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Cognitive and Affective Influences on Decision Quality

Original Research

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Abstract

Introduction: Cognitive and affective factors influence decision outcomes, but few studies have examined both factors simultaneously. Study 1 used cluster analysis to test whether affective profiles related to decision domains could be identified as individual difference factors. Study 2 extended these findings to test whether such profiles can predict decision quality.

Methods: We analyzed importance and meaningfulness ratings from 1123 adults regarding four low-frequency but high-salience decisions. Profile analyses revealed three meaningful profiles. A subset ($n = 56$) of adults completed quasi-experimental decision tasks in two of these domains.

Results: Hierarchical regression examined the contributions of the affective cluster from Study 1 and executive functions to decision quality. We first regressed decision quality onto an index of executive function (F (1, 53) = 4.57, p = .037). At Step 2, affective cluster accounted for an additional 12.5% of the variance in decision quality, F_{change} (2, 51) = 4.01, p = .024. The overall model retained its significance, F (3, 51) = 4.37, p = .008, R^2 = .205.

Conclusions: Together, Study 1 and 2 demonstrate that affective components related to the decision domain can be used as individual difference factors and that these account for unique variance in decision outcomes.

Key Words: Decision-making, Cluster Analysis, Age Differences

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Introduction

Consumer decisions are influenced by both cognitive and affective factors [1, 2]. This "dual process" approach has received significant attention in recent years [3]. However, the interplay between affect and cognition in the area of decision making is complex and each of these systems may exert different influences on decision outcomes. Despite their importance, affective influences in decision making have received less empirical attention than cognitive resources. One reason that investigations of the influence of affective factors have not progressed may relate to the lack of measures of global affective components that can be used across different decision domains. To date, most investigations of affect in decision making have relied on domain-specific affect or state-dependent mood. Individuals are more likely to make a positive appraisal about a decision when they feel positive affect [4], but the influence of affective factors may extend far beyond momentary or domain-specific effects [3]. Thus, the aim of this study was to develop an index of affective factors in decision making that could be used across domains, allowing an examination of the effect of these dual process factors on decision quality. We sought to use cluster analyses related to pre-existing perceptions of how meaningful and important specific decision domains were to the individual.

Among the cognitive resources that influence decision making, measures of expertise and **e**xecutive functioning have been studied most frequently. Executive functioning involves higher-order processes related to an individual's ability to set goals, plan, switch attention, and adjust their behavior accordingly. As people age, changes are often observed in executive functions [5]. Affective changes are also observed with aging, with older adults placing higher value on emotionally meaningful experiences relative to younger adults [6]. This aspect of aging and decision making has not been well-studied, however.

A limitation to the extant literature on emotion and decision-making lies in its neglect to consider other affective aspects of the decision-making context beyond mood state. The seminal work by Blanchard-Fields, Jahnke and Camp [7] demonstrated that the emotional salience of a domain interacts with one's approach to and resolution of a variety of real-world problems. Individual values and experience may also influence one's decisions. Thus, the field of decision making could benefit from an expanded investigation of affective factors in decision outcomes. We propose using person-centered approaches, such as cluster or profile analyses, to investigate whether one's affective orientation to different decision domains can act as a stable affective predictor.

Other limitations in the field relate to tasks used to assess decision making. Lab-based decision tasks ask individuals to choose a target (e.g., a car, a home) for themselves [1, 2] or others [1]. Decisions for others often are offered within the context of a vignette, in which the needs and preferences of the target person can be made explicit and are the same for all participants, allowing a more precise assessment of decision quality [1]. Consumer-based investigations also bring an element of reality to the task because materials can be developed in such a way as to capitalize on the interrelations among features as they exist in the real world. Information matrices can be developed in which one can compare various alternatives on a variety of features. For example, a consumer choosing among several automobile alternatives might compare them on specific features, such as price, reliability, attractiveness and fuel efficiency. In the standard decision-making task, vignettes and information matrices are developed to reflect those found outside the lab. A panel of experts from each domain (e.g., automobiles, senior housing) ranks the "best choice" for the target person, given the needs, resources and preferences presented in the vignette. Participants are asked to select the best choice for the person presented in the vignette; close agreement with the experts is considered to be a measure of decision quality [1]. Although other approaches to determining decision quality include awarding points for choosing the alternative with a higher ratio of positive to negative attributes [8], there are strengths to using an expert panel. Relying on a count of the number of positive attributes may overlook differences in personal values. In addition, some features may be more important to a good decision than others; a single negative attribute in a critical feature might outweigh several positive attributes that are less central.

