INDIVIDUAL DIFFERENCES IN MAKING INTERTEMPORAL CHOICES FOR MONETARY AND FOOD CHOICE TASKS: USING DRIFT−DIFFUSION MODEL (DDM)

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ABSTRACT

In order to better understand the individual differences in the intertemporal choices, extensive research has studied how demographic factors affect an individual's decision-making. Because some intertemporal decisions are made rapidly, the decision-making processes behind those choices are rarely mentioned in past research. Also, research on the effects of gender on intertemporal decisions has shown inconsistency, and even opposing results. To further examine whether and how males and females differ in the cognitive processes of speeding intertemporal choices, I conduct an online choice experiment involving two simple choice tasks. For the monetary choice experiment, the participants made hypothetical choices between receiving immediate smaller rewards and delayed larger rewards. Another task is a food choice experiment, where the participants chose between tastier but less healthy foods and healthier but less tasty foods. Finally, I find that there is no significant gender effect influencing the individual differences in intertemporal choices.

Key Words: Intertemporal Choice, Decision Making, Gender Differences

BIOGRAPHICAL SKETCH

Shenzhe Zhang was born and raised in Guangzhou, China. She obtained her dual Bachelor of Science degree in Agricultural and Forestry Economy Management from China Agricultural University and Agricultural Economics from Oklahoma State University in 2019 with minors in Economics, International Business and Marketing. From 2019 to 2021, Shenzhe continued her graduate study at Charles H. Dyson School of Applied Economics and Management in Cornell University to receive her Master of Science Degree.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

People are involved in making decisions once they open their eyes every morning, and many decisions contain tradeoffs over time; such current choices reflect and affect the ways we live in the long term. Getting up early to take morning exercise or staying up late and sleeping in, eating salads and fresh fruit or cheeseburger and fries for breakfast, completing the task a few days ahead of schedule or working right up to the last minute, spending on immediate consumption or putting that money into investments or savings account, these decisions which are made currently influence the individual not only at the present but also in the future. Sleeping irregular hours, enjoying junk food meals, looking for happiness in the moment from distraction all satisfy the instant gratification, but there are costs for these "benefits", such as unhealthy lifestyle and disease risks.

Some people prefer making the intertemporal choice by "discounting" the value of delayed outcomes, while others tend to go for the long-run benefits. The individual differences in the intertemporal decisions are therefore an important area of research in behavioral economics, and in recent years there has been considerable interests in studying the factors giving rise to the individual differences in intertemporal choice, from age (Reimers et al., 2009; Seaman et al., 2016) and IQ (Shamosh & Gray, 2008; Civai et al., 2016) to health condition (Sutter et al., 2015) and personality (Luhmann et al., 2011; Manning et al., 2014).

Among these potential factors, if women and men differ in intertemporal choice is regarded as a controversial question. Though overall there is a relatively strong and growing range of research findings which have claimed that gender has no effect on the individual difference in intertemporal choice (Lau & Williams, 2002; Silverman, 2003; Harrison, Anderson & Gugerty, 2009; Skylark et al., 2020), other studies have asserted that gender does affect the decision making in intertemporal choice. Women are found to be better at self-regulation and delay gratification (Bjorklund & Kipp, 1996; Kapteyn & Teppa, 2003), more patient (Dittrich & Leipold, 2014), more risk averse (Charness & Gneezy, 2012), and more likely to maintain a healthy eating lifestyle than men (Leblanc et al., 2015; Yahia et al., 2016), which induce the preference of waiting for the long-term benefits. Meanwhile, some studies have argued that men are more willing to go for the future option (Lu & Zhuang, 2014; Seinstra et al., 2015). Consequently, this research aims at further discovering whether gender influences individual differences in intertemporal choice.

Prior investigations into explaining gender differences toward intertemporal choice have focused on factors such as risk acceptance (Charness & Gneezy, 2012), stereotypes (McLeish & Oxoby, 2009), habits (Yahia et al., 2016), hormones (Kaighobadi & Stevens, 2013) and the interactions with age (Seinstra et al., 2015). Although some recent reviews have identified various factors that lead to gender differences in intertemporal decisions, studies discussing how females and males differ in the decision-making process are still scarce.

To fill this gap, this study applies the Drift Diffusion Model (DDM), a sequential sampling model from the perceptual decision-making tradition (Fontanesi et al., 2019), which assumes that the decision-maker accumulates evidence gradually over the time course of the decision until the process hits a stopping boundary and then makes the final choice accordingly (Ratcliff, 1978), to explore the gender effect on intertemporal choice. The DDM and its extensions are successful in illustrating choice and response time data observed in numerous choice tasks and applied to investigate the impacts of potential variables or factors in two-alternative forced choice by describing the temporal dynamics of the decision-making process (Pedersen et al., 2017; Tavares et al., 2017; Milosavljevic et al., 2010; Peters & D'Esposito, 2020). DDM is widely used to explain the observed patterns of choices and response times for different individuals, so this work examines how gender influences intertemporal choice in the decision-making process by comparing the differences of the parameters in DDM for men and women and testing the significance, which would contribute to knowledge in this field.

To answer the research questions and study the gender impact on individual differences in intertemporal choice, I created two online choice tasks using the Qualtrics survey platform and recruited 75 participants through Amazon Mechanical Turk (Mturk); one is a monetary choice task, and another one is a food choice task. The results do not find strong evidence that gender affects individual differences in intertemporal choice behavior.

The current study contributes to the existing literature by providing experimental evidence indicating that individuals' preferences for intertemporal choice are not influenced by gender, and further investigating the gender effect in two-alternative forced choice from the decision-making process. By using the Drift Diffusion Model, this study gives insight into discovering how subjective values are formed and mapped according to single choices and response times from each trial, each individual to each group (i.e., women and men).

