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Age Differences in Cognition–Motivation Interaction during Demand Selection Task

부하 선택 과제에서의 인지–동기 상호작용의 연령 차이

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Age Differences in Cognition–Motivation Interaction during Demand Selection Task

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Abstract

It is natural for human beings to avoid unnecessary effort. In Experiment 1, we used demand selection task with stop-signal task to investigate the effect of motivation on effort avoidance and its age differences. In Experiment 2, drift diffusion model (DDM) was used to analyze the effect of motivation on the undelaying cognitive processing. The results showed that participants tended to choose high-demand task more frequently as their intrinsic motivation increased. The relationship between intrinsic motivation and effort avoidance tendency was only valid for older adults. Moreover, the following DDM analysis gave support for the role of intrinsic motivation on enhancing the efficiency of perceptual processing.

Keyword: Aging, Motivation-Cognition Interaction, Demand Selection, Cognitive Effort
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Chapter 1. Introduction

1.1. Study Background

Motivation is one of the topics of longest interest in psychology. This longstanding interest on motivation is not surprising, given that motivation is a core part of the driving force in our everyday behavior. Another characteristic of motivation is its relation to cognition. In many research areas, from cognitive neuroscience to social and personality psychology, one of the most important research question is the interaction between motivation and cognition (Braver et al., 2014). For example, it is well known that enhancing motivation facilitates cognitive functioning (Logan, Medford, & Hughes, 2011; Robinson et al., 2012). On the other hand, previous studies also reported that motivation sometimes hinder cognition (Roets, Van Hiel, & Kruglanski, 2013). Although the mechanism of this interaction is not straightforward, one thing that is clear is that certain cognitive functioning and behaviors require motivated control (e.g., planning for distant future, maintaining concentration during a boring class). These kinds of cognitive activities are called "cognitive control", and it is assumed that exerting control over one's default mode of cognition accompanies cognitive resources, which is called cognitive (or mental) effort. Recent advances in motivation–cognition interaction mainly focus on identifying the mechanism of how these related concepts—motivation, cognitive control, and mental effort—are related (Froböse et al., 2017; Inzlicht, Shenhav, & Olivia, 2018; Kool & Botvinick, 2014; Kurzban et al., 2013; Sidarus, Palminteri, & Chambon, 2018). One thing to note is that exerting cognitive effort is basically not preferred (Kool et al., 2010), and it is hypothesized that the tendency to avoid effort might be based on cost–benefit tradeoff (Kool, Shenhav, & Botvinick, 2017).

Among the bright insights from previous studies is the age differences in motivation–cognition interaction. In the field of adult development and aging, it is assumed that one of the most salient

outcome of aging is motivational shift, and this shift with aging is viewed as an adaptive process caused by decline in cognitive functioning (Baltes, 1997; Hess, 2014) or change in time perspective in later (Carstensen, Isaacowitz, and Charles, 1999). Moreover, motivational shift in later life results in selectivity effect, which refers to the tendency in older adults to engage in what meets their motivational goals and disengage from what does not (Heckhausen et al, 2010).

The selection, optimization, and compensation (SOC) model (Baltes, 1997) may be one of the most well-known theory dealing with the selectivity effect in the field of lifespan development. According to SOC model, with decline in cognitive resource in later life, one pursue the maintenance of their current level of everyday functioning, disengaging in growth-oriented goals. As a result, older adults selectively involve in activities that supports current level of functioning, aligning their goal priorities in response to a changing life environment.

Selective engagement theory, proposed by Thomas Hess (2014), also views the selectiveness in older adults as a result of a decline in cognitive resource. This theory, however, argues that engagement and disengagement in cognitive activities are determined by the self-implication of the activities. As a result, the theory predicts that older adults, compared to younger adults, exert more cognitive effort when the given task is self-related or when the task is intrinsically motivated. Importantly, this theory assumes that decline in cognitive resource entails an increase in cognitive cost in the engagement in cognitive activities, and this increase in cognitive cost makes older adults more selective in exerting their cognitive resources. Selective engagement has been observed in diverse tasks such as memory (Hess, Germain, Swaim, & Osowski, 2009), attitude (Hess et al., 2005), executive function (Germain & Hess, 2007), and information search (Hess, Queen, & Ennis, 2012).

Many empirical studies have been conducted to examine the theories stated above. The results suggest that selectivity in later life is observed in many aspects in our cognitive processes. However,

it is still unclear how one's age affects the pattern of interaction between motivation and cognition. In other words, so far there has been no attempt to directly examine the age differences of the effect of motivation on effort avoidance. Although the term motivation is used with very different meanings in diverse research fields, it can be summarized as "a psychological state that impacts the direction and intensity of both cognition and behavior" (Botvinick & Braver, 2015). Following this concept of motivation, motivational shift in later life might be result in the age differences in one's effort avoidance tendency.

In relation to the relationship between motivation and cognition, another important question is related to the mechanism of how increased motivation affects cognitive processes. In other words, there is an explanatory gap of why the changes in motivation, which is accompanied by increased cognitive effort, induce the changes in our cognitive functioning and behaviors. According to previous studies, the reward system may be the linkage of this relationship.

It is well known that monetary reward, which is a primary source of extrinsic motivation, modulates the cognitive system (e.g., Leotti & Wager, 2010). In addition to behavioral relationship, neural substrate of the effect of monetary reward has been widely explored (Hampton & O' Doherty, 2007; Knutson et al., 2001; Lin, Adolphs, & Rangel, 2011; McClure, York, & Montague, 2004) by cognitive neuroscientists. Recently, in an attempt to formalize the motivation–cognition interaction, it has been argued that the effect of motivation, whether it is extrinsic or intrinsic, can be viewed from the same theoretical model which is based on the mechanism of reward system (Botvinick & Braver, 2015; Shenhav et al., 2017). According to this view, it can be hypothesized that intrinsic motivation is just another source of valuation, thus operate in very similar mechanism with extrinsic rewards.

Previous studies offer evidences that support this contention. For example, in the field of neuroscience, there has been an effort to find neural mechanism of intrinsic motivation (Baldassarre, 2011; Kaplan & Oudeyer, 2007). Interestingly, it is suggested that intrinsic

motivation is also related to dopamine (DA) system, which is hypothesized to play a key role in reward processing (Beierholm et al., 2013; Murayama et al., 2013; Niv, 2007, Salimpoor et al., 2013). Although interaction between extrinsic and intrinsic motivation is somewhat complicated–e.g., undermining effect–, at least the intrinsic motivation itself may act like extrinsic motivation when it comes to invigorating cognition and behavior.

Motivation–cognition interaction has also been examined in studies using computational models. Drift Diffusion model (DDM), developed by Ratcliff (1978), is one of the most widely–used computational model for analyzing relatively fast binary choice tasks. One advantage of DDM is that its basic parameters reflect actual decision processes (Voss, Rothermund, & Voss, 2004). For example, discriminability of stimuli is reflected in increased drift rate, and response bias is reflected in starting point parameter shifted toward the biased response. Therefore, the analysis of the diffusion model is usually carried out assuming that the experimental manipulation will affect certain parameters.