Thus, adjusting the lab-based tasks to more closely reflect the real world, focusing on individual differences in the affective qualities of the decision domain, and simultaneously examining cognitive influence may enable researchers and clinicians to help adults integrate the most important aspects of a decision, while also acknowledging an individual's personal values. In addition to examining both cognitive and affective influences on decision making, the field has expanded its focus to include interactions with a variety of individual difference variables. In terms of adult age differences in the contributions of cognitive versus affective factors in decision making, Socioemotional Selectivity Theory suggests that older adults value emotional information and outcomes more highly than they value knowledge-related experiences [6]. A deep literature supports the idea that older adults and younger adults differ in their decision-making approach and in outcomes [1, 9]. Other individual difference factors, such as gender [9] and personality [10], also influence decisions in the real-world.

Scientific Methods

Study 1

Participants

Data for Study 1 are drawn from a larger study; other unrelated reports have been disseminated from this data set [11]. Of note, our Institutional Review Board approved all procedures.

A total of 1187 people completed a prescreen survey. After removing three participants who were younger than age 18 years and 64 adults who did not disclose age, our analytic sample included 1123 adults. The sample included adults ages 18 to 87 years (Mean = [2]5.35, SD = 12.2). Although 45.4% were ages 18 and 19 years of age, 29.6% were ages 20 to 24 years, 13.5% were ages 25 to 44 years, 10.5 % were ages 45 to 64 years, and one percent were ages 65 years or older. Among the adults, 68.9% were female, 21.1% were male, and 12.6% did not report gender/sex. Similar to the racial composition of the state, most were white (90%), although 2.2% were Black, 0% were Asian, 0.2% were American Indian/Native Alaskan, 2.5% were Native Hawaiian/Pacific Islander, 2.1% reported "Other", and 2.9% identified as multi-racial.

Protocol

Adults reported their age in years. We used age as a continuous variable and as a grouping variable. We examined age group differences, with groups formed at meaningful developmental stages. We compared late adolescents (ages 18 – 19 years), emerging adults (ages 20 to 24 years), younger adults (ages 25 to 44 years), and middle-aged and older adults (ages 45+). Descriptive statistics for these demographic variables are shown in Table 1.

We focused on four domains that represent low-frequency but high-salience decisions and which have been investigated in previous research [1, 7, 8]. Specifically, we included decisions about a place to live, a school to attend, an automobile to buy, and a health insurance policy in which to enroll. For each decision, participants were asked to use a 5-point Likert-type scale to rate the domain on Importance (Not Very Important to Very Important) and Meaningfulness (ranging from Not Very Meaningful to Very Meaningful). Means are presented in Table 1.

In addition to demographics of age, sex, and race, we included personality dispositions as potential covariates. Only 823 of the 1123 adults completed the 30-item Midlife Development Inventory Personality Scale (MIDI-PS) [12]. The MIDI-PS has acceptable convergent validity with other measures of the Big Five. Correlations between the MIDI-PS and the NEO-PI-R [13] are above .70 for neuroticism, extraversion, and conscientiousness; correlations are greater than .60 for openness. However, correlations between the two scales are lower ($r = .42$) for agreeableness [12]. As shown in Table 1, our means, standard deviations and Cronbach alpha indices were acceptable and comparable to those reported by Lachman and Weaver [12].