This paper is divided into five sections and this section gives a brief overview of the research objectives and conceptual foundation of the work. The next section provides the literature review about intertemporal choices in various fields, factors affecting individual differences in intertemporal choice, previous studies about gender effect on intertemporal choice, and an introduction to the drift diffusion model. Issues regarding the survey design and empirical model are discussed in the later section. Then, I report the results from data analysis and discuss the findings. The paper concludes with a summary of this research and the potential limitations as well as recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

Delay discounting, a phenomenon when individuals tend to place a lower value on distant outcomes and to favor benefits in the moment, which is related to the individual differences, has been widely studied in Psychology (Weiss et al., 2012; Lin & Epstein, 2014; Malesza, 2019), Economics (DeHart et al., 2016; Garza et al., 2019), and Neuroscience (Guo & Feng, 2015; Elton et al., 2017). The determinants of individual differences in intertemporal choice have been discussed in a sizeable literature; numerous factors affecting the individual differences in intertemporal choice have been analyzed in the research, such as the effect of taking a longer nap (O'Connor et al., 2018), acute stress (Lempert et al., 2012), cocaine use disorders (Johnson et al., 2015) and cultural differences (Kim et al., 2012) on delay discounting behavior.

Because the present value of the future reward is decreasing due to the delays, researchers have suggested that the individual's discount rates may explain the individual difference in intertemporal choice behaviors. For instance, the individual who has higher discount rates appears to value the future and larger rewards more highly (Kirby, 2009). More impatient people would tend to receive the rewards now rather than wait for larger rewards in the future (Chabris et al., 2005). A recent systematic review of the literature on this matter has revealed that delay discounting is in relation to psychological variables, socio-demographic variables, neuroimaging, and molecular genetics (Keidel et al., 2021).

Socio-demographic variables (e.g., age, education, income, and gender) are vital in investigating the individual differences in intertemporal choice behavior. For example, children would choose to eat a bag of chips when they are hungry instead of waiting for a healthy and balanced meal. Seniors and elderly people are relatively more risk-averse and cautious about their future; hence they are inclined to sacrifice instant gratification and probably save money to pay for expensive medical expenses or prepare for other potential emergencies in the future. More wealthy people are able to afford luxury goods or pour money into large purchases, so they would not hesitate to fulfill their immediate desires.

Previous studies have underlined that there is an age effect in intertemporal choice, but the findings are inconsistent. Several studies have highlighted that the increase in age leads to the decline in the discount rate, hence older adults are more willing to accept the delayed rewards as compared to younger people, showing the near-linear effect of age (Green et al., 1999; Reimers et al., 2009). However, Read and Read (2004) point out that older and younger people discount more than middle-aged people, which generates a U-shaped model. Besides, a recent study that aims at generalizing age effect across domains has found no evidence of age differences (Seaman et al., 2016) in intertemporal choice. In this study, except for monetary rewards, participants also made intertemporal choices for social or health related rewards.

Education and income are both primary demographic characteristics resulting in individual differences in intertemporal choice. Sutter et al. (2015) provide evidence that

educational attainment, income level, and health status are positively associated with the ability to delay gratification. Green et al. (1999) state that the poor have higher discount rates than the rich, by comparing two groups of participants with annual incomes greater than $40,000 or less than $20,000. Lower-class individuals are more impulsive, so they would pursue instant gratification in intertemporal choices (Liu et al., 2012). These results are in line with the conclusions drawn by de Wit et al. (2007), who claim that the discount rate is negatively associated with better education and higher income. Also, Reimers et al. (2009) observe, lower-income individuals with less education appear to have high discount rates and show significant associations with each other. Jung et al. (2021) conduct an experiment in Indonesia to measure the discount rate and examine the effect of education on intertemporal choice, in which they find that people with higher levels of education are more likely to choose the patient options.

Considering psychological variables, whether individual differences in the big-five personality traits (Manning et al., 2014; Silva et al., 2017; Civai et al., 2016) and intolerance of uncertainty (Ladouceur et al., 2000; Luhmann et al., 2008) affect intertemporal choice behavior or not have been discussed currently.

Manning et al. (2014) demonstrate that conscientiousness and neuroticism are related to delay discounting, and the results yield that conscientious people are more inclined to wait for the patient options while neurotic people are less likely to delay gratification. Among a large sample of international young adults, Mahalingam et al. (2014) also

conclude that people who are highly conscientious or highly open to experience are better able to delay gratification. However, they report that extraversion or neuroticism are positively associated with discount rates, so individuals high in extraversion or neuroticism appear to choose the immediate rewards. Furthermore, the authors suggest that there is no evidence indicating the agreeableness effect on intertemporal choice behavior is significant. More valuable rewards are required to wait, so the decision-makers face potential risks, and they are concerned about if or how they can receive the payoffs. Mitte (2007) affirms that individuals with low intolerance estimate the probability and the cost of the threatening events in the future higher than others. Lower intolerance of uncertainty is in relation to the immediate option because those individuals are more anxious (Luhmann et al., 2011).

A growing body of literature has underlined that women's ability to delay gratification is better as compared to men (Bjorklund & Kipp, 1996; Kapteyn & Teppa, 2003). As Bjorklund and Kipp (1996) have theorized, women tend to outperform men in their ability to self-regulate, including maintaining waiting behavior, controlling emotional arousal, delaying gratification, and resisting temptation, because the evolutionary selective pressures exerted on women are greater than men. Dittrich and Leipold (2014) analyze data from a large online survey in which participants were asked hypothetical intertemporal monetary questions, and they note a significant gender difference such that women tend to be more patient than men.

Making intertemporal choices needs to face uncertainty, which would cause possible individual differences. To study the gender effect in risk preferences, Charness and Gneezy (2012) review 15 studies about individual differences in investment decisions. They provide clear and significant evidence that women are inclined to be more risk averse than men because women prefer safe investments and invest less in high-risk investments than men.

Such statements are consistent with the later studies that have paid more attention to the gender effect on self-control during food choice, which can further examine if and how gender has an impact on delayed gratification. For example, consuming excess calories each meal satisfies instant emotional needs, such as calming stress and reducing anxiety, but it will also put people at the risk of chronic diseases and obesity, which are challenges to long-term health. According to the American Cancer Society, the lack of forward-thinking is affiliated with the decline in healthier, home-prepared food intake. People who are more self-disciplined and able to stick with a healthy diet may care more about future outcomes in intertemporal choice. To look into the individual difference in food choices, researchers usually focus on the health-taste trade-off in decision making. For instance, consumers are found to be willing to partly sacrifice the pleasure of taste in order to improve the healthfulness of their diet (Papoutsi et al., 2021).

