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Does State of Mind Predict Prototype-based Category Learning in Older Adults?

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DOES STATE OF MIND PREDICT PROTOTYPE-BASED CATEGORY LEARNING IN OLDER ADULTS?

by

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ABSTRACT

DOES STATE OF MIND PREDICT PROTOTYPE-BASED CATEGORY LEARNING IN OLDER ADULTS?

By

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The University of Wisconsin-Milwaukee, 2023
Under the Supervision of Professor Caitlin Bowman

Category learning plays an important role in day-to-day lives across all ages, allowing us to organize related experiences, develop expectations, and determine how we behave given those expectations. Despite its importance, the current body of literature on category learning in older adults is much smaller than that of other memory domains. Thus, little is known about how well older adults learn new concepts and what factors best promote learning novel categories. One factor that may affect category learning abilities is an individual's state of mind. A number of studies demonstrate the effects of sleep, stress, affect, and motivation on cognition, especially in older adults. However, the extent to which individual's state of mind affects category learning remains unclear. In this study, older adults have undergone two category learning sessions across separate days and completed several state of mind questionnaires. I examined if participant's state of mind predicted the categorization accuracy of older adults on each day. This study may potentially advance our understanding of the factors that influence category learning and establish the extent to which state of mind contributes to older adults' categorization abilities.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Background

Category learning

Category learning is a key cognitive ability that involves relating items and linking them to a shared label. Generalization, which is the ability to make inferences about new stimuli similar but not identical to previous examples, is a key hallmark of category knowledge. For instance, if an individual sees an animal and categorizes it as a hamster, their expectations and behaviors will be different from classifying the animal as a mouse: finding a hamster cute and petting it vs. standing on a chair to get away from a mouse. The ability to learn new categories is relevant throughout the lifespan as new concepts keep emerging into the world. Despite the importance of category learning, it has received relatively less attention in cognitive aging literature compared to other cognitive domains. Although most of the category learning studies have been conducted with young adults, aging studies of categorization have often shown agerelated impairments in direct learning of new category labels (Ashby et al., 2020; Badham et al., 2017; Bowman et al., 2022; Davis et al., 2012; Filoteo & Maddox, 2004; Rabi & Minda, 2016, Wahlheim et al., 2016).

Lack of age deficits in the performance of prototype category structure

One of the important types of category learning is prototype learning (Homa et al., 1981; Posner & Keele, 1968; Smith & Minda, 1998). In prototype-based categories, the prototype is the central tendency of the category - an ideal member of the category that has all the most common features (Minda & Smith, 2011). Prototype category structures are organized in a way that there is a prototype in every category and other members of the category are distortions away from this central tendency to varying degrees (Rosch & Mervis, 1975). In a typical prototype learning task, participants are presented with a series of objects drawn from one or more categories with a prototype structure. During the training period, participants are asked to classify each object and receive feedback according to their responses. Through the feedback during training, participants may eventually learn to discriminate among the categories. Typically, the prototypes themselves are not shown during training. Then, during the testing period, participants are presented with test items and are asked to categorize the items without feedback. Test items are members of the trained categories, as well as novel items, including the prototypes. A common finding from such prototype category structure is that categorization accuracy diminishes as the number of common features between novel items and the prototype decreased (Hess, 1982; Hess & Slaughter, 1986; Posner & Keele, 1968). This finding aligns with predictions from the formal prototype model of categorization, which posits that individuals derive the prototype from the presented examples and use the prototype as a basis for categorization (Bowman & Zeithamova, 2020; Smith & Minda, 1998).

Studies investigating prototype learning in older adults suggest that the ability to form prototypes in older adults may be comparable to that of young adults (Hess, 1982; Hess & Slaughter, 1986). This lack of age-related deficits in prototype learning may arise because older adults may rely on similarities across experiences and extract the meaning of those experiences rather than focusing on item-specific details that distinguish between similar experiences (Bowman & Dennis, 2015; Dennis et al., 2007; Koutstaal & Schacter, 1997; Stark & Stark, 2017). Indeed, older adults perform as well as young adults in category learning for items close to category center, but they show an impairment for atypical category members (Hess & Wallsten, 1987). Going beyond the aforementioned studies, Bowman and colleagues (2022) additionally suggest that there may be an age-related *increase* in prototype-based learning. The authors found that older adults have performed as well as young adults in prototype-based tasks, and more than 80% of the older participants were best fit by the prototype model. Prototype representations may be a helpful way to compensate for age-related cognitive decline in other aspects of memory, as it can allow for robust generalization to a variety of category members, instead of remembering small details of the items.

While these studies have provided a great deal of insight into age-related differences in category learning, all of them focused on comparisons in mean performance or model fits between age groups. Like many domains with cognitive aging, categorization researchers have paid less attention to the within-persons variability in performance. Intraindividual variability is a sensitive behavioral indicator of cognitive aging, as intraindividual variability increases with age (Bielak et al., 2014). Thus, the first goal of the present study is to not only evaluate whether older adults show categorization performance that differs based on similarity of items to their category prototypes, but also whether that effect is stable within individuals across multiple category learning tasks. Alternatively, older adults might switch their approach in a second session in order to improve their performance, leading to a less robust prototype gradient in accuracy.

State of mind, cognition, and aging

Another factor to consider regarding intraindividual variability is the individual's state of mind. The effect of intraindividual variability in state of mind has not been explored in older adults' category learning. I thus selected several candidate factors based on their known relationship to other cognitive abilities. I will investigate how they affect older adults' abilities to learn prototype-based category structures and whether intraindividual differences are explained by a participant's state of mind during a given session.

Stress: Stress is ubiquitous in modern life, and it is no surprise that researchers show great interest in the effect of stress on cognitive performance. Although the field of stress cognition has been studied extensively, the findings across studies are somewhat equivocal. Acute stress has been associated with poorer executive function (Starcke et al., 2016), spatial memory (Hou et al., 2015), and impulsive responsiveness for an arithmetic task (Qi et al., 2016) in young to middleaged adults. Acute stress has also been associated with *better* risk perception (Sobkow et al., 2016). Specifically regarding category learning, higher stress reactivity in young adults was associated with better performance in an information-integration category-learning task (Ell et al., 2011; McCoy et al., 2014).

Cognitive aging studies suggest that older adults might be particularly affected by everyday stress (Neupert et al., 2006; Aggarwal et al., 2014; Dickinson et al., 2011). Higher levels of subjective stress and stressful life events may exacerbate age-related decline in episodic memory (VonDras et al., 2005). Prior research supports the idea that stress-related coping requires cognitive attention and information processing skills (Stawski et al., 2006), which may be less functional in later life (Smith, 2003). Stress levels vary daily, so it would be effective to assess stress levels every given session. Levels of stress on a given day may particularly affect older adults in category learning.

Positive and Negative Affect: Positive and negative affect are considered the two major mood dimensions (Depaoli & Sweeney, 2000; Merz & Roesch, 2011). Positive affect refers to the individual's propensity to experience enthusiastic, active, alert, and other pleasurable engagements, whereas negative affect is the degree to which an individual tends to experience subjective distress, negative mood states, and unpleasant engagement (Watson et al., 1988). Prior research suggests that positive affect enhances cognitive flexibility, which is the propensity to disengage from a mental task, switch from one mental task to another, revise a mental set, and/or engage in inhibitory control (Rende, 2000). Negative affect may reduce cognitive flexibility

(Ashby et al., 1999). Category learning has also been positively associated with cognitive flexibility (Ashby et al., 1999; Maddox et al., 2006), suggesting that positive affect may improve category learning abilities. However, the association between category learning and positive and negative affect in older adults have not been studied to the best of my knowledge.