Table 1. Descriptive Statistics for the Study 1 Sample

	Mean	SD	Alpha
Age	25.4	12.2	
Sex (% female)	75.0		
Race (% White)	90.0		
Importance/Home	4.9	.4	
Meaningfulness/Home	2.1	1.6	
Importance/School	4.5	1.0	
Meaningfulness/School	2.3	1.4	
Importance/Car	3.8	1.1	
Meaningfulness/Car	2.8	1.3	
Importance/Insurance	4.5	.9	
Meaningfulness/Insurance	2.6	1.5	
Neuroticism	2.6	.7	.68
Extraversion	3.3	.6	.74
Openness	3.5	.5	.68
Agreeableness	3.2	.5	.80
Conscientiousness	3.4	.5	.61

Alt-text: A table of means, standard deviations, and alphas.

Statistical Analysis

Analyses were conducted using SPSS 27.0 [14]. Inspection of the univariate statistics showed that age, gender and race were highly skewed and kurtotic. Because we intended to examine age groups, we left age untransformed. Similarly, because we anticipated using Z-scores for the cluster analyses and Spearman's rho for correlations, we did not transform Importance ratings for Homes, School, or Insurance, each of which was skewed and kurtotic.

Our primary analysis was a two-step cluster analysis. Following the recommendations by Hair and Black [15], we formed clusters with the goal of maximizing within-group similarity and maximizing between-group differences by using

Ward's Method and the squared Euclidian distances. We then conduced a K-means cluster analysis to examine the hierarchical cluster solution found in step 1. Finally, we examined age and personality differences among the clusters.

Study 1 Results

Cluster Analysis

To determine the appropriate number of clusters, a hierarchical cluster analysis was conducted, using the importance and meaningfulness ratings for the four domains. Both the scree plot and dendogram indicated that a three-cluster solution was appropriate. We also examined other solutions based on the dendogram, using the K-means approach. The three-cluster solution did not have equal numbers of cases in each group, although this cluster solution seemed to have utility. Cluster 1 included 699 adults (64.1%) who were generally low to moderate in their ratings of importance and emotional meaningfulness across the four domains. The second cluster was comprised by 144 adults (13.2%) whose scores on meaningfulness of a housing decision were moderately high, but who rated most other domains as less meaningful and not very important. The third cluster contained 247 adults (22.7%) who rendered high meaningfulness ratings for decisions related to living environments, schools, and insurance policies. A graph of these clusters is presented in Figure 1.