Leblanc et al. (2015) propose that, compared to men, women have healthier and more balanced dietary intakes and eating habits; the results show that a higher percentage of women than men eat 5 portions of a variety of fruit and vegetables every day. In a

recent US college sample, Yahia et al. (2016) find that around half of male students are either overweight or obese, while over 75% of female students have normal weight. Women consume more fruits and vegetables than men, but the consumption of fast food, beer are more frequent among males (Yahia et al., 2016). Both studies illustrate that women are better at controlling themselves to follow a healthier diet and focusing more on the long-term health consequences instead of satisfying the instant gratification like frequent consumption of eating junk.

On the contrary, in Lu and Zhuang's (2014) experiment, they identify gender effect in intertemporal choices and conclude that men are more patient and more likely to prefer the patient options than women. The researchers also measure the degree of inconsistency and claim that men have a higher degree of dynamic inconsistency than women, which leads to gender differences in the intertemporal choices. Seinstra et al. (2015) conduct an experiment in Germany that required healthy older adults to complete intertemporal choice tasks, the results yield that for participants with higher memory scores, men show more patience than women.

However, Silverman (2003) states that Bjorklund and Kipp's review work lacked statistical tests and relevant studies. To reassess Bjorklund and Kipp's hypothesis, Silverman conduct a meta-analysis in which participants were asked to make decisions between immediate but smaller rewards and delayed but larger alternatives. The results reveal that the gender difference in delay of gratification is relatively small. A real monetary rewards experiment is carried out in Denmark to estimate the individual discount rates, but the effect of gender on predicted discount rates is not statistically

significant in the results either. Consequently, researchers claim there is no strong evidence that proves women are more patient than men (Harrison, Lau & Williams 2002). Anderson and Gugerty (2009) are also unable to find significant gender differences in their studies in which they examine the impact of demographic and socioeconomic variables on the level of inferred discount rates in Vietnam and Russia by using multivariate analysis. Similarly, Skylark et al. (2020) mention that gender is not appreciably associated with intertemporal choice behavior.

Interestingly, Kaighobadi and Stevens (2013) propose that the gender differences in delay discounting are partially due to hormones. In their study, one group of young women were required to rate the attractiveness of male images while others rated the beauty of neutral landscape images before taking the intertemporal choice tasks. The results indicate that females from the male image condition are more willing to choose larger payoffs than others.

To investigate the factors that influence decision-making, there is a long history of using the simple logit models to identify the factors influencing decision making (Ketaren & Sianturi, 2017). Through the application of the logit regression technique, the potential variables or factors that would affect decision-making, such as individual differences, past experiences, escalation of commitment, and cognitive biases (Dietrich, 2010), all can be linked to each choice. Except for measuring the significance of the possible effects, the importance weights of those key determining factors can be shown as well. However, it is difficult to reflect the subjective values from single choices of

individuals or groups. Value-based decision-making models, the drift-diffusion model (DDM) can demonstrate how subject values are mapped to both choices and response time (Fontanesi et al., 2019).

Drift-diffusion model (DDM) is one of the sequential sampling models, which have been applied broadly for studying two-alternative forced choice tasks, such as intertemporal choice (Milosavljevic et al., 2010; Polanía et al., 2015). DDM assumes that each decision is completed by collecting information from the noise of the environment. The processes of making a decision show how people repeatedly evaluate the cumulative evidence over a certain period of time. Once the accumulated evidence achieves a threshold, the decision would come out.

When people are facing intertemporal choices, whether or not they are willing to wait is the key point. For example, more patient people would be supposed to prefer the delayed option. However, before they make the final decision, they would also be irresolute due to the uncertainty about the future. Smaller amounts can be paid and held in hand immediately while choosing delayed rewards are another way to save money and increase value in the long run. After thinking through the pros and cons of both options, people would give the answer. Consequently, the psychological dynamics of change in the decision-making process can be well explained by the drift-diffusion model.

Most of the literatures pay more attention to which socio-demographic variables are associated with the individual differences in the intertemporal choice, using the simple logit models. However, if and how gender affects the decision-making process has not been estimated thoroughly, and some current findings are conflicting. This paper extends current literature by focusing on the gender effect on the intertemporal preferences by combining the response time of the decision and the choices together. Also, this study enriches the literature by comparing the gender differences in food and monetary choices and further analyzing the correlations between choosing food products and monetary rewards. It provides more evidence on how people differ in accumulating information for different decisions form both individual-level and group-level.

CHAPTER 3: METHODOLOGY

3.1 Survey Design

Seventy-five participants through Amazon Mechanical Turk (Mturk) were recruited. They must be at least 18 years of age and reside in the United States. After completing the survey, they could receive $5 for their participation and no time limits were set during the entire process. The response to the survey was anonymous and voluntary. Participants were required to answer some demographic questions after responding to all questions in the survey, including gender, age, ethnicity, etc. The choices and response time (RTs) in seconds were also collected for each trial from each participant.

In order to make sure the participants paid attention to each question; the study contained an attention check question in the end. Participants were asked to list three foods that they recently purchased in grocery stores and label the approximate prices. Due to the irregular time of completion (less than three minutes or greater than one hour), one participant was excluded from the analysis; 74 individuals were included in the research. The survey contained two studies, one was the monetary choice task, another one was the food choice task.

3.1.1 Monetary Choice Task

The intertemporal monetary choice task contained 216 test trials and each question required a response before the participant could progress to the next one. In each trial, participants were instructed to choose between two hypothetical monetary gain alternatives, an immediate and smaller monetary reward or a later and larger alternative.

For each set of monetary choices, both immediate (0 day) and delayed monetary amounts were from $17 to $60, and the delay was from 7 to 200 days (Fisher, 2021). The delayed rewards were limited to be larger than the immediate ones. Also, every 25 trials, participants were informed how many trials in the choice task they had completed and left.