The relationship between different emotional experiences and category learning in cognitively healthy older adults might be particularly relevant for understanding cognitive aging. Research in emotional aging suggests that older adults show higher levels of positive affect compared to young adults (for a review, see Scheibe & Carstensen, 2010). However, a number of studies investigating age differences in emotional experience and expressions report different results. Some studies indicate no age differences in experiencing negative mood (Knight et al., 2002; Levenson et al., 1991), while another study shows a greater level of negative affect in young adults than older adults (Gross et al., 1997). It is also known that certain types of emotions, such as loss and suffering, may be experienced more and regulated less effectively by older adults (Kunzmann & Grühn, 2005; Kliegel et al., 2007). The proposed study will assess the association between daily experience of emotion and category learning. It may be more difficult to learn categories for participants who experience more negative affect on the day of the given session compared to those experiencing positive affect.

Motivation: Another potential determinant of cognitive performance is motivation. Motivation is a psychological process in the form of several different components such as interest, goals, values, and challenges (Weiner, 1992). Research has shown that motivation is closely associated with learning and cognitive processes including storage, recognition, and retrieval of long-term memory in young adults (Cook et al., 2015; Miendlarzewska et al., 2016; Murayama & Elliot, 2011; Murty & Dickerson, 2017). However, the effects of motivation on category learning have not been directly tested. Cognitive aging studies are increasingly demonstrating that motivation is one of the key factors that influences cognitive performance, and there is an age-related variation in the relationship between motivation and cognition (Hess, 2005; Carstensen et al., 2006). Studies have suggested that cognitive engagement becomes more costly with age, resulting in resource depletion and fatigue (Ennis et al., 2013). For example, Neupert and colleagues (2006) observed a higher cortisol level in older adults during tests of cognitive ability than younger adults, and older adults are slower to recover from such stress-related responses (Seeman & Robbins, 1994). Cognitive and memory performance of older adults tends to increase as the personal relevance to the cognitive task increases, suggesting that older adults are more selective in choosing when to expend their limited cognitive resources and are less likely to make an effortful expansion in situations that have minimal personal implications (Germain & Hess, 2007; Hess et al., 2001; Hess et al., 2005). Thus, although examining the association between motivation and cognition across the lifespan is important, it is particularly essential for the study of aging.

Subjective sleep quality: Prior research suggests that poor sleep quality, including subjective experiences, such as self-reporting difficulties falling asleep, waking up during the night, and tiredness the next morning, affects cognitive performance (Diekelmann & Born, 2010; FortierBrochu et al., 2012; Jones & Harrison, 2001; Nebes et al., 2009). Across age groups, poorer sleep quality has been associated with impaired working memory (Smith et al., 2002; Steenari et al., 2003), executive functioning (Elhami Athar et al, 2020), decision-making (Telzer et al., 2013), and episodic memory (Stickgold, 2005), but there is a lack of understanding of whether sleep quality is associated with categorization learning.

Sleep quality may be a particularly relevant variable for older adults because changes in sleep quality are a common effect of aging. Indeed, insomnia is a very common health complaint in older adults, experienced by 33-42% of people aged 60 years or older. Haimov and colleagues (2008) investigated the association between chronic insomnia and cognitive functioning among cognitively healthy older adults and found that insomnia impaired their performance in attention, executive functioning, and visual and semantic memory. Similarly, Hart and colleagues (1995) reported that subjective sleep disturbance was associated with poorer performance on vigilance, psychomotor speed, recall memory, and executive function in cognitively healthy older adults. Additionally, literature in cognitive aging suggest that episodic memory in older adults might be particularly affected by sleep disturbance (for review, see Yeh et al., 2018). Thus, older adults may have particular difficulty with category learning following nights with poor sleep quality.

Summary: Studies with young adults have suggested that individuals' state of mind is associated with a wide variety of cognitive task performances. However, the association between state of mind and category learning, particularly in older adults, remains unclear. In the study, I investigated how each of these variables was individually related to performance on the categorization task. I also pitted them against each other to see which variable was the most important determinant of categorization performance.

Aims and Hypotheses

1. To investigate whether accuracy of older adults' categorization responses is associated with the similarity between items and their prototype and whether that relationship is relatively stable across different category-learning sessions.

   Hypothesis: Higher accuracy will be observed as prototype distance decreases, and this effect will be relatively stable, reflecting older adults' overall tendency to rely on prototype representations.

2. To examine if participant's state of mind predicts the categorization accuracy of older adults.

   Hypothesis: Lower stress level, poorer subjective sleep quality, negative affect, and poorer motivation will be associated with lower overall categorization accuracy.

Methods and Materials

Participants

Participants were 43 cognitively healthy older adults from the Milwaukee area. Older adults were defined as those 60 years of age or older, which is typically old enough to detect the effects of healthy cognitive aging. Prior to participation in experimental sessions, subjects were screened for signs of clinically relevant cognitive impairment using the Mini-Mental State Examination (inclusion score > 24/30; Folstein et al., 1983). Participants also completed portions of the Wechsler Adult Intelligence Scale IV (WAIS; Pearson Education Ltd.) to assess how the cognitive capacities of the recruited samples compare to normative samples. Scores from the WAIS were reported in terms of four composites of IQ: verbal comprehension (derived from vocabulary and information), perceptual reasoning (derived from matrix reasoning and visual puzzles), working memory (derived from digit span and arithmetic), and processing speed (derived from symbol search and coding). Scores from MMSE and WAIS are represented in Table 1. Among 43 individuals who participated in the study, one was excluded having MMSE score below criterion. Additionally, one was excluded due to missing >30% of the responses during categorization test, and two of them were excluded because they were pressing one button throughout the study. The final sample included 39 participants (mean age = 70.3 years (*SD* = 6.1); 55% female, 45% male, 0% any other gender; 87% white, 5% black, 3% pacific islander, 5% prefer not to answer). All participants completed written informed consent. All procedures were approved by the University of Wisconsin's Institutional Review Board.

Table 1
Means and standard deviations for MMSE and WAIS-IV composite scores

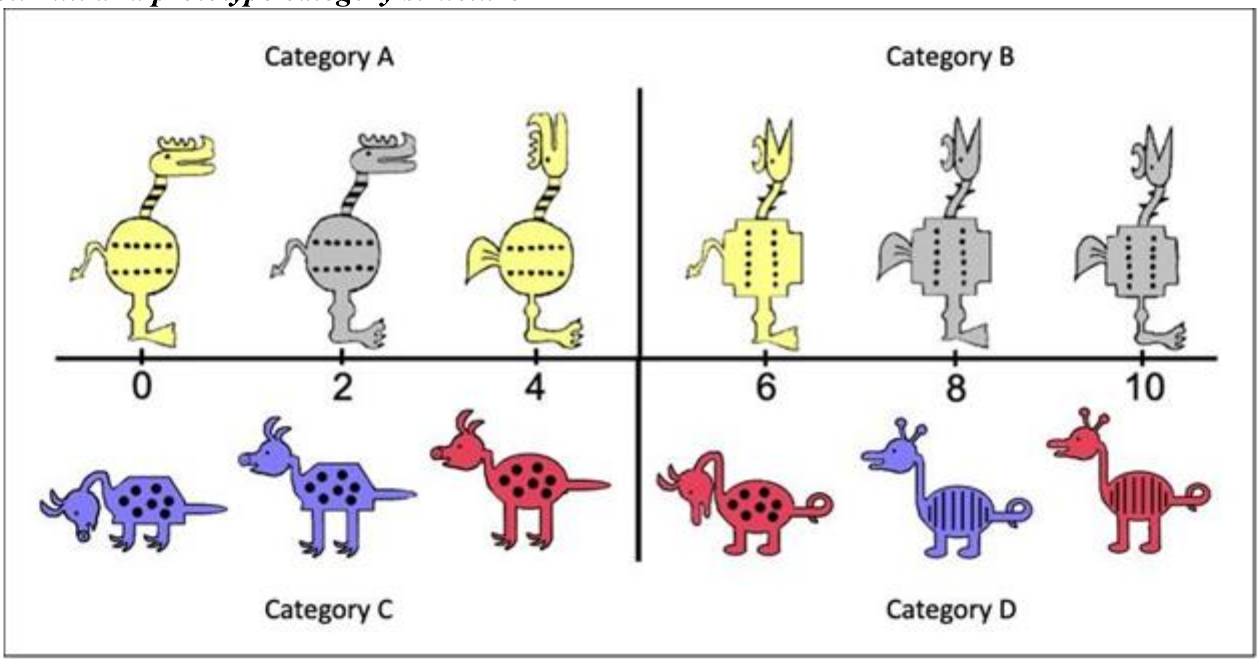
Measure	Mean(SD)
MMSE	28.59(1.5)
WAIS-IV: FSIQ	115.22(15.8)
VCI	24.62(5.1)
PRI	23.31(4.5)
WMI	21.87(4.5)
PSI	22.38(4.0)