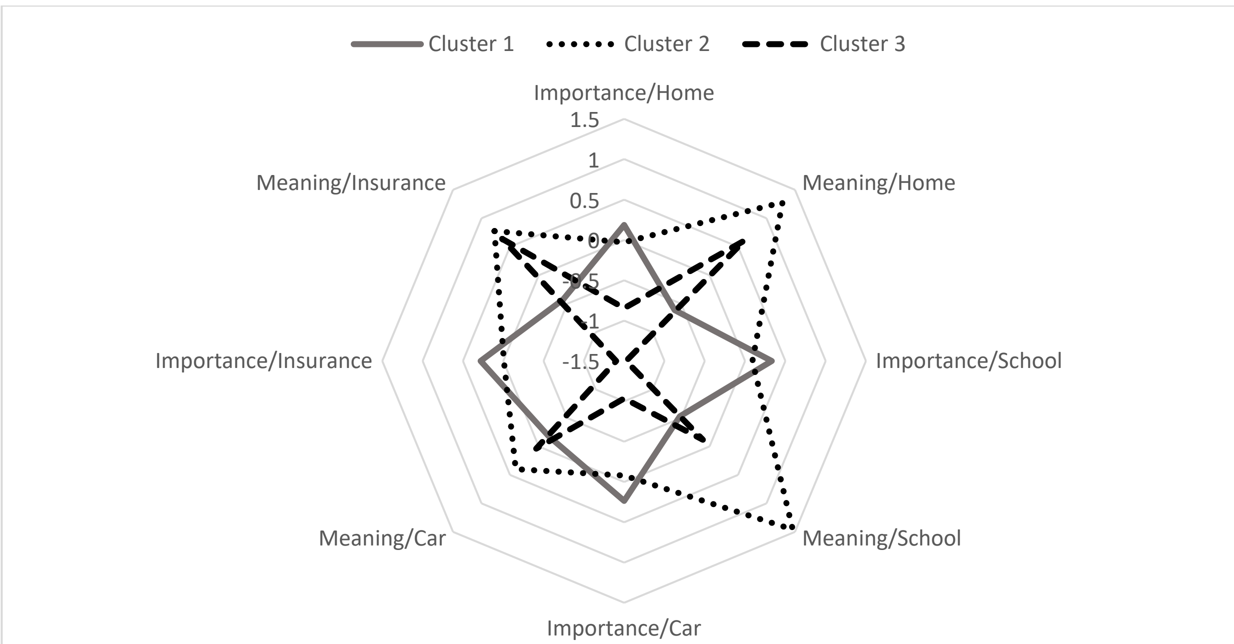

Figure 1.
Clusters are differentiated by Z-scores of importance and meaningfulness ratings.
Alt-text: A radar graph depicting differences across the three clusters

Due to the over-representation of late adolescents and emerging adults in our sample, we examined whether age group interacted with cluster membership using a 4 (age group) by 3 (cluster) cross-tabulation. Age was not equally distributed across the affective clusters, X^2 (DF = 6) = 512.97, $p < .001$. The majority of late adolescents (88%) and emerging adults (72%) were included in Cluster 1, with its overall low-to-moderate ratings across domains. In contrast, the majority of younger adults (59.7%) and middle-aged and older adults (68.1%) were included in Cluster 3, with its higher emotional meaningfulness for living arrangement, school, and insurance policy decisions.

We examined whether gender differences and race differences were present across cluster membership. Significant gender differences in cluster group composition were not detected, X^2 (DF = 2) = 0.18, $p = .19$. Approximately 61% of women and 62% of men were included in Cluster 1. Similarly, 14.3% of women and 13.6% of men were included in Cluster 2. Approximately 25% of women and 24% of men were included in Cluster 3. Similarly, although our sample was predominantly white, no race difference in cluster membership was detected, X^2 (DF = 2) = 0.60, p = .74. A total of 62.4% of non-white adults and 64.3% of white adults were included in Cluster 1.

We further examined these associations using a multinomial logistic regression, with the clusters as the dependent variable and age group and the five personality dispositions as predictors. We used Cluster 1 as the referent group. As shown in Table 2, the variables in the equations did differentiate cluster membership, X^2 (DF = 12; N = 823) = 122.21, $p < .001$; Nagelkerke pseudo $R^2 = .201$. As shown by the likelihood ratio tests, with the exception of neuroticism (X^2 (DF = 2) = 3.17, p = .21), each of the variables in the model differentiated among the clusters, including: age (X^2 (DF = 2) = 15.03, $p < .001$), extraversion (X^2 (DF = 2) = 17.31, $p < .001$), openness (X^2 (DF = 2) = 10.98, p = .004), agreeableness (X^2 (DF = 2) = 15.03, $p < .001$), and conscientiousness (X^2 (DF = 2) = 12.63, p = .002).

Interpreting the odds ratios (*OR*) associated with each predictor shows that for every one year increase in age, holding all other variables constant, and the odds of being in Cluster 2 relative to Cluster 1 increase by a factor of 1.14. Regarding the Big Five, for every one unit increase in extraversion (*OR* = .34), openness (*OR* = .37) and conscientiousness (*OR* = .53), the likelihood of being in Cluster 2 relative to Cluster 1 decreased. In contrast, for every one unit increase in agreeableness, the likelihood of being in Cluster 2 relative to Cluster 1 increased by a factor of 3.43.

Interpreting the odds ratios differentiating Cluster 1 from Cluster 3 shows that only age group and openness significantly differentiated between group membership. For every one year increase in age, holding all other variables constant, the odds of being in Cluster 3 relative to Cluster 1 increases by a factor of 1.16. For every one unit increase in openness, the odds of being in Cluster 3 relative to Cluster 1 decreased by a factor of 0.56.