3.1.2 Food Choice Task

The food choice task included two parts. During the first phase of the task, participants were displayed with 40 different food images and asked to provide ratings for each item to indicate their perceived tastiness preferences on a scale of -3 (not tasty at all) to 3 (extremely tasty), in increments of 1, independent of any health considerations. Next, participants completed the similar healthiness rating section, where they rated the same 40 food items on how healthy they believed that food to be, on a scale from -3 (not healthy at all) to 3 (extremely healthy), independent of taste considerations. In these 40 food stimuli, half of which were commonly considered to be healthy foods (e.g., broccoli and kiwi), and others were understood as junk snacks (e.g., chips and cookies). Those food stimuli set images were provided by Antonio Rangel's Neuroeconomics Laboratory, where they shared the collections of food stimuli that could be used in studies of valuation and decision-making (Hare et al., 2011). These 40 food images were displayed in random order to each participant for rating, with the same probability. After the rating section, participants answered 200 hypothetical two-alternative forced food choice questions. To generate the food pair in each trial, a pilot survey was conducted, in which another 100 participants rated the healthiness and tastiness of those

40 food items, on a scale from -3 to 3. After collecting and analyzing the results from the pilot survey, based on the ratings obtained in the pilot survey, one healthier but less tasty food was paired with another tastier but less healthy food in the current food selection section in the food choice task. In the food selection section, in each trial, participants would see two foods images in pairs on the screen and decide which food they would prefer to eat; they could also know how many trials in the choice task that they had completed and left for every 25 trials.

3.2 Data and Computational Model

3.2.1 Descriptive Results

Table 1 summarizes the socio-demographic characteristics, which lists the distribution of age and ethnicity of individuals in the sample for both genders. 48.9% of participants are under 30 years old and the median age of the sample is 32 years. Also, 40.45% of the participants are men. In each age category, the gender distribution is relatively average, the fractions of women are all higher than men, except for individuals over 60 years old. The gender distribution varies in different ethnic group. Also, 75.7% of participants are White/Caucasian.

Table 1 Percentage of participants by gender, age, and ethnic group

		Women	**Men**	**Total**
Participants		59.55%	40.45%	74
Age Group	18-20	63.47%	36.53%	10.86%
	21-29	64.55%	35.45%	38.04%
	30-39	57.69%	42.31%	32.34%
	40-49	50.70%	49.30%	10.73%

	50-59	66.61%	33.39%	4.04%
	60-69	49.87%	50.13%	2.64%
	Over 70	/	100%	1.35%
Ethnic Group	African American / Black	39.54%	60.46%	8.11%
	Asian / Asian American	27.98%	72.02%	9.47%
	Hispanic / Latino	63.46%	36.54%	5.34%
	Native American	/	100%	1.38%
	White / Caucasian	62.38%	37.62%	75.70%

Overall, in the monetary choice task, the average probability of choosing the patient option (i.e., delayed rewards) was 34.57%, and among all these patient decisions, 59.15% of choices came from women. Participants chose the patient option 33.8% of the time. The results about the average response time for different choices in two tasks are reported in Table 2. The mean response time (RTs) in the sample was 1.49 seconds and there were almost no differences in the average response time for women and men. An independent t-test was conducted on 74 individuals to determine if gender led to a difference in mean response time for making monetary choices. Results revealed that the mean response time was not different between the two groups $(t = -0.3209, \mathrm{w/df} = 74, p = 0.8349)$, at a significance level of 0.05. Participants spend a longer time choosing the patient option in the task $(\Delta\mathrm{RTs} = 0.10 \text{ seconds}, t(74) = 7.12, p = 0.00)$. The average response time for the delayed option was 1.56 seconds, while the average immediate option took 1.45 seconds.

With respect to the food choice task, the average probability of choosing the patient option (i.e., healthier but less tasty food) was 47.34%, and among all these patient decisions, 58.19% of these were made by women. The average response time was 1.07

seconds across all participants and there was also no sufficient evidence to state that the mean response time was different between the two genders (Table 2). Results from the independent t-test to examine if gender effect on average response time for making food choices was significant implied that the average response time was not different for men and women ($t = 0.3278, \mathrm{w/df} = 74, p = 0.7431$) , at a significance level of 0.05. It took the participants a longer time when they tended to go for the healthier food instead of the tastier one ($\Delta\mathrm{RTs} = 0.05$ seconds, $t(74) = 2.94, p < 0.01$).

Therefore, in both tasks, participants spent more time choosing the patient options and gender did not affect the response time significantly. The gender distributions of the patient options were similar in two tasks. Less participants prefer the patient options and 38 out of 74 participants went for the earlier option more often than the patient ones. Also, the mean response time in the monetary choices was greater than the one in the food choices ($\Delta\mathrm{RTs} = 0.42$ seconds, $t(74) = 5.27, p < 0.001$), indicating that participants chose food items sooner than the monetary rewards. Moreover, there was a significant positive correlation between the choice probability of the healthier but less tasty food item and the choice probability of the delayed reward ($corr = 0.37, t(74) = 2.45, p = 0.005$), indicating participants who preferred the healthier foods were also more likely to choose the delayed rewards.

***Table 2** Average response time for choices by gender*

Average Response Time (in seconds) in Monetary Choice Task			
	Total Average	Delayed Rewards	Immediate Rewards
Women	1.488	1.560	1.448
Men	1.491	1.550	1.459
Average Response Time (in seconds) in Food Choice Task			
	Total Average	Tastier but less healthy	Healthier but less tasty
Women	1.075	1.066	1.086
Men	1.070	1.032	1.118

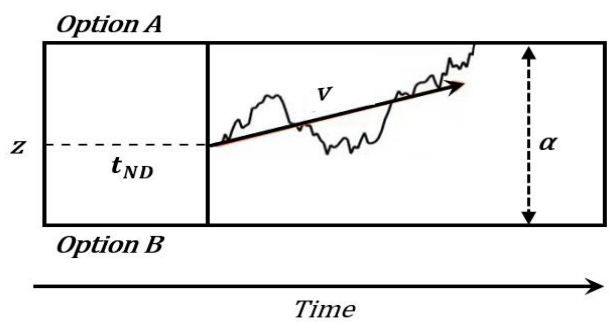
3.2.2 Computational Model

To identify if and how gender affects an individual's intertemporal choice, I apply the Mixed Drift Diffusion Model. In this model, the process of making a decision is assumed as processing the information by accumulating evidence for each of two options until one of the two decision boundaries is met, the associated response is produced. Figure 1 clearly depicts the four parameters that are used to describe the decision-making process in the model.