Thus, DDM was often used by researchers interested in the effect of motivation on cognitive processes. In case of extrinsic motivation, researchers often impose monetary incentive to one group, and compare the result with that of no–incentive group. For example, monetary reward contingent on performance resulted in enhanced stimulus coding (i.e., increased drift rate) (Hübner & Schlösser, 2010). Other study found that older adults showed enhanced perceptual processing on rewarded stimuli during a perceptual discrimination task (Spaniol et al., 2011). DDM also applied to experimental conditions where intrinsic motivation seems to have an effect. For example, Spaniol, Voss and Grady (2008) conducted DDM analysis to examine age differences in motivational influences on response bias. The result showed that older adults tend to endorse positive stimuli as "old" (i.e., biased toward positive stimuli), whereas no response bias was observed for neutral and negative valenced stimuli. Saunders et al. (2018) also reports that intrinsic motivation (i.e., interpersonal touch) may improve

participants' inhibitory control performance by accelerating evidence accumulation (i.e,, higher drift rate).

1.2. Purpose of Research

The aim of this study is twofold. The first is to examine age differences in effort avoidance tendency, focusing on the effect of motivation. The second is to shed light on the cognitive mechanism of the effect of motivation on effort avoidance. For the first aim, we used more task-specific measures of cognitive cost and intrinsic motivation: perceived cognitive cost and task-specific motivation. Specifically, our aim in this study is to examine whether participants' subjective cognitive cost and intrinsic motivation toward the target task relates to actual participation on the task, operationalized as the percentage of the target task is chosen. The hypothesis is based on the previous studies, which suggest that task-specific motivation is more predictive of the related behaviors (Choi, Saperstein, & Medalia, 2012; Harter & Jackson, 1992; Iddekinge et al., 2018). Thus, it is possible that actual activity participation is more closely related to the motivation toward the activity at-hand, rather than trait-like motivation (e.g., need for cognition). Further, previous studies found that perceived demand (i.e., cognitive cost) of the task is a more influential factor on driving behaviors (Desender et al., 2017; Dunn, Lutes, & Risko, 2016, Gilbert et al., 2018). In other words, people does not avoid tasks which effort-consuming, but they avoid what they think it is effort-consuming. Our conjecture based on these studies is that what drives the decision to participate in older adults is their subjective cognitive cost on the activity and their intrinsic motivation toward the activity itself.

For the second aim, we analyzed reaction time (RT) data of participants using drift diffusion model (DDM) to see whether the parameters of the DDM changes as a function of participants' intrinsic motivation toward the task and cognitive effort. It is based on our

conjecture that, if participants' self-reported intrinsic motivation acts like other motivational sources, the relationship between the self-reported intrinsic motivation and DDM parameters should be similar as well. Specifically, we hypothesized that participants' drift rate estimates will increase as a function of their intrinsic motivation score. We further hypothesized that the magnitude of this relationship will be greater in older adults compared to younger adults, following the prediction of theories on motivational adaptation with aging (Hess, 2014)

Two experiments were conducted to test the hypotheses. In experiment 1, participants had to choose between two stop-signal tasks which differed in their cognitive demand. Stop-signal task is a famous experimental paradigm to measure one's response inhibition task, and has been used in wide range of studies (Matzke, Verbruggen, & Logan, 2018). Scores were given to the correct responses, with smaller score for low-demand trials and higher score for high-demand trials. During the task, participants were instructed to maximize their task score. Cognitive demand required for each task was manipulated by varying stop signal delay (SSD), which indicates the time taken for stop signal appears after the presentation of go signal. Participants repeatedly chose between low- and high-demand inhibition tasks. The proportion of high-demand task chosen was used as a primary response variable. We also measured participants' subjective cognitive costs and their intrinsic motivation toward task participation to examine our hypothesis. In experiment 2, participants conducted the same stop-signal task, but this time without freely choosing between them. Participants conducted the same number of trials for each level of task demand, and the resulting data were analyzed with the DDM.

Chapter 2. Experiment 1

2.1 Method

Participants

In this experiment, thirty-one younger participants were recruited through Seoul National University's online research participation system, and thirty older participants were recruited from the local senior center. The age of the younger participants ranged from 19 to 27 (Mean = 23.7, SD = 3.7) and the age of the older participants ranged from 65 to 88 (Mean = 77.2, SD = 8.9). Data collection procedure of 4 younger participants and 3 older participants was interrupted due to program errors and thus excluded from the analysis. Thus twenty-seven participants for each age group were included in the final analysis. For younger participants, it was a part of course requirements to participate in experiments, thus no incentive for the participation were given. Older participants were given KRW 10,000 (equivalent to USD 10) for their participation in the experiment. The study was approved by the Institutional Review Board (IRB) of Seoul National University.

Horse-Race Model

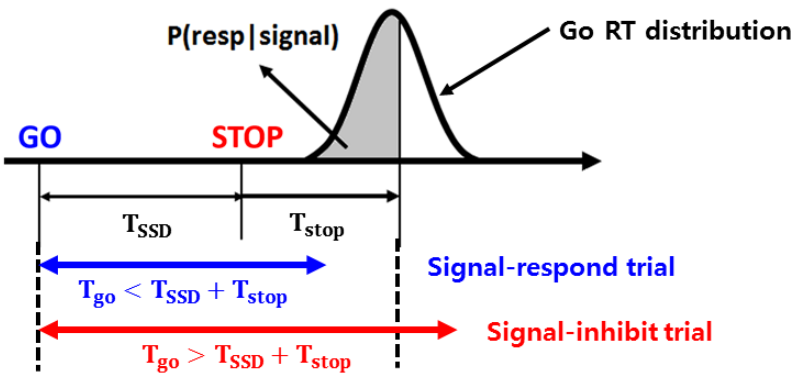

Figure 1. Graphical Representation of Horse-Race Model

To formally analyze stop-signal task performance, we used horse-race model proposed by Logan (1981) and Logan and Cowan (1984). The graphical representation of the model is shown in Figure 1. In this model, response inhibition is viewed as a race between two independent processes: a go process and a stop process. Once a go stimulus is perceived, go process is initiated. In go trials, where stop signal is not presented, the time taken for the go process to be terminated is itself the total RT. On the other hand, in stop trials, stop process is also initiated once the stop signal is presented after some delay (stop-signal delay; SSD). In stop trials, responses toward the go signal are successfully inhibited only when the stop process is terminated earlier than the go process. Thus, according to the horse-race model, success of response inhibition depends on the relative finishing time of the go and stop processes.

Contrary to go process, however, stop process cannot be directly observed. Thus, the delay of stop process—stop signal reaction time (SSRT) — should be estimated from the observed data. A popular method is the integration method (Logan & Cowan, 1984), which assumes that the SSRT is constant and allows for the estimation of SSRT for different SSD separately. Integration method finds SSRT by integrating the go RT distribution to the upper limit of the following equation.

$$P_{resp}(T_{SSD}) = \int_0^{T_{SSD}+T_{stop}} f_{go}(t)dt$$

Where $f_{go}(t)$ is a go RT distribution and $P_{resp}(t_{SSD})$ is the probability of responding in stop trials given a certain SSD, T_{SSD}. In practice, $P_{resp}(t_{SSD})$ is calculated by dividing the number of responses in stop trials by the total number of stop trials. Rank-ordered go RTs are used as $f_{go}(t)$. Then we can get T_{stop} by subtracting T_{SSD} n^{th} RT, where n is the number of go RTs multiplied by $P_{resp}(T_{SSD})$.