Table 2. Distinguishing Correlates of Cluster Membership through Multinomial Logistic Regression

	Cluster 2 /Cluster 1					Cluster 3 / Cluster 1				
	b	*SE*	*p*	*OR*	95% CI	*b*	*SE*	*p*	*OR*	95% CI
Age	.134	.031	<.001	1.14	1.08 - 1.22	.145	.031	<.001	1.16	1.09 - 1.23
Neuroticism	.106	.209	.612	1.11	.74 - 1.68	-.331	.206	.109	.72	.48 - 1.08
Extraversion	-1.079	.271	<.001	.34	.20 - .58	-.525	.279	.060	.59	.34 - 1.02
Openness	-.779	.262	.003	.46	.27 - .77	-.581	.276	.035	.56	.33 - .96
Conscientious	-.852	.237	<.001	.43	.27 - .68	-.202	.264	.444	.82	.49 - 1.37
Agreeableness	1.23	.330	<.001	3.43	1.80 - 6.56	.291	.323	.368	1.34	.71 - 2.52

Model Fit:
Chi-square (DF = 12) =122.21, $p < .001$
Nagelkerke Pseudo R^2 = .201

Notes: N = 823; Unstandardized beta (*b*), Standard Error of Beta (*SE*), *Odds Ratios* (*OR*) and the 95% Confidence Intervals (*CI*) are shown. p-values are 2-tailed tests

Alt-text: A table of beta weights, odds ratios and 95% confidence intervals for each predictor per cluster

Study 1 Discussion

Theorists in several disciplines have stated that decision-making is influenced by both cognitive and affective factors [16]. Individual differences in which of these dual processes is dominant have been noted [8]. Within the area of lifespan developmental psychology, Socioemotional Selectivity Theory (SST) [6] further suggests that the balance between these two factors could be expected to change with age, as middle-aged and older adults begin to prioritize emotionally meaningful experiences. Despite these findings, the experimental and quasi-experimental literature examining age differences in decision-making have not fully incorporated this focus on both cognitive and affective influences. This neglect is partly due to the lack of measures that can be applied across decision domains. We sought to add to the literature by exploring whether we could identify a disposition-like affective factor that could be used in subsequent studies.

Decision domains can differ in a variety of ways, including whether the decision is frequent or rare, important or not, and emotionally meaningful or not. We chose to examine four low-frequency, but highly salient decisions that have received significant research attention, including choosing new living arrangements, an automobile, a health insurance policy, and a school. Using ratings of importance and meaningfulness for each of the four decision contexts, we were able to identify three interpretable clusters. Cluster 1 included decision-makers who rated the decision domains as low to moderate in both importance and meaningfulness. The second cluster was comprised by those who rated housing decisions as moderately meaningful, but who rated most other domains as less meaningful and not very important. The third cluster were those who offered high meaningfulness ratings for decisions related to living environments, schools, and insurance policies.

Individual differences did differentiate cluster membership. Cluster 1, which was the largest cluster, included the majority of late adolescents and emerging adults. In addition to strong age effects, the personality dispositions differentiated cluster membership. Those in Cluster 1 were lower in extraversion, lower in openness, and lower in conscientiousness, relative to those in Cluster 2. Only extraversion significantly differentiated membership between clusters 1 and 3. The magnitude of these effects, however, were small.

Having identified affective clusters and shown them to be related to individual difference variables is an important contribution because these affective clusters may allow researchers to compare affective orientations to decisions as a stable characteristic, similar to the way in which cognitive resources are conceptualized. Thus, with stable indices of cognition and affect, it may be possible to move beyond specific decision domains to address the ways in which individual differences influence issues at the intersection of affective cognition [17]. Such an endeavor may provide avenues for interventions, enabling adults to make higher-quality decisions.