Note. MMSE = Mini Mental State Exam; FSIQ = Full Scale IQ; VCI = Verbal Comprehension Index; PRI = Perceptual Reasoning Index; WMI = Working Memory Index; PSI = Processing Speed Index

Categorization tasks

Stimuli were cartoon animals that varied along 10 binary dimensions (Bowman & Zeithamova, 2020; Bozoki et al., 2006) (Figure 1). Two sets of these cartoons were used in a counterbalanced fashion across sessions to generate category-learning tasks that differ in their superficial details while maintaining the overall category structure. In each session, participants learned to distinguish between members of two categories (Session 1: Category A vs. Category B; Session 2: Category C vs. Category D). For the first session, one cartoon was randomly chosen from the appropriate cartoon set to serve as the prototype of Category A. The stimulus sharing no features with the Category A prototype was the Category B prototype. Members of Category A were defined as stimuli that share more features with the Category A prototype than the Category B prototype. The same process was used to generate Categories C and D using the remaining set of cartoons.

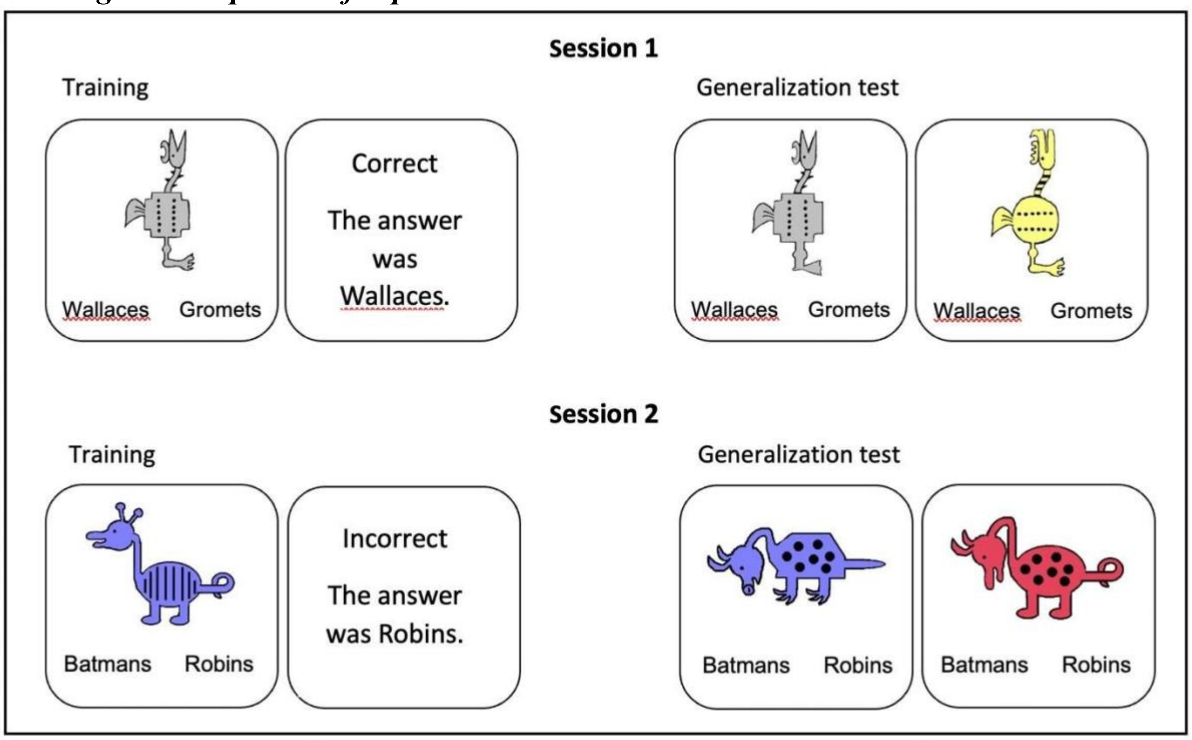
Figure 1
Stimuli and prototype category structure



Note. Separate cartoon animals and category labels were used in each session of two sessions (A/B for session1, C/D for session 2). Stimuli sharing >5 features with prototype A/C were category B/D members.

Training: Training stimuli included 8 items at 2 distance away from the prototype (4 items from each category) and 6 items at 4 distance away from the prototype (3 items from each category), making a total of 14 training items. Participants completed 8 study blocks. Each training item was shown 3 times per block, for a total of 42 trials per block. Each training item was shown once in each block before repeating the same item. For each training trial, the stimulus was shown in the middle of the screen along with both potential category labels (Figure 2). Participants were asked to make a button press response to categorize the item into one of the two categories within 4 seconds. Once participants made a response, they received feedback on whether they were correct or incorrect, as well as the name of the correct category. If a participant failed to give a response within 4 seconds, they were given the correct answer feedback for 1.5 seconds. There were inter-trial intervals (ITIs) of one second between each trial. Between each block, participants were given opportunities to take a short break before continuing with the experiment.

Figure 2
Training and test phases of experimental sessions



Note. Participants completed feedback-based category training followed by a categorization test without feedback.

__**Categorization test**__: Test stimuli included the training items and new items varying in the number of shared features with category prototypes. This consisted of 14 training items shown twice, both prototypes shown twice, and 10 new items at each distance from category, with a total of 112 items presented during the testing phase. The categorization test consisted of 2 blocks. During each block, participants were presented with each training item one time, both category prototypes one time, and 5 new items at each distance from the prototype (56 trials per test block). During each test trial, the stimuli and both category labels appeared on the screen, and participants were asked to make a button press response to categorize the items into one of two groups, and they did not receive feedback on their responses (Figure 2). The test phase was self-paced, and there was one-second ITI following each trial.

State of mind questionnaires

Participants completed a set of questionnaires on the computer that assessed their state of mind at the beginning of each session, with the order of the questionnaires counterbalanced across participants. Sleep quality, and subjective sleepiness were measured by Stanford sleepiness scale (Hoddes et al., 1973; Appendix A) and the St. Mary's hospital sleep questionnaire (Ellis et al., 1981; Appendix A). I used current sleepiness and sleep quality of the night before the session from this scale as a predictor of categorization abilities. Mood was measured with the Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988; Appendix B). I used both the positive affect score and negative affect scores as predictors of categorization abilities. Current stress level was measured with the Short Stress State Questionnaire (Helton, 2004; Helton et al., 2005; Helton & Garland, 2006; Helton & Russel, 2010; Helton & Näswall, 2015; Appendix C). I used the overall average across sub scores as a predictor of categorization abilities. Motivation to complete tasks was measured with the situational motivation scale (Guay et al., 2000; Appendix D), and I used the overall combined score as a predictor of categorization abilities.

Statistical analyses

<u>Category learning and test accuracy</u>: Training accuracy was defined as the proportion of training items correctly categorized within each block. I examined whether participants showed increasing accuracy over the course of training, whether learning differed for items close to the prototypes versus those close to the category boundary, and whether either of those effects differed across the two category learning sessions. I thus computed an 8 (training block:1-8) x 2 (item distance: 2 vs. 4) x 2 (session: 1 vs. 2) mixed factors ANOVA with training accuracy as the dependent variable.

Accuracy in the categorization test was defined as the proportion of correct categorizations (i.e., labeling items sharing 6+ features with the category A prototype as category A members and labeling those sharing 6+ features with the category B prototype as category B members). I tested whether categorization accuracy for new items differed based on proximity to category prototypes and whether the effect of prototype distance differed across the two category learning sessions by computing a 2 (session: 1 vs. 2) x 5 (distance: 0-4) ANOVA.