Procedure

The experimental procedure was comprised of 4 phases.

Phase 1

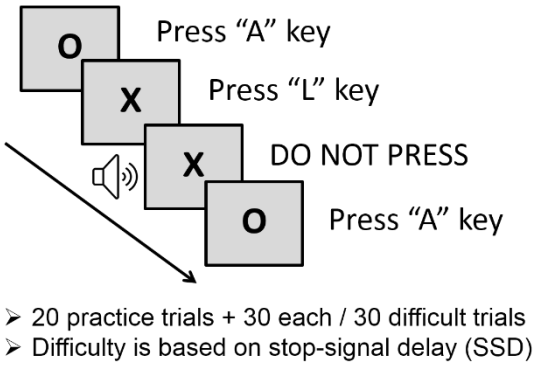

Figure 2. Stop-Signal Task

Stop-signal task was used in Phase 1 of the experiment. Stop-signal task is one of the most widely used experimental paradigm to measure response inhibition. Response inhibition is an ability to suppress prepotent responses and is known to be a very important cognitive ability that supports overall goal-directed behavior. (Verbruggen & Logan, 2008). It is also known that inhibitory control ability is a cognitive function that shows an apparent decrease with chronological aging (Adólfsdóttir et al., 2017; Salthouse, 2010;). In this respect, stop-signal task have been widely used to examine age differences in cognitive functioning (Carver, Livesey, & Charles, 2001; Christ et al., 2001; Hasher, Quig, & May, 1997; Williams et al., 1999).

The experiment was developed using PsychoPy package implemented in Python (Peirce, 2007) and Samsung Galaxy A2016 10.1 tablets were used for stimulus presentation and response collection. All participants performed 20 trials before they began the main experiment. For each trial, letter "O" or "X" appeared on the center of the screen. Participants were instructed to press the A key when the letter "O" appeared on the display, and press the L key when letter "X" appeared on the display. Participants responded as quickly as possible and refrained to respond if the stop signal (beep sound) occurred after the onset of the stimulus display. After the practice session, participants performed two sets of stop signal tasks, including cognitively more demanding task sets and less demanding

task sets. Each set consists of 30 trials of the stop signal task. As Figure 2 shows, cognitive demand was manipulated by adjusting the stop signal delay (SSD) according to individual mean reaction time. Previous studies suggest that adjusting SSD has been proved to be a valid way of manipulating the difficulty of stop signal task, only when it considers the individual differences in reaction time in no-signal trials (GoRT) (Carter et al., 2003; Hughes et al., 2013; Lindqvist & Thorell, 2008). Thus, the mean RT of the practice stop signal task was used as a basis for calibrating SSD in this session: The SSD of the low-demand task was set to the mean RT of the practice session multiplied by 0.4, and the SSD of a high-demand task was the mean RT multiplied by 0.8.

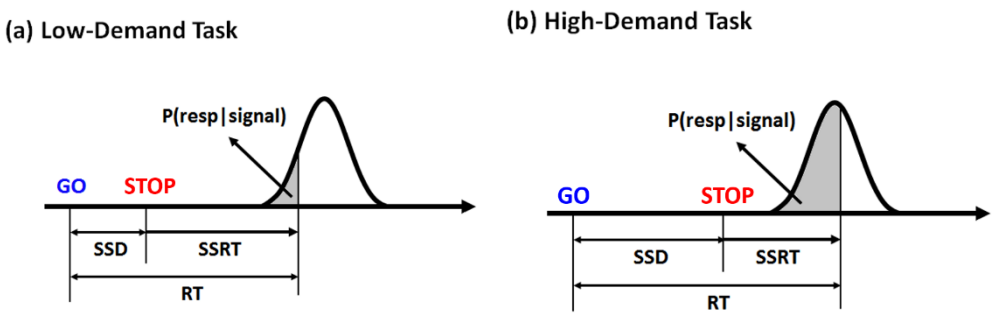

Figure 3. Manipulation of Task Demand

Inhibitory function of participants is assessed by calculating stop-signal reaction time (SSRT, Figure 2). SSRT is the delay of stop process

Phase 2

After performing two sets of stop signal tasks, participants conducted a cognitive effort discounting task. In this task, participants evaluated the monetary value of each task based on the difficulty of the stop signal task performed in Phase 1. The logic of this paradigm is based on the temporal discounting effect, which refers to a tendency to discount the subjective value of an identical reward as the time of getting it increases (Westbrook, Kester, &

Braver, 2013). Similarly, in effort discounting paradigm one can hypothesize that the subjective value of the reward will be decreased as the task requires more effort. Many studies have shown that discounting paradigm is a reliable measure to quantify the relationship between cognitive effort and the target behavior (Apps et al., 2015; Chevalier, 2018; Białaszek, Marcowski & Ostaszewski, 2017; Massar et al., 2016; Massar et al., 2018).

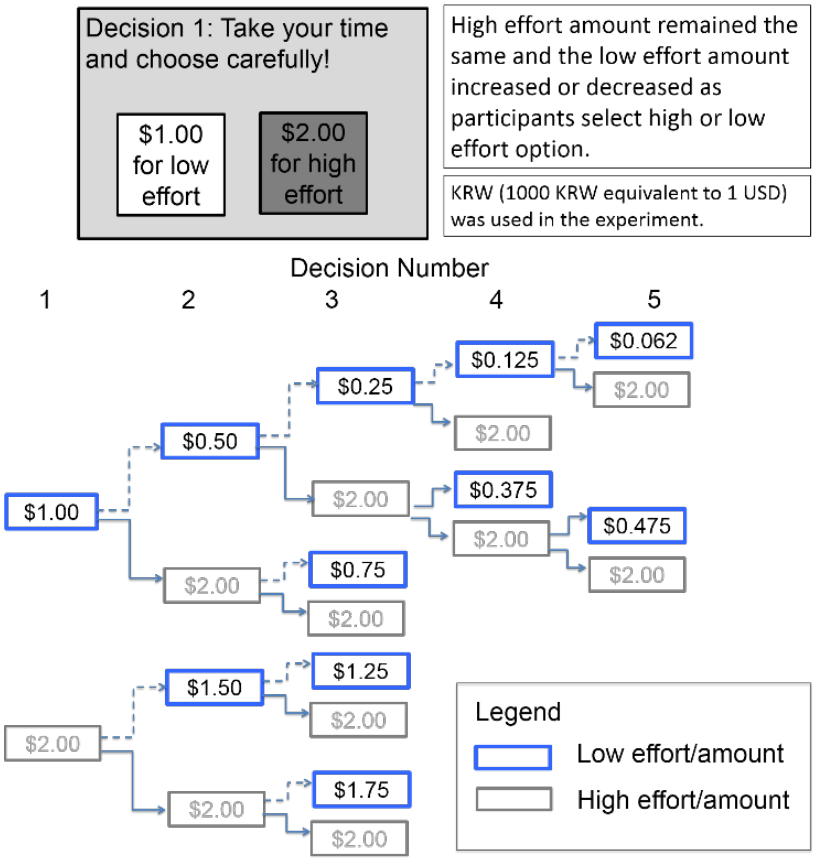

Figure 4. Cognitive Effort Discounting

In the cognitive effort discounting session, participants were presented with two choices of different monetary values, one for the low-demand task with an initial value of KRW 1000 (equivalent to USD 1) and the other for the high-demand task with an initial value of KRW 2000 (equivalent to USD 2). The value of a high-demand task is fixed, and the value of low-demand task changes as