Study 2

Two to 16 weeks after having completed Study 1, 96 adults were invited to take part in four face-to-face health coaching sessions that were the main focus of Study 2. Within two of the four health coaching sessions, we asked adults to complete two decision-making tasks. Thus, decision-making data for the current study were gathered during second and third in-person sessions. Of the 96 adults who were invited into Study 2, only a subset (n = 60) completed the decision task, with 56 participating in both sessions. Adults ranged in age from 18 to 72 years, with a mean of 41.8 years (SD = 15.8). As in Study 1, the majority were White (87.5%), non-Hispanic (96.9%), and female (76.4%). The vast majority, 96.8%, had some education beyond high school. A power analysis, implemented in G*Power [18] suggested that $N = 42$ would provide sufficient power ($\lambda = .80$) to detect a medium-sized effect ($f^2 = .20$) to test the change in R^2 with three predictors in a multiple regression. It was hypothesized that both the affective cluster membership identified in Study 1 and cognitive factors would account for variance in decision quality. Moreover, because affective components may guide the information to which one attends, as well as the weighting one gives to each piece of information [9], we hypothesized that the affective cluster membership would account for a significant amount of variance in decision-making outcomes above that explained by cognitive influences.

Information Matrices, based on actual products available in the environment, provided information about decision alternatives and features. We focused on two low frequency but salient decisions: choosing a place to live and choosing an automobile to purchase. Information was presented in both global and specific terms, such as "Rent is high, $2000 per month" and "The 4wd vehicle has excellent reliability ratings." This aspect adds to the ecological validity of the task and enabled participants to use their existing expertise. An 8 x 8 matrix was used for the housing decisions, with features including rent, size, locale, medical services, non-medical services, social, safety, and rules/options. An 8 x 8 matrix was used to display the automobile alternatives and features. The features included price, style, appearance, safety, reliability, fuel, equipment, and performance. Participants viewed matrices on the computer and were able to view one cell of information at a time, in any order. Participants were not allowed to write down any information but could look back through information as many times as they wished before making a decision. Time spent on the task was recorded in milliseconds.

Participants engaged in two initial practice scenarios in which they chose a candy bar for themselves and a suit of clothing for a female lawyer. This helped to acquaint them with navigating the decision matrices. Each of these practice matrices was written in such a way that some choices were more appropriate than others. For example, the 2-bar candy choice included deciding between a small, expensive and poor-tasting bar and one that was larger, less expensive and tastier. For the clothing, choices varied on cut (pants versus short skirts), color (neutrals versus brights), fabric (linen, wool, corduroy) and price.

Participants were then presented with the first 8 by 8 matrix and asked to choose an alternative for themselves. Following the two practice decisions and the self-decision, the participants received the vignettes for the housing domain. The two vignettes and their matching matrices were always counterbalanced across participants within domain. The vignettes describe the individuals' lifestyle and financial situation; thus, some the needs of these individuals were implied, while others were clearly stated. Participants viewed two vignettes for selecting a home. One of the targets was an older woman in poor health who did not want to continue to burden her adult daughter with her daily caregiving needs. The other target was a healthy widow with a secure income who wanted more engagement with adults similar to her in age [1]. An excerpt from a housing matrix is shown in Figure 2. Automobile decisions were completed during session 3. They followed a similar format to the housing decisions, with two practice trials and a self-purchase condition preceding the decisions for target others. One vignette featured a middle-aged professional couple who needed a vehicle for work and leisure. The other vignette featured a college student who commuted daily to school and work

Figure 2. Excerpt from a housing matrix.

	Rent (1)	Size (2)	Locale (3)	Medical Services (4)
A	$1,505 per month; utilities; No Medicaid or Medicare	Average; 2 bedrooms; 1 bath; 950 sqft.	Good; Near large city	Good; Full – time RN & personal care assistants
B	$300 per month; No utilities paid; Medicaid & Medicare	Average; 1 bedroom; 1 bath; 900 sqft.	Poor; Downtown area; close to business district & night clubs	Good; trained supervisor; 24 hr. emergency call
C	$1,100 per month; utilities, Medicare & Medicaid accepted	Small; 1 bedroom; 1 bath; 300 sqft.	Average; secluded grounds; 40 miles from nearest city	Excellent; 24 – hr. physician & nurses; acute care facilities

Alt-text: a table depicting some of the alternatives and features for the housing matrices.

