.24, 2.34]	.11	2.41			359.24	.08
Household income[c]	10.10	[4.38, 15.82]	.23	3.72			17.47	.01
		Financial Loss Deferment						
FL2					.14 (.02)	2.63	4, 254.09	.14
(Intercept)	-56.49	[-127.51, 14.52]	0	-1.71			13.79	.31
Delayed gains	-.39	[-.97, .20]	-.07	-1.32			66.52	.43
Delayed losses	-.61	[-1.07, -.16]	-.13	-2.65			190.60	.05
Probabilistic gains	-.17	[-.82, .49]	-.03	-.50			199.18	.80
Probabilistic losses	.36	[-.20, .91]	.07	1.27			222.02	.45
Gender[a]	7.13	[.98, 13.27]	.1	2.28			374.01	.11
Age[b]	-.50	[-.68, -.31]	-.23	-5.33			311.78	<.01
Years of education	.29	[-.87, 1.45]	.02	.50			85.92	.80
Household income[c]	7.95	[1.53, 14.37]	.18	2.68			12.69	.09
FL3					.05 (.02)	2.49	4, 351.82	.16
(Intercept)	17.43	[-56.97, 91.84]	0	.50			15.48	.80
Delayed gains	-.32	[-.94, .29]	-.05	-1.04			99.44	.53
Delayed losses	-.56	[-1.05, -.08]	-.12	-2.29			328.79	.11
Probabilistic gains	-.05	[-.74, .64]	-.01	-.15			390.04	.94
Probabilistic losses	.59	[-.01, 1.18]	.11	1.94			309.84	.19
Gender[a]	5.32	[-1.43, 12.08]	.07	1.55			328.29	.33
Age[b]	-.28	[-.48, -.08]	-.13	-2.71			267.97	.04
Years of education	.72	[-.53, 1.96]	.06	1.14			105.21	.49
Household income[c]	1.31	[-5.98, 8.61]	.03	.39			11.57	.85
FL6					.07 (.01)	2.12	4, 426.05	.25
(Intercept)	-26.95	[-91.08, 37.19]	0	-.87			23.50	.61
Delayed gains	-.01	[-.63, .61]	0	-.02			62.87	.99
Delayed losses	-.39	[-.91, .13]	-.08	-1.49			67.56	.37
Probabilistic gains	.70	[.04, 1.36]	.1	2.07			461.31	.15
Probabilistic losses	.47	[-.12, 1.05]	.09	1.58			222.53	.32
Gender[a]	-1.41	[-8.16, 5.35]	-.02	-.41			180.09	.84
Age[b]	-.39	[-.60, -.19]	-.18	-3.85			136.89	<.01
Years of education	.15	[-.96, 1.26]	.01	.27			411.73	.90
Household income[c]	5.05	[-.35, 1.45]	.11	1.92			28.20	.22
FL7					.08 (.01)	1.86	4, 319.20	.33
(Intercept)	22.33	[-39.49, 84.15]	0	.74			24.59	.67
Delayed gains	-.34	[-.88, .20]	-.06	-1.24			298.33	.46
Delayed losses	-.52	[-1.01, -.04]	-.11	-2.13			117.29	.14
Probabilistic gains	.18	[-.47, .83]	.03	.54			373.22	.79
Probabilistic losses	.26	[-.32, .85]	.05	.90			149.41	.59
Gender[a]	-1.30	[-7.49, 4.90]	-.02	-.41			486.93	.84
Age[b]	-.48	[-.68, -.28]	-.23	-4.68			92.95	<.01
Years of education	1.61	[.48, 2.74]	.13	2.81			176.86	.04