participants make a choice. If a low-demand task is selected, the value of the low-demand task decreases, and if the high-demand task is selected the value of the low-demand task increases. The amount of change in percentage and in monetary value in each round are shown in table 1. For example, if a participant chooses a high-demand task in the first round, the choice options in the next round will be $ 1.5 for the low-demand task and $ 2 for the high-demand task. If participants choose the low-demand task at the second round, the reward of the low-demand task will be $ 1.25 and $ 2 for the high-demand task. In this way, participants make iterative choices between low- and high-demand tasks. The amount of change in the monetary value decreases by half of the previous round (Table 1). Since the amount of value change becomes 0 after the sixth round, proceeding further rounds becomes meaningless. As a result, the resulting value of the low-demand task is the subjective value of $ 2 reward for the high-demand task. It is also possible to calculate the indifference point, where the subject value of performing the two tasks are identical: the ratio between the value for the low-demand task and the high-demand task in the 6th round.

Round	Value Change (%)	Value Change (US dollar)
1	50	0.5
2	25	0.25
3	12.5	0.13
4	6.25	0.06
5	3.125	0.03
6	1.56	0.01

Table 1. Value Change in Each Round

Phase 3

Demand selection task (DST) was used to measure the tendency to avoid cognitive effort expenditure. The idea of DST is that as people tend to avoid to exert mental effort, their choice will be inclined to the less cognitively demanding task. This prediction has

been supported in various experimental settings, including experiments with healthy young adults (Desender et al., 2017; Dunn et al., 2016; Kool et al., 2010), children (Niebaum et al., 2018), and participants with mental disorder (Culbreth et al., 2018; Green et al., 2015; Reddy et al., 2015).

During this session, participants repeatedly select one of two stop signal tasks with different difficulty levels. Once a task is selected, participants performed the task 10 times. In this way, participants repeated the choice 25 times and performed 250 trials in total. In each trial, participants received scores that match the difficulty of the task if they correctly responded. In the low-demand task condition, participants received 5 points for each correct trial, whereas in the high-demand condition, they received 10 points for each correct trial. Therefore, it is more advantageous for participants to choose the low-demand task if the percent correct in the high-demand task is less than half of that in the low-demand task. Participants were asked to make choices so that the resulting score would be as high as possible.

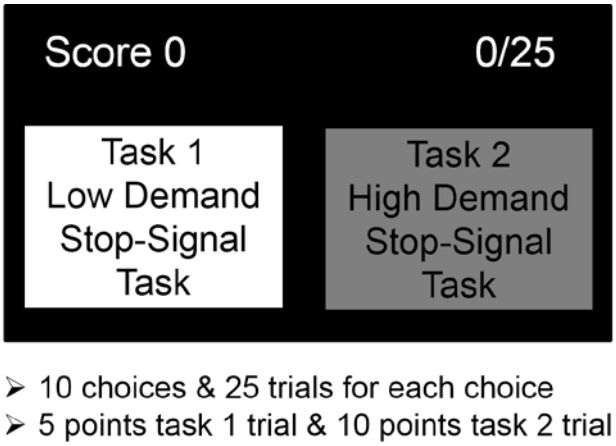

Figure 5. Demand Selection Task

Phase 4

After completing DST, participants perform a questionnaire asking motivation for task participation. The intrinsic motivation

inventory (IMI) was used to measure participants' task-specific intrinsic motivation toward the task. IMI is a self-report measure of motivation to assess motivational constructs relating to target activities. The scale has been used to assess situational intrinsic motivation in various studies, including sports, school, medical procedures, and laboratory studies (McAuley, Duncan, & Tammen, 1989; Markland & Hardy, 1997; Plant & Ryan, 1985).

The IMI assesses the participant's interests/enjoyment, perceived competence, effort, value/usefulness, felt pressure and tension, and perceived choice during the activity. This in turn yields six subscale scores, and each of them assess different aspects of intrinsic motivation. Among the six subscales, the interest/enjoyment subscale is considered a respondent's self-reported measure of intrinsic motivation. Perceived choice and perceived competence subset are theorized as positive predictors of intrinsic motivation, whereas pressure/tension subset is theorized as negative predictors. Thus, they are considered as a less direct measure of intrinsic motivation. Effort subset is a separate variable related to some motivational questions and is used when relevant to research questions. Value/usefulness subset is used in internalization studies (e.g., Deci et al, 1994) and are used to suggest that people are internalized and self-regulated in relation to activities they consider useful or valuable. The scale is comprised of 26 questionnaires, with 6 questionnaires for interest/enjoyment subscales and 5 questionnaires for others (see Appendix).

The distinction presented above suggests that intrinsic motivation is assessed by only one subscale, even though the overall questionnaire is called the Intrinsic Motivation Inventory. As each subscales measure slightly different aspects of intrinsic motivation, researchers often use only a part of the scale that are relevant to their research topic. In this experiment, we used interest/enjoyment subscale as a measure of participants' intrinsic motivation toward the task.

2.2. Result

Performance Assessment

Table 1 shows the overall performance assessments in both age groups. In both age groups, the mean RT of easy task was lower than that of difficult task. Differences in mean RT was significant in younger adults ($t = -4.62$, $p < .0001$), but not in older adults ($t = -0.91$, $p = .37$). SSRT of each participants was estimated by the integration method (Verbruggen & Logan, 2009). Theoretically, SSRT calculated by integrating go RT distribution from 0 to the point where the stop process is finished.

SSRT was shorter in high-demand task condition for both age groups, but the difference was statistically significant only in younger adults ($t = 2.67$, $p = .01$). Since the two demand conditions have different SSD, P(respond|signal) (i.e., probability of responding when a stop signal appears) was used as a measure of task performance in the same age group. t-test showed that both younger ($p<.0001$, $t=-29.385$) and older adults ($p = .0001$, $t = -4.7386$) performed more poorly on the high-demand (i.e., longer SSD) stop-signal task.

		RT		SSRT		P(respond|signal)	
Age	**Demand**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Younger	Low	754.6	56.78	276.78	59.14	0.05	0.06
	High	832.47	123.42	240.65	37.02	0.75	0.1
	p	< .0001		.01		< .0001	
	t	-4.62		2.67		-29.39	
Older	Low	837.77	157.86	399.28	133.87	0.39	0.3
	High	898.03	198.74	311.85	117.4	0.8	0.14
	p	.37		.06		.0001	
	t	-0.91		1.9		-4.74	

Table 2. Summary of Task Performance (Exp 1)

Effect of Motivation and Subjective Cognitive Cost on Task Performance

Firstly, we conducted a multiple regression analysis to see if there are main effect of intrinsic motivation level, subjective cognitive cost, and participants' age on SSRT. The result showed that age was statistically significant, $\beta = 99.198,\ t = 5.003, p < .0001$. Intrinsic motivation level was only marginally significant, $\beta = -18.57,\ t = -1.918, p = .0586$. The overall results of main effect analysis is shown in Table 3.