Quality of Decisions was determined based on data from an expert panel. Each set of matrices and vignettes were reviewed by a panel of experts who had access to all of the information simultaneously. Based on the stated and implied needs of the hypothetical others, experts ranked the alternatives regarding appropriateness for the target person in the vignette. For the housing decisions, a panel of social workers and long-term care placement advisers served as experts. For the automobiles, sales staff who were top-ranked in customer satisfaction served as experts. We analyzed whether participants made high-quality decisions for each of the four target others. No age differences were observed for housing decision quality, X^2 (DF = 3) = 4.96, p = .174. Likewise, age differences were not observed for automobile decision quality, X^2 (DF = 3) = 1.44, p = .696. Combining across scenarios in the housing and automobile domains, 4.1% made three high-quality decisions, 38.8% made two high-quality decisions, 24.5% made one high-quality decision, and 32.7% failed to make a high-quality decision. Of note, no significant age group differences were observed for combined decision quality, X^2 (DF = 9) = 10.24, p = .33.

We used the cluster group membership from Study 1 as the affective factor. In the subset of adults moving into Study 2, 18% belonged to Affect Cluster 1, 72% were part of Cluster 2, and 10% were included in Cluster 3. In the reduced Study 2 sample, no age differences in cluster membership were observed, X^2 (DF = 6) = 3.85, p = .70.

An electronically-administered Letter-Digit Substitution task was used to index executive functions [19]. Substitution tasks involve multiple components of executive functions, including perceptual scanning, working memory, attention, and motor function. Thus, given our limited power to test a variety of specific cognitive factors and our goal to examine disposition-level predictors of decision quality, the use of a single multidimensional task was an appropriate cognitive counterpart to our affective cluster variable. In the Letter-Digit Substitution task, the participant was asked to use nine letter-digit pairs to complete a series of prompts. Participants were given a trial period with feedback to start, and then progressed to the experimental condition where no feedback was given. We used the number of trials to reach 100% (Mean = 29.6; SD = 0.7).

Study 2 Results

Hierarchical Regression

We hypothesized that both the affective cluster membership identified in Study 1 and executive functions would account for variance in decision quality. Moreover, because affective components may guide the information to which one attends, as well as the weighting one gives to each piece of information [9], we hypothesized that the affective cluster membership would account for a significant amount of variance in decision-making outcomes above that explained by cognitive influences.

Spearman's rho coefficients showed that Decision Quality was significantly related to fewer Letter-Digit trials $\varrho = -.41$, $p = .006$). We also examined Spearman coefficients between Decision Quality and dummy-coded variables related to the affective clusters. Membership in cluster 1 was negatively associated with decision quality ($\varrho = -.42$, $p = .007$); associations with membership in cluster 2 ($\varrho = .196$, $p = .224$) and cluster 3 ($\varrho = .194$, $p = .230$) did not reach significance. Although failing to reach statistical significance, a potentially meaningful association was detected between Decision Quality and age ($\varrho = -.25$, $p = .08$).

In order to test whether affective cluster membership would explain variance in decision outcome above and beyond that explained by cognitive factors, we conducted a hierarchical regression in which the number of letter-digit trials was entered at Step 1 and the two dummy-coded affective cluster membership variables were entered at Step 2. The equation including only the cognitive measure accounted for 7.9% of the variance in Decision Quality, F (1, 53) = 4.57, $p = .037$. As indicated by the standardized Beta ($\beta = -.26$, p = .044), fewer trials on the Letter-Digit Substitution task explained unique variance in Decision Quality. At Step 2, dummy-coded variables for membership in affective cluster 1 and membership in affective cluster 2 were entered into the equation. Both the step (F (2, 51) = 4.01, p = .024) and the model (F (3. 51) = 4.37, p = .008) were significant. Affective cluster membership accounted for an additional 12.51% of the variance in decision quality. Overall, fewer trials in Letter-Digit Substitution ($\beta = -.26$, $p = .044$) and not belonging to Cluster 1 ($\beta = -.33$, $p = .015$) uniquely accounted for variance in Decision Quality.

Study 2 Discussion

Although researchers have argued that complex decision making is a function of both cognitive and affective factors [16], few studies have incorporated comparable measures of these predictors, with executive function being viewed as a stable characteristic and affect related to one's appraisal of the importance and meaningfulness of the domain being included. The goal of Study 2 was to test whether the affective cluster derived from importance and meaningfulness ratings in Study 1 would explain additional variance in Decision Quality, beyond that explained by executive functions.