<u>Relationship between state of mind variables and categorization accuracy</u>: To assess whether individual's state of mind is associated with the categorization accuracy, I used multilevel modeling (MLM), which is frequently used to model intraindividual variability (Grzywacz et al., 2004). As a first approach, I assessed how each state of mind variable or set of variables relates to categorization accuracy. To do so, I computed a separate MLM for sleep quality, current subjective sleepiness, positive and negative affect, stress, and motivation predicting overall categorization accuracy from the test phase with the subject as a random factor. As a second approach, I determined which, if any, of the state of mind variables predicted categorization accuracy above-and-beyond the shared variance across the predictors. To do so, I computed a multiple regression model for combined sessions that include all state of mind variables as predictors of categorization accuracy.

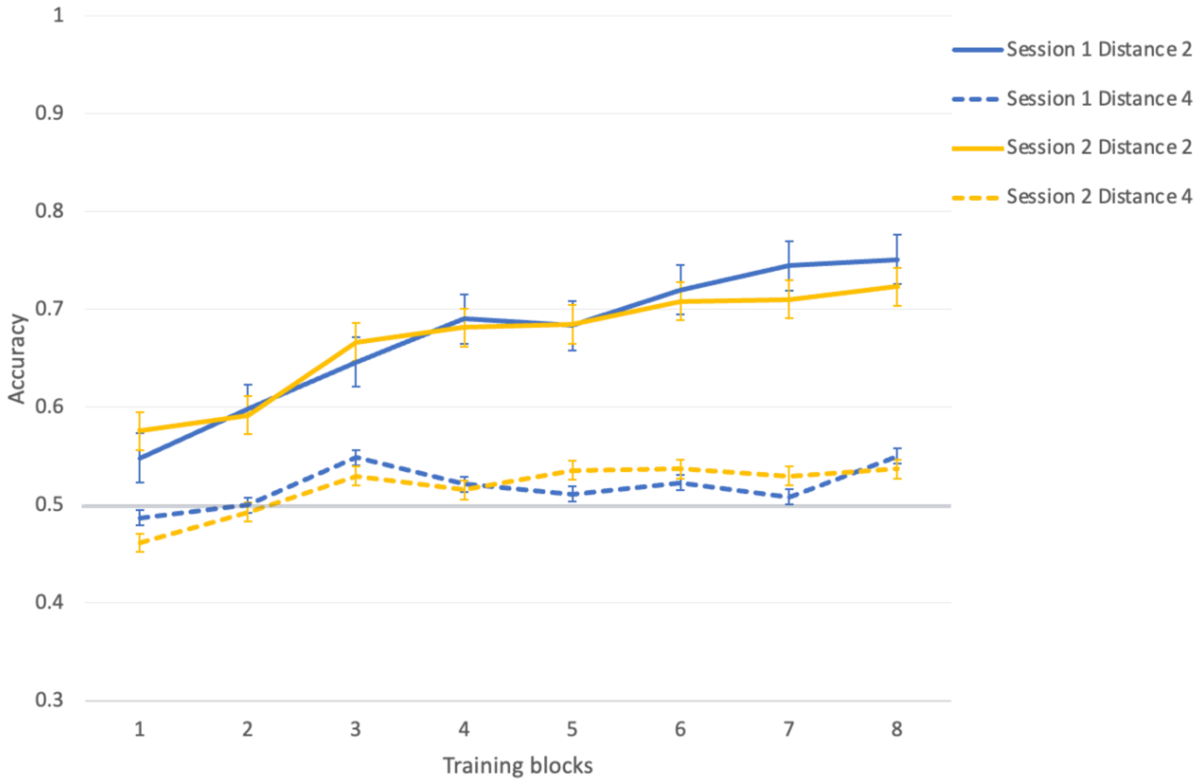
Results

Training accuracy

Figure 3 demonstrates mean training accuracy for each training block separated by sessions and training item distance from prototypes. To test for 1) learning during the training phase, 2) differences in learning based on training items' proximity to the prototype, and 3) practice effects across the two sessions, I compared training accuracy for distance 2 and distance 4 items across training blocks and across two sessions. Full ANOVA results are presented in Table 2. There was a significant main effect of training blocks. The more training blocks participants completed, the higher categorization accuracy became. There was also a significant main effect of training item distance, with better training accuracy for items differing from prototype by two features ($M = .67$, $SD = .17$) compared to those differing by four features ($M = .52$, $SD = .13$). Moreover, there was a significant block x distance interaction effect. Participants showed greater linear relationship between accuracy and blocks for distance 2 items, $F(7,304) = 9.50$, $p <.001$, compared to distance 4 items, $F(7,304) = 2.22$, $p = .03$. There was no significant main effect of sessions, meaning that older adults did not show a reliable practice effect when completing a second category learning task.

Figure 3

Training accuracy



Note. The proportion of correct responses during training for distance 2 (solid lines) and distance 4 (dashed lines) items separated for session 1 (blue lines) versus session 2 (yellow lines). Error bars depict the standard error of the mean across subjects.

Table 2

Block x Item Distance x Session ANOVA Results for Training Accuracy

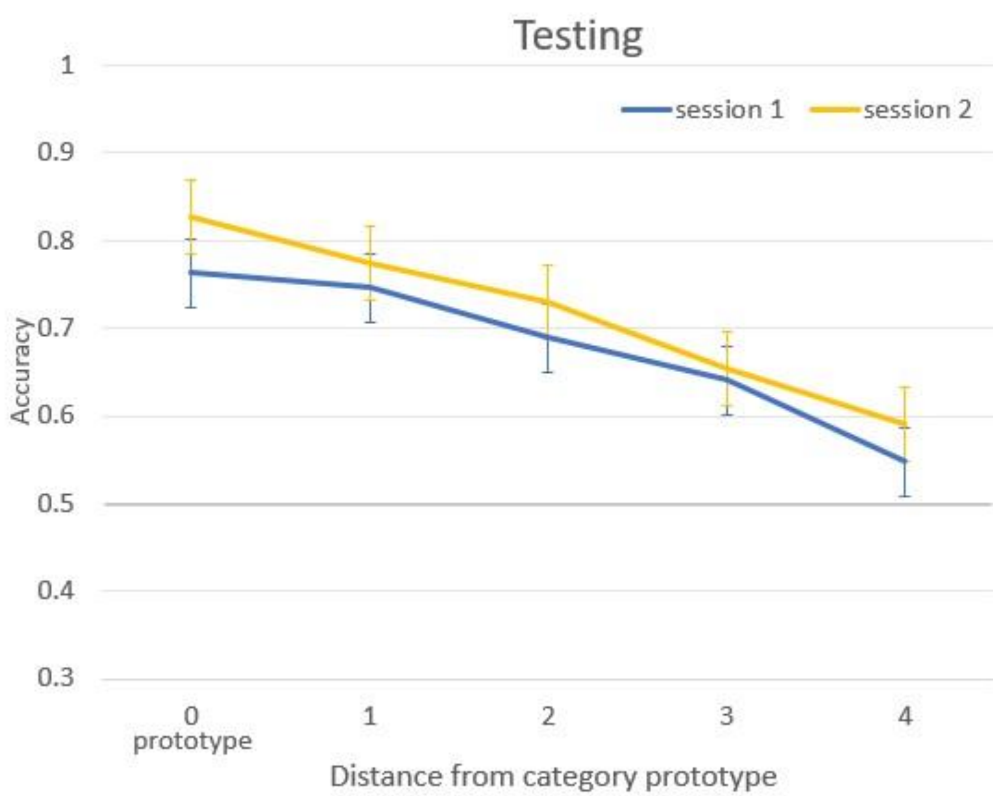
Effect	df	*F*	*p*	η_{p2}
Block[a]	4.70, 178.42 GG	18.72	<.001	.33
Item distance [a]	1, 38	87.37	<.001	.70
Session	1, 38	0.05	.83	<.001
Block x item distance [a]	5.03, 190.98 GG	6.40	<.001	.014
Distance x session	1, 38	0.01	.92	<.001
Block x session	5.25, 199.32 GG	0.37	.88	.01
Block x item distance x session	5.74, 217.93 GG	1.09	.37	.03

Note. ANOVA = analysis of variance; GG = Greenhouse Geisser correction. [a] Significant effect with α level = .05.