Decision-makers probably have pre-existing (pre-decision) bias towards a specific choice before seeing the options at the beginning, so z denotes the starting point bias to select one option before the evidence accumulation process, ranging from -1 to 1. α is the threshold, which determines the level of evidence needed to make a decision. When the information is accumulated till the stopping boundary, the decision is produced successfully, and 0 is the lower boundary. Higher threshold leads to an increase in response time, meaning the decision criteria for the options of the decision-maker is changing during the evidence accumulation process that needs longer time to

hit the boundary and make the final choice. In this paper, the upper boundary is corresponding to the immediate rewards in the monetary choice task and the tastier but less healthy option in the food choice task with self-conflict trials only. The drift rate (v) is the average rate of information uptake during the evidence accumulation process, indicating the speed of making the decision, so a higher rate represents a faster decision and vice versa. t_{ND} reflects the time used for everything except for making a decision. For example, if an individual is more familiar with the stimuli and task after taking training, the non-decision-time will decrease. The response time in a trial is assumed to be the time taken for the accumulating evidence to reach a decision threshold added to a fixed non-decision-time. In Figure 1, the trajectory represents a hypothetical accumulation process in a single trial.

Figure 1 Information Accumulation in DDM



For the monetary choice task, I use two different models of intertemporal preferences to fit the data. First, I build on previous applications of DDM to intertemporal choice by Zhao and colleagues (2019), they have suggested that the intertemporal preferences can be modeled as a linear function of the differences in rewards and time delays and especially the drift rate depends on the weights on monetary amounts and time delays attributes. Consequently, I assume the drift rate to be

$$v = v_0 + w_{\Delta R}(R_D - R_I) + w_{\Delta TIME} T_D$$

where R_D is the delayed reward, R_I is the immediate reward, T_D represents the time delays in days, v_0 is the drift rate intercept, $w_{\Delta R}$ and $w_{\Delta TIME}$ are the weights on the monetary amounts and time delays differences between the delayed and immediate option. The directions of $w_{\Delta R}$ and $w_{\Delta TIME}$ show the preferences for monetary amounts and time delays. If $w_{\Delta R}$ and $w_{\Delta TIME}$ are positive, the response is more likely to be the delayed option. In this model, I keep the nominal values of the monetary amounts for both R_D and R_I in each trial and fit the model.

Secondly, I construct the value of the delayed reward (R_D) from the discount function. I follow the approach taken by Chabris and colleagues (2008) to assign the value R_D by fitting a hyperbolic discount function

$$R_D = \frac{A_D}{1 + kT_D}$$

where R_D is the value of the delayed option, A_D is the monetary amount, T_D is the time delays in days, and k is the discount rate. The discount rate is fit using the choice data, and I find the optimal k-value by selecting the value that is most likely to generate the observed choice data, in order to measure the value of the delayed reward for each participant.

Since the delayed amounts are always greater than the immediate amounts ($R_D \geq R_I$), we have: $\frac{A_D}{1+kT_D} \geq R_I$. The probability of choosing the delayed rewards would be

$F_{Logistic}\left(\frac{A_D}{1+kT_D} - R_I\right) \geq \frac{e^{\frac{R_I}{1+kT_D}}}{e^{R_D}+e^{\frac{R_I}{1+kT_D}}}$, as the preferences rise from a logit distribution.

By using the Maximum Likelihood Estimation, I can identify the optimal k-value for each participant, and the likelihood function is

$L(k,D) = \prod_{t=1}^{216}\left[F_{Logistic}\left(\frac{A_D}{1+kT_D} - R_I\right)\right]^{D_t}\left[1-\left(\frac{A_D}{1+kT_D} - R_I\right)\right]^{1-D_t}$, where D_t is the dummy variable ($D_t = 1$ means the delayed option is chosen in this trial t). The average value of the estimated hyperbolic discount parameter k is 0.017 (SD = 0.022).

In the second model for the monetary choice task, the drift rate would be:

$$v = v_0 + w_{\Delta R}(R_D - R_I)$$

where R_D is the discounted value of the delayed reward. However, when these two models are compared using the Akaike information criterion (AIC), the AIC of the model with discount rate k (AIC = 54527) is larger than the one with nominal values (AIC = 54460). Lower AIC value indicates a better-fit model, so the first model fit the data better and is selected in further analysis.

For the food choice task, I follow the approach to fit DDM by Enax and colleagues (2016) in which they assume that binary food preferences would be influenced by the taste ratings differences and healthiness ratings differences between the healthy and unhealthy food items, and the drift rate depends linearly on the weight on the taste and healthiness attributes. Similarly, I assume the drift rate to be:

$$v = v_1 + w_{\Delta TASTE}(T_H - T_U) + w_{\Delta HEALTH}(H_H - H_U)$$

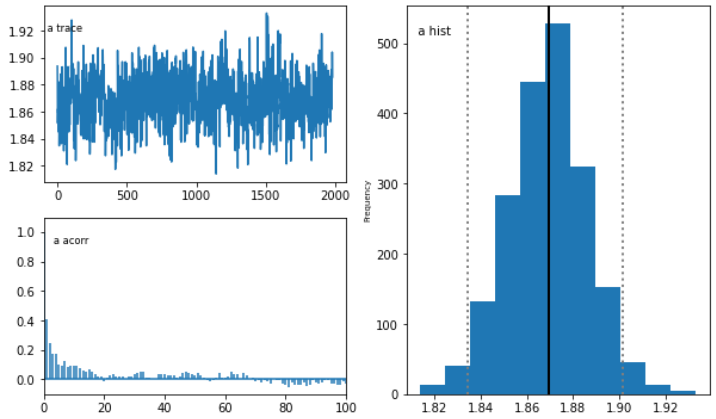
where $w_{\Delta TASTE}$ and $w_{\Delta HEALTH}$ are the weights on the differences between the taste ratings and healthiness ratings of the healthy food item, T_H and H_H, and the unhealthy one, T_U and H_U, accordingly. v_1 is the drift rate intercept. Positive $w_{\Delta TASTE}$ indicates the preference for tastier food item, similarly, positive $w_{\Delta HEALTH}$ shows the preference for healthier food item. However, for the no-conflict trial, the attribute weight of tastiness would be the difference between the tastier food and the less tasty food, so the upper boundary of the no-conflict trial is the healthier and tastier food.