Variables	Value	SE	t	p
Intercept	258.183	11.648	22.165	< .0001***
Intrinsic Motivation	−18.57	9.683	−1.918	.0586
Subjective Cognitive Cost	−1.787	9.685	−0.185	.854
Age	99.198	19.828	5.003	< .0001***

Table 3. Result of Main Effect Analysis (SSRT), $\mathbf{R^2 = 0.2551, adj.R^2 = 0.228,\ F(3,47) = 9.362,\ p < .0001}$

A multiple regression analysis was conducted to test if age moderates the effect of intrinsic motivation level and subjective cognitive cost. A full model was fitted first, and the results showed that only age X motivation interaction was statistically significant, $\beta = -57.731$, $t = -2.63$, $p < .01$.

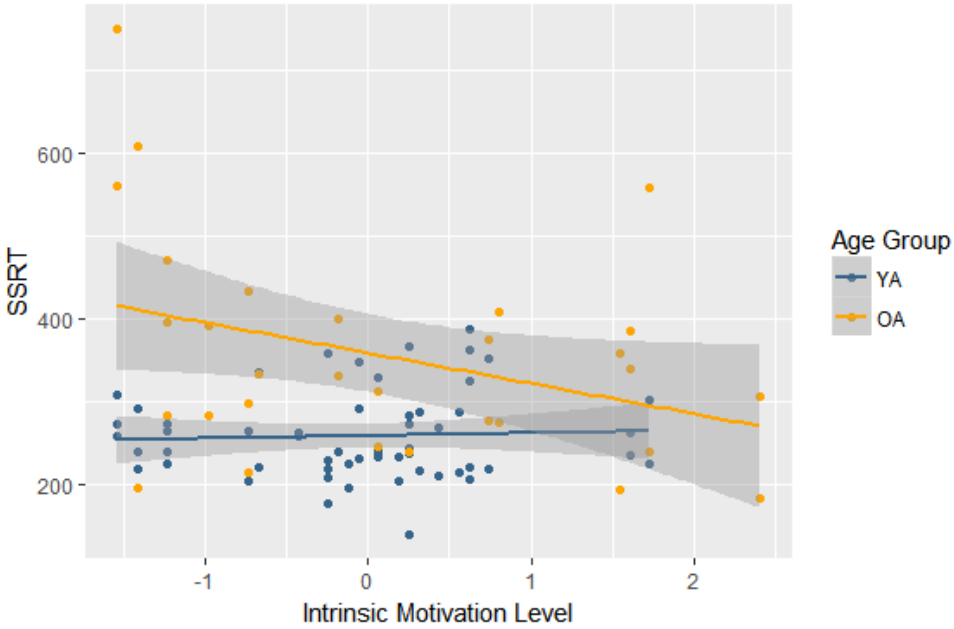

Figure 6. Regression Plot of Intrinsic Motivation Level and SSRT

Variables	Value	SE	*t*	*p*
Intercept	228.78	86.62	2.641	< .01**
Motivation level	7.95	21.94	0.36	.72
Subjective cognitive cost	−58.12	80.89	−0.72	.47
Age	444.33	135.25	3.29	.0015**
Motivation X Cost	13.83	19.46	0.71	0.48
Motivation X age	−88.96	33.83	−2.63	.01*
Cost X age	−16.19	146.8	−0.11	.91
Motivation X cost X age	13.06	37.44	0.35	.73

Table 4. Result of Interaction Effect Analysis (SSRT), $\mathbf{R^2 = 0.318}$, $\mathbf{adj.R^2 = 0.26}$, $\mathbf{F(7,47) = 5.198}$, $p < .0001$

Effect of Motivation and Subjective Cognitive Cost on Effort Avoidance

The result of multiple regression analysis showed that there was a significant association between intrinsic motivation level, cognitive cost, age and effort avoidance, $\chi^2(3) = 54.77,\ p < .001$. Both intrinsic motivation level, β =0.29, z = 6.34, p < .0001, and subjective cognitive cost, β =−0.22, z = −4.82, p < .0001 had significant main effect on the effort avoidance (proportion of high−demand task chosen). Age, on the other hand, had no significant effect on the effort avoidance, β =−0.001, z = −0.02, p =.99.

Variables	Value	SE	z	p
Intercept	0.1	0.05	1.89	.058
Motivation level	0.29	0.05	6.34	<.001***
Subjective cognitive cost	−0.22	0.05	−4.82	<.001***
Age	−0.001	0.09	−0.02	.987

Table 5. Result of Main Effect Analysis (effort avoidance), $\chi^2(3) = 54.77,\ p < .001$

To see how participants' age affected the relationship among the three variables—effort avoidance, intrinsic motivation, and cognitive cost, a multiple regression analysis with interaction terms was conducted. The results showed that age was found to moderate the effect of intrinsic motivation level on demand selection ratio ($\beta = -0.17$, p < .01). Subjective cognitive cost predicted demand selection ratio ($\beta = 0.87$, p = .03), which indicate that less cost on high−demand task increased the selection ratio of high−demand task. However, there was no meaningful difference in age groups on the effect of cognitive cost on demand selection ratio.

Variables	Value	SE	z	p
Intercept	0.08	0.05	1.45	.148
Intrinsic Motivation level	0.09	0.07	1.34	.18
Subjective cognitive cost	−0.17	0.05	−3.06	<.01**
Age	0.24	0.12	2.01	<.05*
Motivation X Cost	−0.17	0.06	−2.68	<.01**
Motivation X age	0.6	0.11	5.44	<.001***
Cost X age	−0.54	0.13	−4.06	<.001***
Motivation X cost X age	−0.25	0.13	−1.95	.051

Table 6. Result of Interaction Effect Analysis (effort avoidance), $\chi^2(7) = 99.24,\ p < .001$

2.3. Discussion

Our primary interest in Experiment 1 was to examine whether intrinsic motivation level and subjective cognitive cost can predict participants' effort avoidance. Overall, the result of Experiment 1 support the initial hypothesis that age differences in intrinsic motivation and subjective cognitive cost predict participants' effort avoidance. The result showed that participants' subjective cognitive effort and their intrinsic motivation toward the task have impact on counteracting effort avoidance, specifically for older adults. The result of multiple logistic regression analysis indicated that, considering participants' age alone, the tendency of effort avoidance appeared to be greater in older adults than in younger adults ($\beta = -3.43, p < .001$). In addition, intrinsic motivation level ($\beta = 0.14, p =$

0.18) did not predict participants' effort avoidance by on its own. However, the effect of intrinsic motivation level on effort avoidance was moderated by age ($\beta = 0.93, p < .0001$), suggesting that older adults were affected by their intrinsic motivation level when they choose to participate in a more demanding task. Subjective cognitive cost predicted participants' effort avoidance ($\beta = 0.87, p = .03$).