Variable	b	b 95% CI	β	t	R^2 (ΔR^2)[d]	F[e]	df[f]	p
Household income[c]	-.25	[-5.42, 4.93]	-.01	-.10			30.75	.96
FL5					.08 (.02)	1.64	4, 354.13	.39
(Intercept)	38.47	[-17.44, 94.38]	0	1.37			63.75	.41
Delayed gains	-.51	[-1.08, .05]	-.08	-1.79			319.15	.24
Delayed losses	-.44	[-.94, .06]	-.09	-1.74			138.01	.26
Probabilistic gains	-.08	[-.79, .63]	-.01	-.22			183.17	.91
Probabilistic losses	.12	[-.45, .69]	.02	.42			442.99	.84
Gender[a]	2.51	[-4.43, 9.44]	.03	.71			159.06	.68
Age[b]	-.51	[-.71, -.32]	-.23	-5.19			369.21	<.01
Years of education	1.22	[.11, 2.32]	.1	2.15			494.11	.13
Household income[c]	-.60	[-5.52, 4.32]	-.01	-.24			60.71	.90
FL1					.07 (.02)	1.58	4, 324.44	.41
(Intercept)	57.20	[-9.16, 123.57]	0	1.77			25.35	.27
Delayed gains	-.61	[-1.25, .03]	-.1	-1.90			76.55	.22
Delayed losses	-.34	[-.90, .22]	-.07	-1.22			55.50	.46
Probabilistic gains	-.11	[-.81, .60]	-.02	-.30			375.95	.88
Probabilistic losses	.30	[-.35, .95]	.05	.92			104.50	.58
Gender[a]	3.86	[-3.71, 11.42]	.05	1.01			77.26	.54
Age[b]	-.48	[-.69, -.28]	-.21	-4.67			298.40	<.01
Years of education	.54	[-.63, 1.70]	.04	.90			404.39	.59
Household income[c]	-1.53	[-7.62, 4.57]	-.03	-.52			20.60	.80
FL4					.04 (.01)	.90	4, 438.51	.67
(Intercept)	23.57	[-37.03, 84.17]	0	.79			31.53	.65
Delayed gains	.04	[-.55, .63]	.01	.13			117.38	.95
Delayed losses	-.36	[-.87, .14]	-.08	-1.42			100.76	.39
Probabilistic gains	-.41	[-1.15, .34]	-.06	-1.09			80.89	.51
Probabilistic losses	-.15	[-.73, .42]	-.03	-.53			356.16	.79
Gender[a]	.80	[-6.19, 7.79]	.01	.23			112.38	.91
Age[b]	-.32	[-.51, -.13]	-.15	-3.28			372.39	.01
Years of education	-.29	[-1.51, .92]	-.02	-.48			94.69	.80
Household income[c]	2.16	[-3.11, 7.43]	.05	.84			32.72	.62

Note. All questions were ordered according to ΔR^2 by category. [a]Female = 0; Male = 1. [b]Age was mean-centered. [c]Due to a highly skewed distribution, a natural logarithm transformation was applied to household income for the analysis. [d]The ΔR^2 indicated the difference in R^2 between models with and without degree of discounting as a predictor. [e]The F-test compared models with and without degree of discounting as a predictor. [f]The degrees of freedom in multiple imputation was calculated based on the proportion of the variation attributable to the missing data.

3.3 Discussion

Experiment 2 served as a replication of Experiment 1 and also examined the association between the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses and everyday behaviors that involve delayed and/or probabilistic consequences. Consistent with the findings of Experiment 1, all four choice questionnaires were found to be reliable discounting measures, and a robust magnitude effect was observed in the discounting of delayed gains. Although a considerable number of individuals had negative slopes on the questionnaires for losses, no negative discounting subgroup was identified in the mixture model analysis. As in Experiment 1, there were significant correlations between the discounting of delayed gains and probabilistic gains, between the discounting of delayed losses and probabilistic losses, and between the discounting of probabilistic gains and probabilistic losses. The demographic variables explained only small proportions of the variance in degree of discounting. Regarding the everyday behaviors that were considered, neither the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses nor the demographic variables were strong predictors.

A major goal of Experiment 2 was to investigate associations between the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses and 51 everyday behaviors that involve delayed and/or probabilistic consequences. The 51 everyday behaviors were grouped into eight categories, and their associations with degree of discounting were modeled through SEM. The convergence of the models ascertained the presence of the hypothesized associations, and the measurement invariance tests showed that most of the associations did not depend on the age groups. The analyses of the coefficients, however, revealed that the associations were generally weak, at best; The degree of discounting delayed gains was significantly associated only with impulsive purchasing in the 18-34 year-old group; the degree of discounting delayed losses was significantly associated only with risk-taking behaviors; the degree of discounting probabilistic gains was significantly associated only with future-oriented financial decisions; the degree of discounting probabilistic losses was significantly associated only with impulsive purchasing in the 35-49 year-old group. The lack of significant findings in SEM is consistent with the overall picture in the literature, where only the relations between the discounting of delayed gains and delayed losses with general, everyday choice behaviors have been examined. The current study expanded the investigation to the discounting of probabilistic gains and probabilistic losses and found limited associations.