Categorization test accuracy

Figure 4 depicts mean categorization accuracy separated by item distance and session. My primary interests were whether categorization accuracy differed based on the distance of the test items to the prototypes and whether any differences were stable across sessions. ANOVA results for testing phase are summarized in Table 3. There was a significant main effect of item distance with higher accuracy for items closer to prototypes. Although accuracy was numerically higher in the second session (M = .72, SD = .20) compared to the first session (M = .68, SD = .22) for all distances from the prototype, the main effect of session did not reach significance.

Figure 4
Categorization test accuracy



Note. The proportion of correct categorization responses for items differing from prototypes by 0–4 features presented separately for session 1 (blue line) and session 2 (yellow line). Error bars depict the standard error of the mean across subjects.

Table 3
Item distance x session ANOVA results for categorization test accuracy

Effect	df	*F*	*p*	η_{p2}
Item distance[a]	2.38, 90.58 GG	42.38	<.001	.53
Session	1, 38	1.66	.21	.04
Item distance x session	2.77, 105.29 GG	0.51	.66	.01

Note. ANOVA = analysis of variance; GG = Greenhouse Geisser correction. [a] Significant effect with α level = .05.

State of mind and categorization accuracy

Multilevel model analysis was conducted for the state of mind variable as a predictor in a separate model with each participant as a random factor to account for intraindividual variability of the time-varying predictors. Categorization accuracy was an average score during categorization test in each session. Comparisons between simple linear model and multilevel model are presented in Table 4. None of the state of mind variables were significant predictors for categorization accuracy accounting for random factors, and there were no significant differences between the linear versus multilevel models**.**

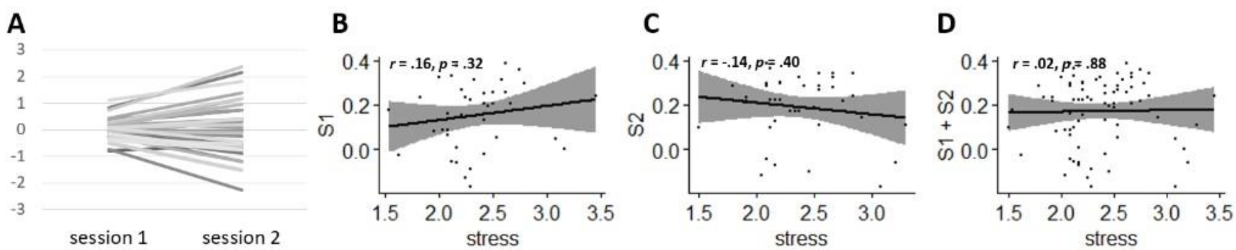
Table 4
The coefficients of the linear model and multilevel model

	Linear model			**Multilevel model**		
Effect	Estimate (SE)	*t*	*p*	Estimate (SE)	*t*	*p*
Stress	.007 (.044)	1.47	.88	.008(.050)	.16	.87
Positive affect	.003 (.002)	1.50	.14	.003(.002)	1.22	.23
Negative affect	-.003 (.005)	-.57	.57	.001(.005)	.26	.80
Motivation	-.001 (.001)	-.62	.54	-.001(.001)	-.64	.52
Sleep quality	.022 (.014)	1.63	.11	.018(.014)	1.37	.18
Sleepiness	-.000 (.010)	-.01	0.99	-.002(.011)	-.17	.87

Note. β coefficients of linear model and multilevel model.

Stress: Figure 5A depicts the differences of stress response across sessions for each individual participant. Even though there was more variability in responses for session 2, there were no significant differences between stress levels of participants across sessions, $t(38)=-.99$, $p = .33$. The correlation between accuracy and stress responses are represented in Figure 5B (session 1), C (session 2), and D (combined across sessions). There was a numerically positive relationship between stress and categorization performance in session 1 and a numerically negative relationship in session 2, which averaged to an overall relationship that was very close to 0 across sessions. Linear regression and multilevel models both showed very weak positive coefficient for the relationship between stress and categorization performance of .007 and .008, respectively.

Figure 5
Stress and categorization accuracy across sessions

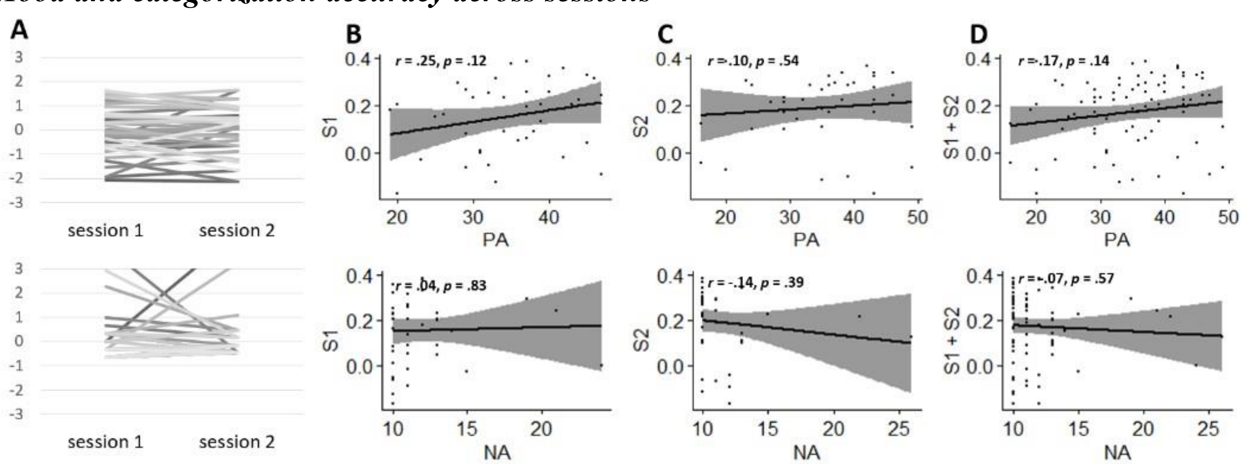


Note. (A) Spaghetti plot for n = 39 subjects and questionnaire scores for stress. Z-score is shown. (B) The relationship between categorization accuracy for session 1 (S1) and stress, (C) for session 2 (S2) and stress, and (D) for session 1 and 2 combined (S1 + S2) and stress.

Mood: Figure 6A shows the participant's mood state across two sessions. Across sessions, there was no statistical differences in participants' experiences of positive affect, $t(38) = .09$, $p = .93$, or of negative affect, $t(38) = .80$, $p = .43$. The correlations between accuracy and mood state are represented in Figure 6B, C, and D. There was a numerically positive relationship between positive affect and categorization performance in both sessions, but it was slightly stronger in the first session. The two sessions averaged to an overall non-significant positive relationship. A weak positive correlation in sessions 1 between categorization accuracy and negative affect and non-significant negative relationship between accuracy and negative affect for session 2 led to the averaged negative relationship which was very close to 0 for both sessions. However, there was a limited range for the negative affect measure because very few participants reported high negative affect. Results from both the linear regression and multilevel models showed a small positive relationship between positive affect and categorization that did not reach significance. Negative affect had negative overall relationship in linear regression model, compared to the positive relationship shown by multilevel model. However, both models agreed that there was a minimal relationship between negative affect and categorization accuracy.