However, interaction effect of age and subjective cognitive cost was not significant ($\beta = 0.96, p = .2$), contrary to previous findings that the effect of objective load on subjective cost was higher in older adults (Piquado, Isaacowitz, & Wingfield, 2010; Smith & Hess, 2015; Westbrook, Kester, & Braver, 2013). This contradictory result might be due to different task paradigm. In previous studies, age differences in cognitive effort were assessed using either memory recall tasks (memory search task, digit span task) or working memory task (e.g., N-back task). In this experiment, however, stop-signal task was used to test participants' effort aovidace. Although previous studies indicate age differences in stop-signal task performance (Christ et al., 2001; Ridderinkhof, Band, & Logan, 1999), individual differences may exist in the degree of awareness of the cue. Considering the accumulating empirical evidences on the role of metacognitive evaluation on effort avoidance (Desender et al., 2017; Dunn, Gaspar, & Risko, 2018; Dunn, Lutes, & Risko, 2016), awareness of required effort may be a source of the discrepancy. Although participants' rated their subjective value of each demand levels, one-time evaluation might not enough as a cue in the subsequent selection task.

Chapter 3. Experiment 2

3.1. Method

Participants

Twenty-six younger participants were recruited through the Seoul National University's online research participation system, and twenty-three older participants were recruited from the local senior center. The age of the younger participants ranged from 19 to 30 (Mean = 22.8, SD = 3.4) and the age of older participants ranged from 65 to 88 (Mean = 76.7, SD = 8.9). For younger participants, it was a part of course requirements to participate in experiments, thus no incentive for the participation were given. Older participants were given 10,000 KRW (equivalent to USD 10) for their participation in the experiment. The study was approved by the Institutional Review Board (IRB) of Seoul National University.

Drift Diffusion Model

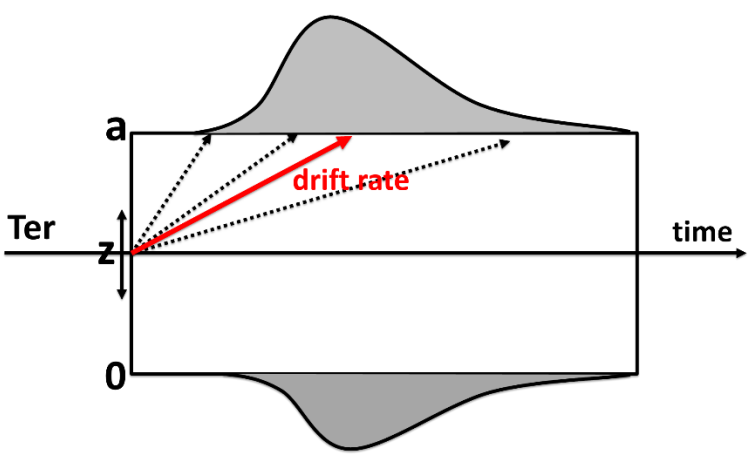

Figure 7. Drift Diffusion Model

The Drift Diffusion model (DDM) is one of the most widely used computational model to analyze behavioral data. DDM is a

computational model for analyzing the ratios and time distributions of the positive and false responses obtained from the cognitive task of speeded binary choice tasks (Ratcliff, 1978; Ratcliff & McKoon, 2008). In DDM, decision process is assumed to be an evidence accumulation which continues until a certain level of evidence reaches the decision criteria. In addition to the evidence accumulation process, the DDM also assumes that the accumulation is noisy. Consequently, the time of the evidence reaching the decision boundary is bound to change from trial to trial, forming a distribution of decision times.

There are several sources that causes the variance in decision time. One of them is the starting position of the accumulation process. When the process starts near the decision boundary, it is more likely for the process to reach that boundary faster than when the process starts at a distance. Another factor is the location of the decision boundary. If the boundary is set close to the starting position of the decision process, the decision will be faster than when the boundary is far from it. The last factor is the velocity of the accumulation process itself. When the velocity of the evidence accumulation is fast, it is more likely to reach the boundary earlier than when it is slow. This rate is called the drift rate (v). DDM also includes encoding and motor response in the model. These are considered as a non-decision processes, and the total reaction time (RT) is the sum of the decision time (DT) and the non-decision time (ter).

Model Parameters

Diffusion model is comprised of six parameters.

One thing that is important about DDM is that the model parameters directly reflect experimental manipulations (Voss, Rothermund, & Voss, 2004). As stated above, there are various sources that cause variation in model parameters. If there is a systematic deviation of the parameter values from that of a neutral condition, it is considered there is bias in the related cognitive processes. In DDM, response biases are often modeled either by the changes in drift rate or the changes in the starting point (Leite &

Ratcliff, 2011), and it is suggested that response bias in the context of DDM can be distinguished in either perceptual or judgmental bias (Voss, Rothermund, & Brandtstädter, 2008). Perceptual bias relates to the process of information uptake, reflected in increased drift rate toward the biased response. On the other hand, judgmental bias relates to the changes in the acceptance criteria of the accumulated information, reflected in the change in decision threshold parameter.

In this study, the DDM parameters were estimated by using SNUDM (Koh, Choo, Lee; in preparation). Using this program, we approximated discrete random walk process to continuous one, following Ratcliff's original method (Ratcliff, 1978). Specifically, when the parameters of the diffusion process are determined, a large number of discrete random walks are simulated to generate a time distribution, and the optimal parameter values are found by comparing the simulated distribution with the actual time distribution from the experimental data. We used Simplex method to estimate the optimal parameter values given the initial values (Nelder & Mead, 1965; Luersen, M. A., et al., 2003). The initial parameter values were calculated using EZ-diffusion (Wagenmakers, van der Maas, & Grasman, 2007). The Simplex method was implemented using the open-source C code downloaded from http://www.mikehutt.com.

Procedure

As experiment 1, the procedure in experiment 2 was comprised of 4 phases.

Phase 1 & 2

Phase 1 and phase 2 were identical to experiment 1.

Phase 3

In phase 3, participants performed stop-signal task. Unlike experiment 1, participant had no free choice between low- and high-demand tasks. Participants performed 150 trials of the low-demand task and high-demand task, respectively. Thus, all participants

performed 300 trials of stop-signal task in total. The sequence of the task demand was randomized.

Phase 4

Phase 4 was identical to experiment 1.

3.2. Result

Assessment of Performance

		RT		SSRT		P(respond|signal)	
Age	**Demand**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Younger	Low	708.84	73.03	273.87	79.09	0.13	0.08
	High	832.84	82.4	285.36	44.93	0.52	0.15
	p						
	t						
Older	Low	798.16	170.37	448.32	180.57	0.38	0.31
	High	894.97	185.32	332.71	148.6	0.68	0.2
	p						
	t						

Table 7. Summary of Task Performance (Exp 2)

Table 4 shows the overall performance assessments in both age groups. In both age groups, the mean RT of easy task was lower than that of difficult task. Differences in mean RT was significant in younger adults ($t = -4.62$, $p < .0001$), but not in older adults ($t = -0.91$, $p = .37$). For younger adults, SSRT in high-demand task condition was longer than in low-demand task condition. For older adults, SSRT in high-demand task was shorter than in low-demand task, but the difference was statistically significant only in younger adults ($t = 2.67$, $p = .01$). T-test showed that both younger ($p<.0001$, $t=-29.385$) and older adults ($p = .0001$, $t = -4.7386$) performed more poorly on the high-demand (i.e., longer SSD) stop-signal task.