When each everyday behavior was regressed on degree of discounting separately while controlling for the demographic variables, only 2 out of 204 regression coefficients (4 types of discounting tasks x 51 everyday behaviors) reached statistical significance. The analysis showed that steep discounting of probabilistic gains (preferring certain gains) significantly increased the frequency on “Drank plenty of water each day”, and steep discounting of delayed losses (preferring delayed losses) significantly increased the frequency on “Drove without wearing a seat belt”. Although the lack of significant findings is consistent with the results from the SEM, to what extent delay and probability discounting could account for everyday choice behaviors in general remains to be determined. The analysis on the change of R^2 values when degree of discounting was removed from the regression model revealed that delay and probability discounting as a whole accounted for only limited proportions of variance in everyday behaviors beyond that of the demographic variables. One goal of Experiment 2 was to investigate the associations between degree of discounting and everyday behaviors within different subgroups. Although we did not obtain a sufficient number of negative discounters in the sample to conduct such an analysis, considering the overall weak associations obtained, it seems unlikely that a significant difference in everyday behaviors would be identified between subgroups.

Chapter 4: General Discussion

Delay and probability discounting provides a useful framework within which to study human choice behavior (Frederick et al., 2002; Green & Myerson, 2004). Although considerably more studies have focused on gains than on losses, significant differences between the discounting of gains and losses, either delayed or probabilistic, have been documented. A recent study, which investigated similarities and differences between the discounting of delayed gains, delayed losses, and probabilistic losses, found qualitative individual differences (i.e., subgroups) present only in the discounting of losses (Yeh et al., 2020). The current study expanded the previous investigation of subgroups to the discounting of probabilistic gains (Experiment 1) and examined to what extent the discounting of gains and losses, both delayed and probabilistic, are associated with everyday behaviors that involve delayed and/or probabilistic consequences (Experiment 2).

In Experiment 1, there was no evidence of subgroups in the discounting of either delayed gains or probabilistic gains, a finding consistent with previous studies. However, no negative discounting subgroup was identified in the discounting of delayed losses, a result inconsistent with the findings of Yeh et al. (2020). Moreover, the negative discounting subgroup identified in the discounting of probabilistic losses had a choice pattern much different from that reported previously. Nonetheless, further examination of individual performance revealed that there were far more individuals with negative slopes on the losses questionnaires than on the gains questionnaires, a finding consistent with that of Yeh et al. who found that the negative discounting subgroups were present only in the discounting of losses. Similar findings were observed in Experiment 2, in which no negative discounting subgroup was identified by the mixture model analyses in either the discounting of gains or the discounting of losses, although there were a considerable number of individuals with negative slopes on the losses questionnaires. We suspect the failure to find negative subgroups in the current study likely is due to the different proportions of individuals in the samples who show typical and atypical choice patterns. As an example, in the current study, more participants had a negative slope on the probabilistic losses questionnaire in Experiment 1 than in Experiment 2 (as may be seen by comparing Figures 3 and 8), and the subsequent mixture model identified a negative discounting subgroup in Experiment 1 but not in Experiment 2.

In Experiment 2, we found limited associations between the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses and 51 everyday behaviors. Specifically, the degree of discounting delayed gains was significantly associated only with impulsive purchasing in the 18-34 year-old group; the degree of discounting delayed losses was significantly associated only with risk-taking behaviors; the degree of discounting probabilistic gains was significantly associated only with future-oriented financial decisions; and the degree of discounting probabilistic losses was significantly associated only with impulsive purchasing in the 35-49 year-old group. Further analysis showed that steep discounting of probabilistic gains significantly increased the frequency of water drinking, and steep discounting of delayed losses significantly increased the frequency of driving without wearing a seat belt. Neither degree of discounting nor the demographic variables of gender, age, years of education, and household income were strong predictors for everyday behaviors, and degree of discounting accounted for only limited proportions of variance beyond the demographic variables.