To fit all the described models to the data I use the hddm package (Wiecki et al., 2013) in the Python programming language. With the hddm package, users can estimate diffusion model parameters, in a hierarchical Bayesian method, with minimal use of computer code. The hddm estimation technique depends on Markov Chain Monte Carlo sampling, which means that the posterior distributions are approximated by repeatedly drawing very many samples from those distributions (Krypotos et al., 2015).

DDM is fit to every participant separately and all the parameters are estimated on the individual-level. As the MCMC algorithm is used in DDM for sampling, it is necessary to check if the chains of the model have properly converged. By plotting and checking the trace, the autocorrelation, and the marginal posterior, I examine the convergence for the model in two tasks. The posterior trace plots depict the variability in estimates by the chain. The autocorrelation plots imply the stability of the parameters and the relationship among the drawn samples. For the marginal posterior histogram, the distributions of the estimates are displayed.

As shown in Figure 2, there are no apparent anomalies in the trace plots for both parameters in the food choice task, showing fairly constant mean and variances. Also, the fluctuations are around zero, without having long tails of the distributions, indicating the samples are independent draws from the posterior. The histograms represent the approximation of the marginal posterior distribution for the parameters and the group mean posteriors are all normally distributed. Consequently, the samples in the food choice task converge appropriately. Figure 3 displays the convergence of the model in the monetary choice task, there are also no obvious drifts or large jumps in the trace plots and the autocorrelation for t is large at short lags, but then goes to zero quickly. Also, the marginal posteriors of the parameters are normally distributed. In the monetary choice task, the model demonstrates convergence of the MCMC chains.

Figure 2 Trace plots, autocorrelation plots, and marginal posterior for food choice task



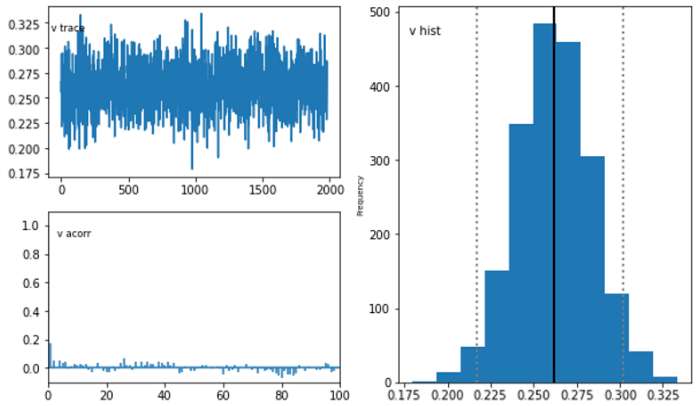
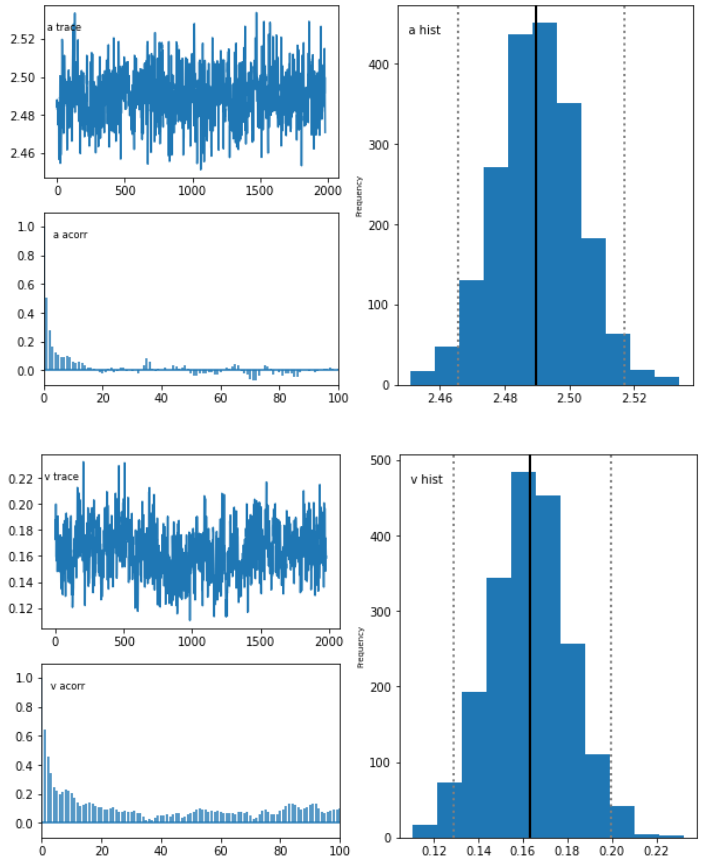


Figure 3 Trace plots, autocorrelation plots, and marginal posterior for monetary choice task



For both monetary and food choice tasks, I estimate the drift-rate (v), boundary (a), bias (z), and non-decision time (t_{ND}) for each participant and compare those parameters between two

tasks. Also, for the food choice task, I additionally fit the model with the self-control trials only. Each individual was required to rate the health and taste of each food image, so if one food item is considered to be healthier and the alternative one is tastier, this trial would be defined as a self-control trial. On average, 88 out of 200 trials for each individual are excluded from the model with self-conflict trials only, since these are no-conflict trials. Overall, 44.8% of trials are self-conflict trials in the food choice task.