Diffusion Model Analysis

Parameters	YA	OA
a	0.25 (0.05)	0.22 (0.07)
z	0.15 (0.04)	0.12 (0.05)
sz	0.04 (0.04)	0.07 (0.06)
ter	0.59 (0.11)	0.62(0.16)
ster	0.29 (0.1)	0.2 (0.12)
drift (low−demand)	0.77 (0.23)	0.5 (0.2)
drift (high−demand)	0.45 (0.04)	0.39 (0.12)
eta	0.08 (0.06)	0.1 (0.07)

Table 8. Results of Diffusion Model Analysis

Relative starting point

Variables	Value	SE	z	p
Intercept	0.82	0.17	4.7	> .0001***
Motivation level	−0.06	0.04	−1.49	.15
Subjective cognitive cost	−0.39	0.27	−1.47	.15
Age	−0.34	0.31	−1.09	.28
Motivation X Cost	0.11	0.06	1.78	.08
Motivation X age	0.07	0.08	0.94	.35
Cost X age	0.57	0.49	1.18	0.25
Motivation X cost X age	−0.15	0.12	−1.2	0.24

Table 9. Result of Multiple Regression (relative starting point)

Following Voss et al. (2008), we calculated the relative starting

point as z divided by a (z/a), for which the value of 0.5 indicates a starting point located in the midpoint between the thresholds. The relative starting point can be used to determine whether the participants' decision criteria changes as a function of their motivation toward the task.

A multiple regression analysis was conducted to test if the internal motivation level and subjective cognitive cost significantly predicted the variation in the relative starting point in each age groups. The result showed that the relative starting point has no relationship with any predictors.

Drift rates

Variables	Value	SE	t	p
Intercept	0.94	0.34	2.73	.009**
Motivation level	−0.004	0.08	−0.05	0.96
Subjective cognitive cost	−0.61	0.53	−1.15	0.25
Age	−1.16	0.62	−1.88	.067
Motivation X Cost	0.09	0.13	0.71	0.48
Motivation X age	0.18	0.16	1.12	0.27
Cost X age	1.26	0.96	1.3	0.2
Motivation X cost X age	−0.23	0.24	−0.97	0.34

Table 10. Result of Multiple Regression (drift rate in low−demand trials) $R^2 = 0.4,\ \text{adj}\ R^2 = 0.3,\ F(7, 41),\ p = .002$

At first, t−test was conducted to see if there is a difference in drift rate between age groups. As Table 5 shows, the average values of drift rate in both demand conditions were higher in younger adults

(t = 4.11, df = 46.93, p < .001; t = 2.37, df = 26.8, p =.02). Moreover, the difference of the drift rate between age groups was also significant (t = 3.22, df = 46.67, p = .002).

As with relative starting point, a multiple regression analysis was conducted to test if the internal motivation level, subjective cognitive cost, and age predicted drift rate. The analysis was conducted on the drift rate in low- and high-demand trials separately. Additional analysis included the difference between the drift rate of low- and and high-demand task as a response to see if the predictors affects the change in drift rate in different demand conditions.

Variables	Value	SE	t	p
Intercept	0.36	0.13	2.69	.0104*
Motivation level	0.02	0.03	0.69	.49
Subjective cognitive cost	0.08	0.2	0.4	.69
Age	−0.42	0.24	−1.75	.08
Motivation X Cost	−0.02	0.05	−0.44	.66
Motivation X age	0.1	0.06	1.66	.1
Cost X age	0.68	0.18	3.604	< .001***
Motivation X cost X age	−0.19	0.09	−1.99	.05

Table 11. Result of Multiple Regression (drift rate in high-demand trials)

The result showed that drift rate in low-demand trials was not predicted by internal motivation and cognitive cost. Only age showed a marginal significance ($\beta = -1.16, p = .067$). In high-demand trials, intrinsic motivation level ($\beta = 0.02, p = .49$) and cognitive cost ($\beta = 0.08, p = .69$) failed to predict the drift rate. On the other hand, age

($\beta = -0.42, p = .08$) appeared to be marginally significant, and interaction term between cognitive cost and age was a significant predictor of drift rate ($\beta = -0.68, p < .001$). Also, three-way interaction among intrinsic motivation, cognitive cost, and age was also marginally significant ($\beta = -0.18, p = .054$). Additional analysis showed that intrinsic motivation level, subjective cognitive cost, and age did not predict the change of drift rate in both age groups. The result of the analysis is presented in Table 9.

Variables	Value	SE	t	p
Intercept	0.79	0.45	1.77	0.08
Motivation level	−0.11	0.1	−1.17	0.25
Subjective cognitive cost	−0.8	0.56	−1.42	0.16
Age	−0.81	0.5	−1.62	0.1
Motivation X Cost	0.2	0.12	1.63	0.1
Motivation X age	0.12	0.11	1.05	0.29
Cost X age	0.52	0.74	0.7	0.48
Motivation X cost X age	−0.08	0.17	−0.53	0.6

Table 12. Result of Multiple Regression (drift rate difference)

3.3. Discussion

The primary goal of experiment 2 was to investigate the effect of intrinsic motivation and subjective cognitive cost of the task on the basic cognitive processes. Specifically, we aimed to examine whether

intrinsic motivation also act like extrinsic reward on the information processing. Specifically, we hypothesized that participants' drift rate will increase as a function of their motivation level and subjective cognitive cost. We also hypothesized that the magnitude of this relationship will be larger in older adults compared to younger adults.

We used diffusion model to test these hypotheses. The result partially support the two hypotheses. The effect of proposed predictors was found only in high-demand trials. In high-demand trials, the effect of subjective cognitive cost was moderated by age ($\beta = 0.68, p < .001$), indicating the efficiency of decision process was increased as their subjective cost toward high-demand task decreases. Although the age × motivation interaction was nonsignificant, the results suggest that older adults may be affected more by their intrinsic motivation, given that a close relationship between intrinsic motivation and subjective cognitive cost (Hess et al., 2018).

Chapter 4. General Discussion

The goal of this study was twofold: a) to investigate the age differences in the effect of intrinsic motivation and cognitive cost on effort avoidance, and b) to investigate its underlying cognitive mechanism. Specifically, we sought to examine whether the motivational influence on the cognitive processing is related to judgmental bias or perceptual bias. To this end, we conducted demand selection task, in which older and younger participants chose either low- or high-demand stop-signal tasks. The percentage of high-demand task chosen was used as an indicator of participants' effort avoidance tendency. In experiment 2, we analyzed the stop-signal performance data using Ratcliff's drift diffusion model. This allowed us to analyze the accuracy and reaction time simultaneously. Also, diffusion model allowed us to decompose the reaction time data into several subcomponents, providing more insights on the underlying cognitive processes during the task.