Using a measure of decision quality that summarized the number of decisions in which the participant made a high-quality decision for a target other, we examined the influence of affective cluster membership and an index of executive function. Our equation accounted for 20% of the variance in decision quality. The hierarchical regression demonstrated that the affective cluster membership accounted for unique variance in decision quality beyond that explained by executive functions alone.

General Discussion

The dual process approach to decision-making [3, 16] has not been fully examined across the many disciplines that focus on complex cognition. Early research in the dual process approach focused attention on integral emotion rather than incidental emotion [3]. A deep literature shows that integral emotion often influences decision outcomes [4]. Although recent studies have begun to examine the unique and often complimentary contributions of incidental emotions and cognition [20], more work is needed.

We examined whether we could detect a stable, affective profile related to infrequent but salient decisions. Using data from a large and age diverse sample, Study 1 analyzed ratings of importance and meaningfulness across four low-frequency but high-salience decision domains, including where to live, which school to attend, which automobile to purchase, and which health insurance policy to choose. Using cluster analyses, three clusters were detected. Individual characteristics such as age and personality differentiated among cluster membership.

A subset of adults was invited to participate in Study 2. Among other tasks, Study 2 participants completed quasi-experimental decision-making tasks wherein they chose automobiles for two hypothetical others and housing for two hypothetical others. We used the affective clusters derived in Study 1 and a well-known measure of executive functions. Results of our hierarchical regression showed that both affective cluster membership and executive function uniquely account for variance in decision quality.

In terms of contributions to the field, our work helps to clarify some of the contradictory findings in the literature. For example, using a college-age sample and a measure of decision quality that prioritizes the ratio of positive to negative features, Mikels et al. [8] asked participants to either focus on their current feelings or on the rational details of the decision. Those focusing on their current emotions choose alternatives that had a higher positive to negative ratio. However, in the real world, many adults rely on their wealth of knowledge and experience and other stable resources when making a decision [1]. Moreover, good decisions are not merely the sum of positive attributes, but rather, some features are more important than others. This is exactly the point in which individual values, experiences, and affect should be brought to the decision-making context. Finally, Mikels et al. [8] focused on late adolescents enrolled in college. Our data show that the late adolescents, ages 18 and 19, approach and value decisions differently than their older peers.

Our data from Study 1 show strong support for Socioemotional Selectivity Theory (SST) [6]. Late adolescents and emerging adults were much more likely to be included in clusters 1 and 2, which placed low to medium importance and meaningfulness on the four decision domains examined. This finding is particularly exciting because it suggests that there may be developmental trends in these affective clusters, but also that interventions and decision supports may need to be age-adjusted. To the best of our knowledge, this idea has not been applied to the study of decision quality. Although Delaney et al. [9] suggest gender differences in decision making styles, we did not detect such differences. Future research might examine whether affective cluster membership relates to other measures of decision-making style and whether they uniquely contribute to decision quality.

A limitation to our study is that our clusters are based on only two affective evaluations, importance and meaningfulness. Future studies are well-advised to expand beyond such simple assessments. In addition, we only focused on low frequency/high salience decisions. These might push for a balance between affect and cognition. Future studies should examine affective profiles for more frequent and/or less salient domains. Additional covariates beyond personality are also advised. Another limitation included our small sample size in study 2, which prohibited the use of a variety of predictors of decision quality. Larger studies will be needed to explore more nuanced associations among different aspects of cognition and affective approach. Finally, although our task allows a better examination of decision quality than other such tasks, we do note that in the real-world, consumers often take careful notes and consult outside sources.

Conclusion

Despite these few limitations, we are encouraged by the results which show that it is possible to derive an index of affective approaches to decision domains that may be able to be used along with other stable individual difference variables, such as age, gender, personality, and executive function. Combined with ecologically-valid measures of decision quality, such affective profiles may support examinations of the dual-process approach to decision making.

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