Figure 6

Mood and categorization accuracy across sessions

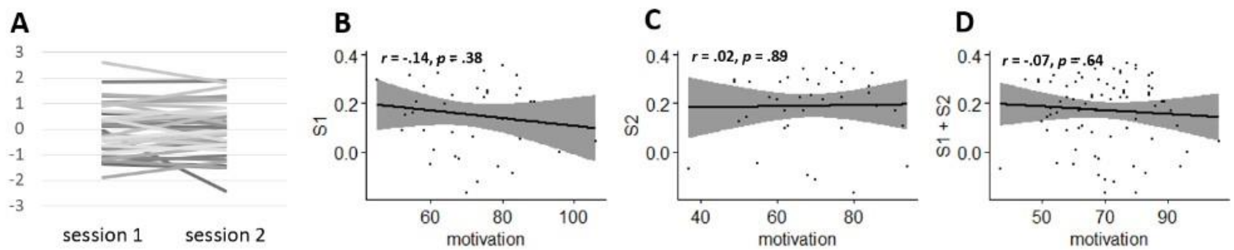


Note. (A) Spaghetti plot for n = 39 subjects and questionnaire scores for positive affect (top) and negative affect (bottom). Z-scores are shown. (B) The relationship between categorization accuracy for session 1 (S1) and mood, (C) for session 2 (S2) and mood, and (D) for session 1 and 2 combined (S1+S2) and mood.

<u>Motivation</u>: Figure 7A depicts the differences of motivation across sessions. There were no significant differences between levels of motivation of participants across sessions, *t*(38)= 1.44, *p*

= .16. Correlations between accuracy and responses for motivation are shown in Figure 7B, C, and D. Surprisingly, the relationship between motivation and categorization performance was numerically negative in the first session, but it did not reach significance. There was almost no relationship in session 2, which averaged to an overall relationship that was very close to 0 but negative across sessions. Motivation was not a significant predictor of categorization accuracy in both linear regression and multilevel models.

Figure 7
Motivation and categorization accuracy across sessions

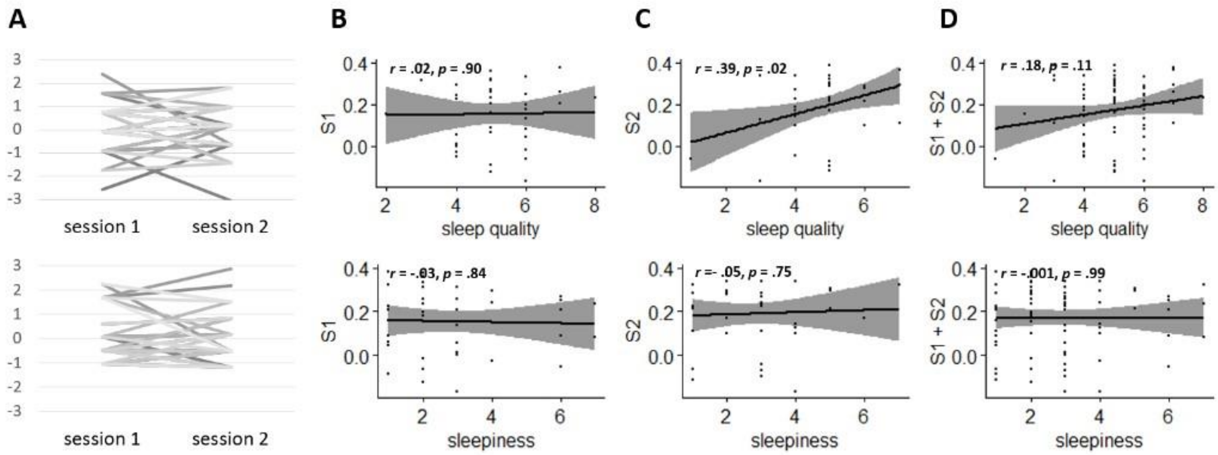


Note. (A) Spaghetti plot for n = 39 subjects and questionnaire scores for motivation. Z-score are shown. (B) The relationship between categorization accuracy for session 1 (S1) and motivation, (C) for session 2 (S2) and motivation, and (D) for session 1 and 2 combined (S1+S2) and motivation.

Sleep: Figure 8A shows the participant's sleep quality and current sleepiness across two sessions. There were no statistical differences in sleep quality of the night before, $t(38) = 1.41$, $p = .17$, or in current sleepiness, $t(38) = .53$, $p = .60$, across sessions. Correlations between accuracy and sleep are represented in Figure 8B, C, and D. There was almost no relationship between sleep quality and categorization performance in session 1, but there was a significant positive relationship between sleep quality and categorization accuracy in session 2, which averaged to an overall non-significant positive relationship across sessions. For current sleepiness, there were no correlations between sleepiness and categorization performance in session 1, session 2, and combined sessions. Similar positive coefficients were associated with sleep quality predicting categorization abilities by fitting both linear regression and multilevel models, and almost no relationship was reported between sleepiness and categorization accuracy by both models.

Figure 8

Sleep and categorization accuracy across sessions



Note. (A) Spaghetti plot for n = 39 subjects and questionnaire scores for sleep quality (top) and current sleepiness (bottom). Z-scores are shown. (B) The relationship between categorization accuracy for session 1 (S1) and sleep, (C) for session 2 (S2) and sleep, and (D) for session 1 and 2 combined (S1+S2) and sleep.

Correlation between state of mind variables

Table 5 summarizes correlation between state of mind variables. Stress and positive affect were positively correlated for session 1, session 2, and cross sessions. A significant positive correlation for session 1 and non-significant correlation for sessions 2 became an overall significant positive correlation between negative affect and stress for cross sessions. Stress was also found to be positively correlated with motivation in both sessions. Non-significant negative correlation for session 1 and significant negative correlation for session 2 were averaged to an overall negative correlation between stress and sleep quality. A weak negative correlation for session 1 and a strong negative correlation for session 2 are averaged to show a significant negative correlation between positive and negative affect. Motivation and positive affect were found to have a significant positive correlation. Finally, motivation and sleep quality showed a significant positive relationship for session 1, but when averaged with session 2, the correlation did not reach significance.

Table 5
Correlation matrix between state of mind variables

A

Variables		Session 1 1	2	3	4	5
1. Stress	Person's r	—				
	p-value					
2. Positive Affect	Person's r	.43**	—			
	p-value	.006				
3. Negative Affect	Person's r	.54***	-.05	—		
	p-value	<.001	.77			
4. Motivation	Person's r	.46**	.54***	.08	—	
	p-value	.004	<.001	.64		
5. Sleep quality	Person's r	-.15	.14	-.26	.33*	—
	p-value	.38	.40	.11	.04	
6. Sleepiness	Person's r	-.02	-.20	.10	.01	.14
	p-value	.95	.23	.55	.94	.41

B

Variables		Session 2 1	2	3	4	5
1. Stress	Person's r	—				
	p-value					
2. Positive Affect	Person's r	.61***	—			
	p-value	<.001				
3. Negative Affect	Person's r	.04	-.39**	—		
	p-value	.82	.01			
4. Motivation	Person's r	.51***	.66***	-.23	—	
	p-value	<.001	<.001	.16		
5. Sleep quality	Person's r	-.44**	-.10	-.19	-.22	—
	p-value	.005	.53	.24	.18	
6. Sleepiness	Person's r	.16	-.17	.30	-.03	-.14
	p-value	.34	.29	.06	.86	.39

C

Variables		Cross session 1	2	3	4	5
1. Stress	Person's r	—				
	p-value					
2. Positive Affect	Person's r	.52***	—			
	p-value	<.001				
3. Negative Affect	Person's r	.28**	-.23*	—		
	p-value	.01	.04			
4. Motivation	Person's r	.48***	.60***	-.07	—	
	p-value	<.001	<.001	.54		
5. Sleep quality	Person's r	-.30**	.01	-.21	.06	—
	p-value	.008	.94	.06	.59	
6. Sleepiness	Person's r	.06	-.18	.19	-.003	.01
	p-value	.59	.11	.09	.98	.90

Note. (A) correlation matrix for session 1, (B) correlation matrix for session 2, and (C) correlation matrix for session 1 and session 2 combined. Green shades indicate significant positive relationship, whilst red shades indicate significant negative relationship.
* indicates p < .05, ** indicates p < .01, *** indicates p < .001.