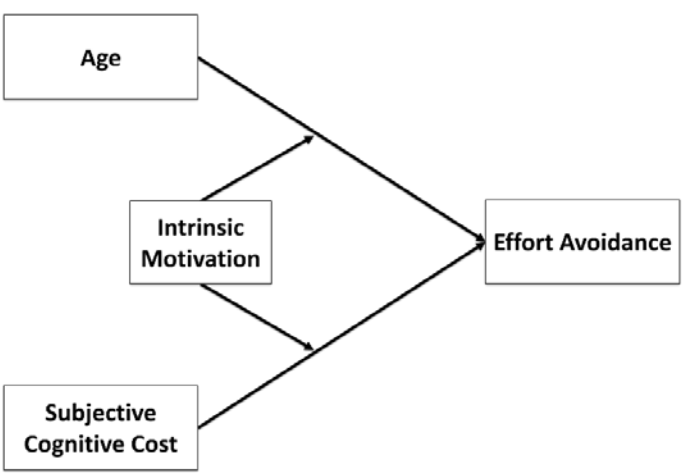

Figure 8. Possible Relationship of Motivation, Cognitive cost and Age

In Experiment 1, Mean RT differences were observed only in younger adults, but SSRT and P(respond|signal) differences by demand was observed in both age groups. With respect to task performance (SSRT), Age was a significant predictor. Also, Age moderated the effect of intrinsic motivation on task performance.

With respect to effort avoidance tendency, subjective cognitive cost, but not intrinsic motivation level, showed significant main effect on effort avoidance tendency. Intrinsic motivation level, however, appeared to have significant interaction effect with Age, meaning that intrinsic motivation level predicted effort avoidance pattern only in older adults. The implication of these results can be summarized in 3 points (Figure 6). First, as previous studies showed, the result of Experiment 1 support the claim that effort avoidance is the result of comparison between the cost of exerting effort and the benefit of participating cognitively demanding activities, with decreasing cost increases the tendency of choosing the high-demand task. Second, Age itself is negatively related to the effort avoidance tendency. In other words, effort avoidance tendency increased as a function of Age. Third, intrinsic motivation level moderates the effect of cognitive cost and Age on effort avoidance tendency. In particular, increasing level of intrinsic motivation reduced the effect of cognitive cost and Age on effort avoidance tendency. In contrast, intrinsic motivation and cognitive cost did not predicted stop-signal task performance, though motivation showed an interaction effect with Age.

In Experiment 2, the results of diffusion model analysis showed that there is no relationship between intrinsic motivation, subjective cognitive cost, and relative starting point (i.e., judgmental bias). Thus, excluding the possibility that intrinsic motivation and cognitive cost has no relationship with participants' top-down cognitive control. We next examine whether intrinsic motivation and cognitive cost have a systematic relationship with drift rates. Given that increased drift rate can be a result of enhanced error monitoring (Saunders et al., in press), systematic relationship between drift rate and intrinsic motivation may suggest that intrinsic motivation enhances perceptual processing. The results showed that drift rate in high-demand trials increased as participants' intrinsic motivation level increased, and this relationship was valid only for older adults. Interestingly, drift rate in low-demand trials did not show similar relationship. Based on these results, it is not likely that intrinsic motivation enhances

perceptual processing. Rather, as Shenhav et al. (2017) suggested, intrinsic motivation may act like increasing the likelihood of exerting more cognitive resources when there needs to do so. In other words, when the task is easy (shorter SSD), no motivational influences were detected since it is not necessary to exert extra cognitive resources. On the other hand, when the task is difficult (longer SSD), only intrinsically motivated people can exert more resources. This is typically the case for older adults, who are often characterized as limited inhibitory control (Rey-Mermet & Gade, 2018).

There are a few limitations to resolve in future research. First, due to the limited effect of motivation manipulation, the results are at best correlational, not causal. Although there are some experimental manipulations that are known to be effective in enhancing intrinsic motivation (Lerner & Tetlock, 1999), it is not always effective and due to large individual differences. Instead directly manipulating intrinsic motivation, using personal trait (e.g., curiosity, need for cognition, etc.) can be an alternative.

Second, since the demand selection task (Experiment 1) and diffusion model analysis (Experiment 2) were conducted in separate experiments, it is not possible to directly like the change in cognitive processing to effort avoidance tendency. Although we collected reaction time data when participants choose between two task alternatives, it was not possible to conduct diffusion model analysis due to its small sample size (n=25). Also, the choice between low- and high-demand tasks were autonomous, the majority of the RT was longer than 2000ms, which are not appropriate for diffusion modeling.

Third, the result of diffusion model analysis was limited in that it only use go trials (i.e., trials that participants responded). Thus, the analysis could not incorporate the trials where participants correctly or incorrectly stopped. Since whether participants correctly stopped during when stop signal presented is a major indicator of inhibitory control performance, including these trials in the analysis would give us more insight on the relationship between intrinsic motivation and inhibitory control task performance.

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Appendix

Intrinsic Motivation Inventory (IMI)

Interest/Enjoyment

1. I enjoyed doing this activity very much.
2. This activity was fun to do.
3. I thought this was a boring activity. (R)
4. I would describe this activity as very interesting.
5. I thought this activity was quite enjoyable.
6. While I was doing this activity, I was thinking about how much I enjoyed it.

Perceived Competence

7. I think I am pretty good at this activity.
8. I think I did pretty well at this activity, compared to other students.
9. After working at this activity for a while, I felt pretty competent.
10. I am satisfied with my performance at this task.
11. I was pretty skilled at this activity.

Effort/Importance

12. I put a lot of effort into this.
13. I didn't try very hard to do well at this activity. (R)
14. I tried very hard on this activity.
15. It was important to me to do well at this task.
16. I didn't put much energy into this. (R)

Pressure/Tension

17. I did not feel nervous at all while doing this. (R)
18. I felt very tense while doing this activity.
19. I was very relaxed in doing these. (R)
20. I was anxious while working on this task.
21. I felt pressured while doing these.

Perceived Choice

22. I believe I had some choice about doing this activity.
23. I felt like it was not my own choice to do this task. (R)
24. I did this activity because I had no choice. (R)
25. I did this activity because I wanted to.
26. I did this activity because I had to. (R)

국문초록

부하 선택 과제에서의 인지-동기 상호작용의 연령 차이

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인간은 불필요한 노력을 피하려고 하는 경향이 있다. 실험 1에서는 이러한 노력 회피 경향에 대한 나이 차이에 동기부여 수준이 미치는 영향을 연구하기 위해 정지 신호 과제 (stop-signal task)와 함께 부하 선택 과제 (demand selection task)를 사용하였다. 실험 2에서는 확산 모형 (drift diffusion model; DDM)을 사용하여 동기부여 수준이 행동에 기저하는 인지 과정에 어떤 영향을 미치는지를 분석하였다. 연구 결과, 참여자들은 내적 동기부여 수준이 증가함에 따라 인지적 노력을 많이 요구하는 과제를 더 자주 선택하는 경향이 있음을 보였다. 이러한 내적 동기부여 수준과 노력 회피 경향 사이의 관계는 노인 참여자들에 대해서만 유의미하게 나타났다. 또한, DDM 분석 결과는 내적 동기부여 수준이 지각적 처리의 효율성을 향상시키는 역할을 한다는 가설에 대한 부분적인 증거를 제공하였다.