CHAPTER 4: RESULTS

The estimations of posterior means of the parameters for 74 individuals in the food choice tasks are reported in Table 3. As you can see from the posterior estimates the differences of threshold (α), bias(z), non-decision time (t_{ND}), and weights on tastiness attribute ($w_{\Delta TASTE}$) and healthiness attribute ($w_{\Delta HEALTH}$) under different conditions seem negligible, and the differences of these parameters between two conditions were not significant. The posterior mean of drift rate (v) with the self-control trials only is significantly less than the one in the original model with a 95% credible level, which means that participants make decisions slower when they are facing self-conflict trials. For example, if one of the food options is healthier and tastier, the individual would be more likely to pick it without too much hesitation. Actually, the self-conflict trials are more typical intertemporal choice because it depends upon the tradeoff between a sooner outcome with high value and a later outcome with low value (Zauberman & Urminsky, 2016). The healthier but less tasty food will bring long-term benefits of health while the less healthy but tastier alternative will have immediate benefits of taste.

In Table 3, I check the posterior means of $w_{\Delta HEALTH}$ and $w_{\Delta TASTE}$ from the results for all trials and find that $w_{\Delta TASTE}$ was not significantly different from zero for 27 participants (17 negative and 10 positive), and $w_{\Delta HEALTH}$ were not significantly different from zero for 30 participants (12 negative and 18 positive), as determined by 95% credible intervals. Therefore, I remain the results from the self-conflict trials only for further analysis.

Overall, in the self-conflict trials, the posterior means of $w_{\Delta TASTE}$ were negative for 32 participants, indicating a preference for tastier but unhealthy food, while 29 participants had a positive posterior mean for $w_{\Delta TASTE}$. As for the posterior means of $w_{\Delta HEALTH}$, 36 participants had a positive posterior mean for $w_{\Delta HEALTH}$, and 27 participants had a negative one.

The result of the posterior means of the parameters in the monetary choice task are summarized in Table 4. As expected, 62 participants had positive posterior means for $w_{\Delta R}$ and negative posterior means for $w_{\Delta TIME}$. 9 participants had a negative $w_{\Delta R}$ and 5 participants had a positive posterior mean for $w_{\Delta TIME}$, but none of these were significant with 95% credible intervals.

Table 3 Group-level parameters posterior means in food choice task

		a	v	z	t_{ND}	$w_{\Delta TASTE}$	$w_{\Delta HEALTH}$
Food Choice Task	Mean	1.69	0.21	0.490	0.11	-0.03	0.02
	1st quantile	1.55	0.18	0.482	0.06	-0.11	-0.06
	Median	1.70	0.21	0.487	0.11	-0.01	0.02
	3rd quantile	1.85	0.26	0.495	0.23	0.09	0.08
	SD	0.18	0.06	0.011	0.15	0.16	0.12
Food Choice Task with Self-conflict Trials	Mean	1.60	0.18	0.482	0.15	-0.05	0.01
	1st quantile	1.52	0.14	0.478	0.10	-0.07	-0.02
	Median	1.59	0.19	0.483	0.16	-0.03	0.01
	3rd quantile	1.67	0.21	0.488	0.28	0.14	0.04
	SD	0.13	0.05	0.008	0.12	0.19	0.07

Note. v indicates the drift rate in the model; a indicates the threshold in the model; t_{ND} indicates the non-decision time in the model; z indicates the bias in the model.

Table 4 Group-level parameters posterior means in monetary choice task

		a	v	z	t_{ND}	$w_{\Delta R}$	$w_{\Delta TIME}$
Monetary Choice Task	Mean	2.49	0.18	0.446	0.08	0.11	-0.09
	1st quantile	2.46	0.14	0.444	0.04	0.05	-0.12
	Median	2.49	0.18	0.446	0.06	0.12	-0.08
	3rd quantile	2.52	0.22	0.447	0.11	0.17	-0.04
	SD	0.03	0.06	0.003	0.06	0.05	0.03

Note. v indicates the drift rate in the model; a indicates the threshold in the model; t_{ND} indicates the non-decision time in the model; z indicates the bias in the model.

The posterior means of boundary parameter (α) were lower and the drift rate (v) were higher in the food choice task (Table 3) than the ones in the monetary choice task (Table 4), with 95% credible level, specifying that the time needed to accumulate information was longer and the speed of information processing was slower in the monetary choice task. This is in line with the previous findings when I compare the means response time (RTs) across two tasks, so food items seemed to be chosen faster than monetary rewards in the experiment. The estimated posterior means of non-decision time (t_{ND}) and bias (z) both differed slightly between the two tasks, which are not significant. Given that participants should not be able to know where a sooner or later option would be presented in each trial in both tasks, I assume that different task would not affect t_{ND} and z.

I also compute the correlations between posterior means of parameters in the food choice task and the ones in the monetary choice task, and the results are reported in Table 5. I find that both α and v in the food choice task were positively correlated with the ones in the monetary choice task. There were no significant correlations of bias (z) or non-decision time (t_{ND}) across two tasks.

Table 5 Parameter correlations across two tasks

Parameters	a	v	z	t_{ND}
correlations	0.312**	0.230*	-0.103	-0.078

Note. * indicates p < 0.05; ** indicates p < 0.01

To further observe if there is a gender effect on an individual's intertemporal choice, I estimate the posterior means for four parameters: drift rate (v), threshold (α), bias(z), and non-decision time (t_{ND}) on the group level and compare differences of the two genders mean posteriors for these parameters in two tasks, then I can detect whether the gender effect is significant or not in two tasks separately.