Comparison across state of mind predictors

Table 6 presents the results of multiple linear regression analysis that includes all the state of mind variables in a model. The average categorization accuracy combined across sessions 1 and 2 was the dependent variable, and it was predicted by stress, positive affect, negative affect, motivation, sleep quality and current sleepiness. It was found that higher levels of positive affect and lower levels of motivation were significantly associated with higher categorization accuracy after controlling for other variables. Though not significant, there was a trending effect for sleep quality with better sleep quality indicating higher categorization accuracy. Figure 9 depicts each participant's categorization accuracy predicted by state of mind scores, with the estimated slope.

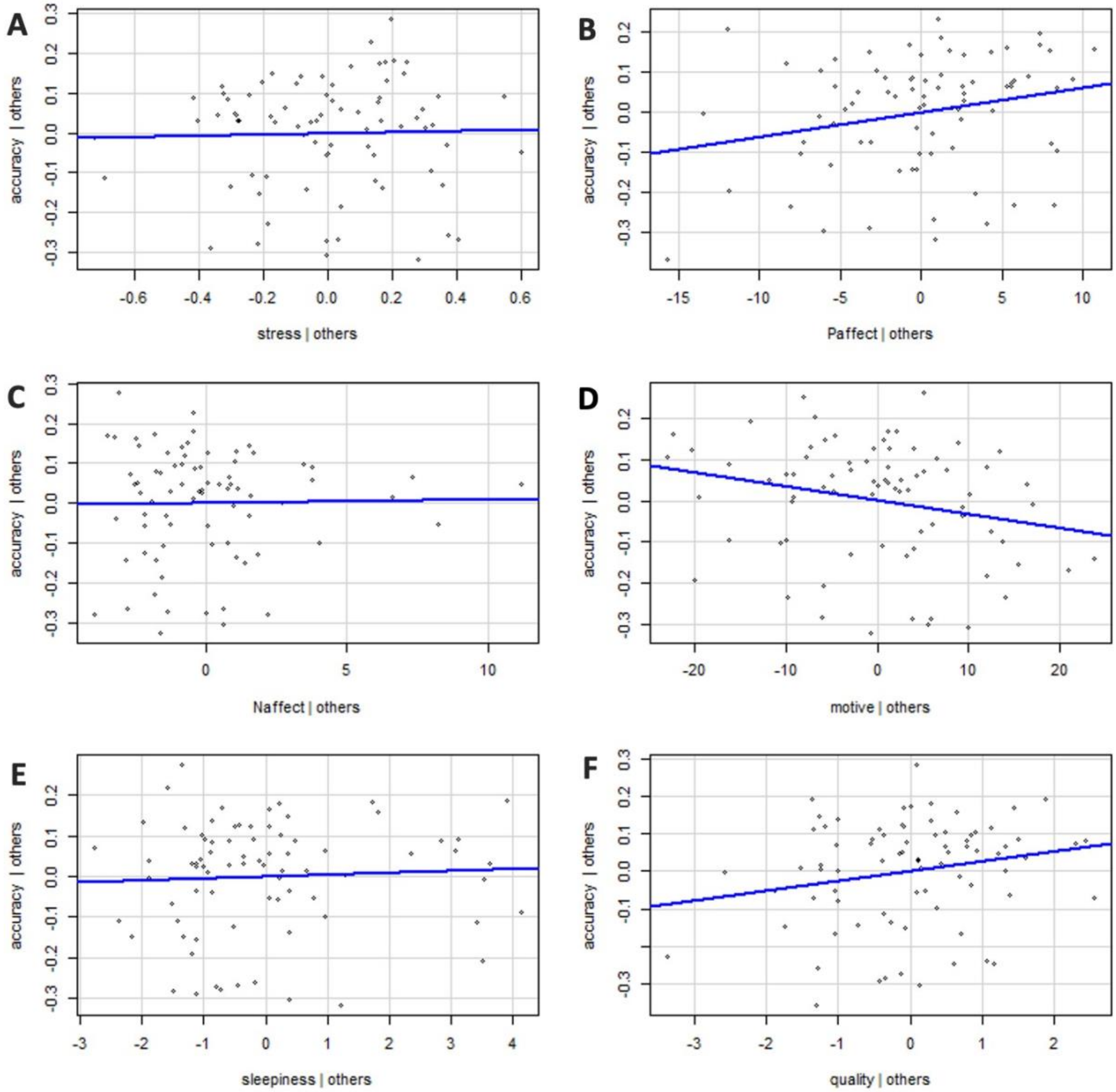
Table 6

Multiple linear regression analysis: State of mind variables and categorization test accuracy

Effect	Estimate	*SE*	*t*	*p*
Stress	.016	.063	.25	.80
Positive affect [a]	.006	.003	2.07	.04
Negative affect	.001	.006	.14	.89
Motivation [a]	-.003	.001	-2.11	.04
Sleep quality	.026	.015	1.78	.08
Sleepiness	.005	.010	.44	.66

Note. β coefficients (95% confidence intervals) adjusted for other variables. [a] Significant effect with α level = .05.

Figure 9
Predicting categorization accuracy by state of mind



Note. Partial correlation plots for multiple regression analysis adjusted for other variables in the model. Categorization accuracy was centered at .5 (i.e., chance when there are two categories). Combined accuracy test scores for both sessions were used for this analysis. (A) stress, (B) positive affect, (C) negative affect, (D) motivation, (E) sleepiness, (F) sleep quality

Discussion

In the present study, I measured whether higher categorization accuracy would be observed as item's distance from its prototype decreases. I also tested whether this effect would be relatively stable across two sessions or instead show signs that older adults change their strategy across sessions, leading to a different pattern of classification responses. I also investigated whether each individual's state of mind influences category learning, using prototype-based category structure. I hypothesized that participants would show better accuracy for items closer to the prototype, and their performance would be relatively stable across sessions given that both sessions have the same category structure and older adults' tendency to rely on prototype representations (Bowman et al., 2022). The findings from training and categorization test phases were largely consistent with this hypothesis. During training, participants showed increasing learning rates across training blocks, but their accuracy was lower for items differing four features from the prototype compared to those differing two features from the prototype. A similar effect of distance was also observed during the categorization test, with decreasing accuracy as item distance from the prototype increased. These findings are consistent with my prediction and with prior work (Bowman et al., 2022; Hess & Wallsten, 1987), suggesting that older adults may be able to learn prototype-based categories effectively because they rely on abstract representations of category center. While none of the state of mind variables predicted categorization performance on their own, state of mind analyses found that higher positive affect and lower motivation were associated with better categorization accuracy in older adults after accounting for other variables.

Consistent with prior work (Bowman et al., 2022; Hess & Wallsten, 1987), older adults showed higher learning rates for the prototype-adjacent items. This pattern is consistent with the predictions of the prototype model, although we did not fit the formal prototype model. Bowman and colleagues (2022) suggest that older adults rely on prototype representations more than young adults because it is relatively easy for them to average across items and create a prototype rather than remembering small details of each member of the category. For items close to the category boundary, we observed slower learning rate and less accuracy in our sample. This result was similarly observed by Bowman and colleagues (2022) that older adults show more category learning deficits for boundary items than younger adults. This difference in categorization abilities in older adults may be a result of older adult's well-known deficits in encoding specific details of individual items (Stark & Stark, 2017), which may make it difficult to rely on memory for individual items in making categorization decisions and increase their reliance in prototype representations. Another important finding from the present study is the stability in category learning performance across sessions. Participants were not significantly faster learning the second category even though the exact same category structure was employed as the first category. Participants were not quicker to discover this underlying structure on their second exposure to it. However, they showed numerically higher accuracy in the categorization test phase in the second session compared to the first session. Bowman and colleagues (2022) found age deficits in category learning that were not present during category generalization. Thus, there may be a dissociation in how aging affects learning vs. generalization with generalization being less affected by age. It is also possible that some individuals developed a certain way to approach categorization based on their experience in the first session, but further research will be needed to better understand this dissociation between learning and categorization test performance.