With regard to the main findings, across both experiments the four monetary choice questionnaires were shown to be reliable measures of individuals' degree of discounting. Although these measures can be useful tools to study individual differences in the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses, it should be noted that the robust magnitude effect in the discounting literature was only observed with the delayed gains questionnaire. In both experiments, no effect of amount was observed with the probabilistic gains questionnaire. While these results suggest that the weighting of amount for delayed gains was likely greater than that for probabilistic gains, the absence of an effect of amount indicates that the probabilistic gains questionnaire may not be a desirable measure for future studies that aim to investigate the magnitude effect.

With regard to the question of whether amount differentially affects the degree of discounting losses, previous research has revealed little if any effect of amount (Estle et al., 2006; Green, Myerson, Oliveira, et al., 2014; McKerchar et al., 2013; Mitchell & Wilson, 2010). Although choices on the delayed losses questionnaire did differ significantly across amounts in Experiment 2, a close examination revealed that the change in choices was not systematic. Specifically, although the likelihood of choosing the immediate payment was greater with small amounts than with medium or large amounts, there was no difference between degree of discounting medium and large amounts. Compared with the systematic change in discounting with amount on the delayed gains questionnaire (i.e., choices of the delayed gain systematically increased with amount), there was no clear evidence to support the notion of an effect of amount on the discounting of delayed losses. Similarly, we did not find an effect of amount on the discounting of probabilistic losses. This pattern of results, combined with that from Experiment 1, suggest there is little if any magnitude effect in the discounting of losses, consistent with the null findings in the literature.

Half of the correlations between the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses were statistically significant and consistent across experiments, while the other half, although in the same direction between the two experiments, were not statistically significant. Specifically, both experiments found that choices on the delayed gains and probabilistic gains questionnaires and on the delayed losses and probabilistic losses questionnaires were significantly positively correlated, and the choices on the probabilistic gains and probabilistic losses questionnaires were significantly negatively correlated. However, the statistical significance of the correlations between choices on the delayed gains and delayed losses questionnaires, between the delayed gains and probabilistic losses questionnaires, and between the delayed losses and probabilistic gains questionnaires was not the same between Experiments 1 and 2, although the direction of those correlations was. Because the samples in Experiments 1 and 2 had different age distributions, there is the possibility that the relations between choices on the different types of discounting tasks might be differentially influenced by age. A follow-up analysis of the data in Experiment 2, however, showed no difference between age groups. It may be worth noting that for two of the three correlations that were not significant in one experiment but were in the other, the discounting questionnaires did not share joint attributes (i.e., the delayed gains and probabilistic losses questionnaires, and the delayed losses and probabilistic gains questionnaires). For these two pairs with no joint attributes, the correlations were expected to be low if not close to zero (the correlations for the delayed gains and probabilistic losses questionnaires in Experiments 1 and 2 were -.20 and -.00, respectively; the correlations for the delayed losses and probabilistic gains questionnaires in Experiments 1 and 2 were -.07 and -.18, respectively).

There were some notable differences in relations between the demographic variables and the degree of discounting between Experiments 1 and 2. Specifically, in Experiment 1 only age and household income significantly predicted the degree of discounting delayed gains, whereas in Experiment 2, only years of education was the significant predictor. In addition, in Experiment 1, none of the demographic variables significantly predicted the degree of discounting delayed losses, probabilistic gains, and probabilistic losses, whereas in Experiment 2, both gender and age were significant predictors. Although these discrepancies may be due to the different makeup of the samples, they suggest that relations between the demographic variables and degree of discounting are generally weak and less reliable. Consistent with this suggestion, it is to be noted that the demographic variables explained only small proportions of variance in degree of discounting.

Finally, we recognize that a substantial number of participants were excluded from the analysis in the study, particularly in Experiment 1 (i.e., 441 out of 875 participants were excluded). Although the exclusion significantly reduced our sample sizes, it was a necessary step to ensure data quality. Chmielewski and Kucker (2020) conducted a longitudinal study and found that there was a significant decrease in MTurk data quality beginning in 2018. Specifically, the percentage of participants who failed at least one validity indicator in the four-wave data (first wave from December 2015 to January 2016; second wave from March 2017 to May 2017; third wave from July 2018 to September 2018; fourth wave in April 2019) was considerably greater in the last two waves than in the first two: 10.4%, 13.8%, 62.0%, and 38.2%, respectively. Their observation is consistent with the high exclusion rate in the current study, in which the participants of Experiment 1 were recruited from MTurk between the years of 2018 and 2019. Although there are concerns regarding MTurk data quality, most of the findings in Experiment 1 were replicated in Experiment 2, which utilized a different subject pool (i.e., Qualtrics panel) to recruit participants. Moreover, because the participants in Experiments 1 and 2 had dissimilar age distributions, the replication adds generalizability to the general findings.