Table 6 Group-level parameters posterior means by gender in two tasks

		Women				**Men**			
		a	v	z	t_{ND}	a	v	z	t_{ND}
Monetary Choice Task	Mean	2.471	0.184	0.444	0.08	2.492	0.175	0.445	0.08
	1st quantile	2.452	0.145	0.442	0.06	2.465	0.137	0.439	0.07
	Median	2.473	0.184	0.444	0.08	2.494	0.174	0.444	0.08
	3rd quantile	2.490	0.218	0.446	0.12	2.513	0.215	0.449	0.10
	SD	0.022	0.055	0.004	0.06	0.024	0.058	0.009	0.04
Food Choice Task with Self-conflict Trials	Mean	1.584	0.134	0.484	0.14	1.550	0.153	0.483	0.15
	1st quantile	1.549	0.097	0.481	0.11	1.498	0.109	0.477	0.08
	Median	1.591	0.133	0.485	0.15	1.562	0.154	0.485	0.16
	3rd quantile	1.621	0.174	0.488	0.18	1.627	0.198	0.491	0.22
	SD	0.049	0.051	0.006	0.05	0.073	0.062	0.008	0.07

Note. v indicates the drift rate in the model; a indicates the threshold in the model; t_{ND} indicates the non-decision time in the model; z indicates the bias in the model.

Table 5 reports the group-level parameter statistics by gender in two tasks. In the monetary choice task, the posterior mean of drift rate for men was slightly lower than that for women. I also did significance tests on the posterior directly and examine

whether the drift-rate for women was greater than that for men and the probability was 0.625. The difference in the posterior means of drift rate for men and women was not statistically significant, so there was no gender effect on the speed of making decisions in the monetary choice task accordingly. As for the threshold, the group-level posterior mean for men was greater than the one for women (Table 5), and the probability that the posterior mean of threshold for women was higher than men's one was 0.657, so it is hard to conclude there is a significant difference in the threshold for different genders. As a result, gender did not serve as a driving factor affecting the time taken to accumulate evidence and make decisions in monetary choice task. Similar to drift-rate and threshold, there was no distinct evidence to show that gender influences non-decision time; the posterior means of times for two genders were nearly the same (Table 5). The probability that the posterior means of non-decision time for men was greater than that for men was 0.508, so gender is not a cause of the small difference in non-decision times in the task. Also, the effect of gender on the bias was not significant here due to the counterbalancing strategy. The probability that the posterior means of bias for men was greater than that for men was 0.516.

With respect to the food choice task, the averaged group-level posterior drift-rate for men was slightly higher than women (Table 5), but the probability that the drift rate for men was greater than that for women was 0.643. The difference in the posterior means of the drift rates for two genders was not statistically significant, so gender would not affect the speed of making decisions in the food choice task. Regarding the threshold, the posterior means of threshold for women was greater than that for men (Table 5), and

the probability for this was 0.676, so the difference in the threshold for these two genders was not significant either. There is no gender effect on the time taken to reach the decision threshold in food choice task. As for the non-decision time, on average, women took less time than men (Table 5), but the probability that the posterior means of non-decision time for men is greater than women is 0.513; thus, gender has no impact on the non-decision time in this task. There are no significant differences in the posterior means of bias for two genders, as the probability that the bias for women was greater than the one for men as 0.515. According to the results, I find a similar absence of gender differences that leads to the individual differences in both monetary and food choice tasks, which is in line with previous research (Anderson et al., 2009; Harrison et al., 2002). The slight distinction is probably due to the interaction effect or random effect, which can be studied in future research.

CHAPTER 5: CONCLUSION

To explore if and how gender has impact on the individual differences in intertemporal choice, this paper conducts an online choice experiment including a monetary choice task and a food choice task, through Amazon Mechanical Turk (Mturk) and analyzes the gender effect using drift-diffusion Model. In the survey, participants were asked to choose between an immediate but smaller reward and a larger but later reward for 216 hypothetical trials in the monetary choice task. Also, in the food choice task, they needed to rate the health and taste of 40 different food items and select a preferred food in each pair for 200 sets, where one is a healthy but less tasty food and another one is a tasty but less healthy food. For both tasks, I collect the responses of each individual, record the response time for each trial and obtain the demographic information at the end of the survey.

By fitting the Drift Diffusion Model to the data, I quantitatively estimate the various parameters in the model, such as the drift rate (v), threshold (α), bias(z), and non-decision time (t_{ND}) with a combination of choice and response time data on the individual-level for the two tasks, and I compare the parameters across the tasks. I also find that the drift rate and threshold in the food choice task are positively correlated to the ones in the monetary choice task. Furthermore, I look into the gender impact on intertemporal choice regarding the decision-making process. To identify if and how gender affects the individual differences in intertemporal choice, I do the comparison of these parameters between men and women and do the hypothesis test for each parameter. The results indicate that there are no significant differences in v, α, z, and

t_{ND} for men and women in both tasks, therefore I do not find profound gender effect on individual differences in intertemporal choices.

The current study sheds light on discussing if and how women and men differ in intertemporal choices, which is an arguable question in previous research. Instead of using traditional logistic regression to obtain the significance and importance of potential factors or variables, this work uses the drift-diffusion model to explore how the factors or variables influence the decision process. DDM can be applied to decompose the process into quantitative parameters and analyze with the choice and response time in the tasks, so the combination of choice and response time in DDM is different from investigating their relationships with the variables separately and estimating the coefficients.

However, this study remains limitations and can be improved for future research. Fundamentally, the results of the current work are based on purely hypothetical decisions, because participants in two tasks would not actually receive any monetary reward or snack, they had chosen. Non-consequential choices and hypothetical scenarios in the survey would affect the accuracy and validity of the responses of participants. For example, when the participants are confronted with a large number of hypothetical choices sets or more complex questions, they would get impatient and repeated answers would be submitted. Hence, future research can consider asking participants to make decisions that had actual consequences in the survey, in order to minimize fake or inconsistent responses and avoid bias. Also, the individual across-trial

variability parameters are not discussed in this paper, due to the constraint and assumption of the model, so the estimated parameters are not trial-specific. Moreover, the parameters are fixed for a single trial in the assumption of DDM, so other extensions should be applied to explain possible time-varying parameters. Additionally, the hddm package cannot support the evidence which changes in magnitude throughout a single trial (Shinn et al., 2020). More work is needed to address the inter-trial variabilities during decision process by expanding the model or using other advanced techniques.

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