4.1 Future Directions

Although the current study failed to replicate the findings of negative discounting subgroups in Yeh et al. (2020), the analysis of individual-fitting parameters showed noticeable differences between the discounting of gains and losses, consistent with the view that there are subgroups in the discounting of losses. That the subgroups failed to emerge in the current analysis was likely due to the lower proportion of individuals with negative slopes in the sample, which signals a potential issue of using unsupervised clustering methods (e.g., the mixture modeling) to study subgroups. The outcomes of classification with unsupervised clustering methods are sample dependent, which is not ideal for studying subgroups that may be underrepresented in a given sample. The sample dependency could also lead to unstable boundaries separating subgroups, which makes the comparison of results between studies difficult. To solve this issue, the establishment of a classification method with clear criteria or cutoffs to identify subgroups is needed. For example, Myerson et al. (2017) used the sign of a correlation between choices and logarithmic *k* values as the basis for classification. Although their method provides a reliable and convenient way to identify different subgroups, it suffers from the arbitrariness involved; whereas individuals with correlations of +.01 and +.99 would be placed in the same subgroup, individuals with correlations of +.01 and -.01 would be placed in different subgroups.

To establish objective criteria or cutoffs for identifying subgroups, future studies need to pinpoint variables that capture important characteristics differentiating the subgroups other than the discounting patterns. For example, in the current study, part of our goal was to determine whether the frequency of different everyday behaviors that involve delayed and/or probabilistic consequences relates to the presence of subgroups. The proposed analysis, however, became impractical due to not only the failure to identify sufficient numbers of individuals showing negative discounting, but also the limited association between degree of discounting and everyday behaviors in general. Given an association between degree of discounting and maladaptive behaviors (e.g., drug addiction; gambling problems) is quite a common finding (Amlung et al., 2017; MacKillop et al., 2011; Kyonka & Schutte, 2018), an avenue to be considered for future studies would be to investigate how the presence of subgroups relate to those maladaptive behaviors.

Another approach to pinpoint variables that may capture important characteristics differentiating the subgroups is to ask participants to self-report their decision-making processes. For example, Furrebøe (2020) asked participants to provide verbal reports on their strategy or reason for their choices after completing discounting of delayed gains and delayed losses tasks. Analysis of the verbal reports revealed noticeable differences in decision-making when discounting gains and when discounting losses, partially accounting for the observed sign effect (i.e., gains were discounted at a higher rate than losses of the same magnitude). Specifically, when making their choices, most of the participants seemed to evaluate both time and amount for gains but only time (e.g., “get the fine out of the way”) or only amount (e.g., “pay the least possible”) for losses. Furthermore, whereas the gratification of getting a loss out of the way was often mentioned, the gratification of deferring a loss was not. Future studies adopting this approach to exploring decision rules (e.g., the strategy or reason for one’s choices) may provide critical information for establishing criteria or cutoffs to identify subgroups and further our understanding of the differences between the discounting of gains and losses.

4.2 Conclusions

The present study investigated similarities and differences in the discounting of delayed gains, delayed losses, probabilistic gains, and probabilistic losses and the presence of subgroups. In addition, the association between degree of discounting and everyday behaviors with delayed and/or probabilistic consequences was examined. Across two experiments, there was no indication of negative discounting subgroups either in the discounting of delayed gains or probabilistic gains, in contrast to a noticeable proportion of individuals who showed negative discounting in the discounting of delayed losses and probabilistic losses, consistent with the notion that people evaluate gains and losses in different ways. When the association with everyday behaviors was examined, the discounting of gains and losses, both delayed and probabilistic accounted for only limited proportions of variance beyond the demographic variables. This result suggests that although delay and probability discounting capture important characteristics of choice behaviors, the degree of discounting alone is not sufficient to predict individuals' everyday behaviors.

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