Based on the hypothesis that older adults show increased intraindividual variabilities, we explored the relationship between state of mind and categorization abilities using both multilevel and linear regression models. The findings from the state of mind analyses were somewhat inconclusive. Although state of mind variables did not significantly predict categorization abilities on their own, results from multiple regression analysis partially supported the hypothesis that higher positive affect was associated with better categorization performance. Surprisingly, I also found that *lower* motivation was significantly correlated with better categorization abilities after controlling for others.

Based on the prior work showing that stress improved categorization abilities in young to middle-aged adults (Ell et al., 2011; McCoy et al., 2014), I hypothesized that higher stress level would be associated with better categorization accuracy in older adults. Results were not significant, with a numerically positive relationship in session 1 and a numerically negative relationship in session 2 that average to be very close to zero relationship overall. There remained no reliable effect of stress on categorization when we controlled for other state of mind variables in the multiple regression model. Prior studies show nuanced relationship between stress and cognition (Hou et al., 2016; Qi et al., 2016; Starcke et al., 2016; Ell et al., 2011; McCoy et al., 2014), and it is possible that category learning might rely on neural systems that are less deeply intertwined with physiological stress responses. Another possible explanation lies within the positive correlation between stress and motivation. In this study, participants who were more stressed were also more motivated to do the task, making it difficult to untangle the unique role stress could have on learning. Further, I only collected self-reported stress through a questionnaire, whereas other studies manipulated stress during cognitive tests. Lab-induced stress may more directly and more intensely influence cognition than daily stress. Previous studies have also used physiological stress measures such as cortisol levels and heart rate, which allow for more direct measure of online stress than the short stress state questionnaire (Starcke et al., 2016; Dickerson & Kemeny, 2004). Further investigation remains to be conducted in order to disentangle the relationship between stress and categorization in older adults.

Because both positive affect and category learning have been associated with cognitive flexibility, I hypothesized that higher positive affect would be associated with better categorization abilities in older adults. When tested alone in regression and multilevel models, there was a positive relationship between positive affect and categorization performance that did not reach significance. When we entered other aspects of state of mind into the same model, there was a significant positive relationship between positive affect and categorization accuracy. This finding indicates that positive emotions are associated with better categorization abilities in older adults, which has not been previously demonstrated. Prior studies have demonstrated the correlation between cognitive flexibility and positive affect mainly with young adults (Ashby et al.,1999), and this correlation may be shown in the present study with older adults. Isen and Daubman (1984) argued that positive affect increases the tendency to integrate across experiences and form associations, both of which are relevant for learning new categories. Though these prior studies did not include older adults, the findings from this study may support this hypothesis that positive mood influences categorization ability through cognitive flexibility. Promoting cognitive flexibility may be particularly useful for older adults because some prior studies show poorer cognitive flexibility in older adults. For example, older adults tend to perseverate in rule-switching tasks such as Wisconsin Card Sorting Test (Ashendorf & McCaffrey, 2008). Johnco and colleagues (2015) further investigated older adults with late-life anxiety and depression, and their clinical sample showed poorer cognitive flexibility compared to the age-matched healthy control. This finding further supports the hypothesis that a more positive mood may allow for better cognitive flexibility in older adults, leading to improved categorization abilities.

Results did not provide support for the hypothesis that lower levels of negative affect are significantly correlated with better category learning in older adults. Both models showed minimal relationships between negative affect and categorization. It is interesting, however, that positive affect was a significant predictor for category learning abilities, and there was much more variability in the scores for positive affect. This is empirical evidence supporting the assumption that positive and negative differently predict cognitive abilities (Sobkow et al., 2016) and verify our motivation of investigating positive and negative affect separately. These null results are not surprising because most of the participants responded that they have either no or very little negative affect in the questionnaire, which is in line with prior studies suggesting that older adults may show lower levels of negative emotions compared to younger adults (Gross et al., 1997). Due to lower variabilities of negative affect in our sample, our results are inconclusive about the relationship between negative affect and categorization abilities in older adults. A larger sample with more variability in negative affect scores is needed to fully address the relationship between affect and categorization abilities.

I hypothesized that higher motivation would be associated with better categorization accuracy in older adults. When tested alone, higher motivation showed a non-significant negative relationship with categorization abilities. However, this negative relationship became significant when other variables were included in a regression model. This finding was surprising because prior studies showed the association between better cognitive performance and higher motivation (Germain & Hess, 2007; Hess et al., 2001; Hess et al., 2005). There is a recent study, however, that shows similar results of situational motivation on cognitive tasks. Ryan and Campbell (2021) studied both younger and older adult’s motivation on cognitive tasks and found that highly motivated older adults performed worse on cognitive tasks. They argue that this is likely due to a stereotype threat, a phenomenon by which individuals underperform when they are under pressure to deny a negative stereotype against their group. In this case, the negative stereotype is age-related cognitive decline, and older adults may have performance-related anxiety, which leads to a great task-related interference. Motivated older adults may have been more anxious about their performance in the present study knowing that their cognition was tested. Moreover, participant's stress level was positively associated with motivation, which supports the assumption that more motivated older adults were more stressed about completing the sessions. However, to complicate this relationship further, there was a positive correlation between positive affect and motivation, which does not easily align with greater stress. Instead, there seems to be a complex relationship between stress, motivation, and positive affect that may be difficult to tease apart in a relatively small sample. Overall, the exact mechanism by which categorization is influenced by motivation remains to be investigated further.

Given that the prevalence of insomnia increases with age and that bad sleep quality is associated with deficits in cognitive performance, we hypothesized that better sleep quality and less sleepiness would enhance category learning ability in older adults. A non-significant positive relationship for session 1 and significant positive correlation for session 2 resulted in a trending effect of sleep quality on categorization accuracy in older adults, but it was not statistically significant. Results from both linear regression and multilevel models showed that current sleepiness was not a significant predictor of categorization accuracy. Though sleep duration was excluded from the regression analyses due to a number of missing answers, there was a significant correlation between sleep quality and duration, meaning that higher numbers of hours of sleep indicated higher quality of sleep. Thus, though not significant, this finding was largely in accordance with previous studies suggesting that fewer hours of sleep and worse sleep quality are associated with worse cognitive performance in older adults (Haimov et al., 2008; Hart et al., 1995; Miyata et al., 2013; Yeh et al., 2018). Current sleepiness was not correlated with either sleep duration or sleep quality and did not predict categorization abilities. These results were rather surprising given that sleep quality showed non-significant trend for category learning abilities. It is possible that previous night's sleep quality was not strongly related to current sleepiness because individuals can reduce sleepiness after poor quality sleep the night before (i.e. by drinking coffee), but that does not necessarily help them fully overcome the consequences of poor sleep quality in terms of cognitive performance. Although the results were not significant in the present study, more studies should be conducted to investigate the different effects of sleepiness aside from sleep quality or duration, as most of the existing studies have combined those variables.

While the current study revealed informative results about category learning and the influence of state of mind in older adults, more sessions are needed to determine the pattern and magnitude of the effects of state of mind more accurately on category learning abilities. More time points would especially be informative with the use of multilevel model analyses, allowing us to study heterogeneous effects of state of mind and reveal its intraindividual variabilities. The null results of the random factor analysis may suggest that intraindividual variability of older adults are not a significant factor that influences the results for regression analyses. Alternative explanations for this lie within the lack of levels to compare. The present study only had two time points to compare individuals' state of mind variable scores, whereas other studies employing multilevel models tend to apply their model to five or more levels (Vanderhasselt et al., 2014; Almeida et al., 2009; Smith et al., 2004). For example, in order to really understand the relationship between motivation and categorization abilities in older adults, it is necessary to disentangle motivated individuals from state motivation. Is it that really enthusiastic people are not very realistic about their abilities, leading to a negative relationship between motivation and performance? Or if we looked within individuals, would higher state motivation be a positive predictor? If we introduce more time points in the future studies, it would allow us to better assess the role of motivation in cognitive performance.

Another limitation of the current study is that the sample was predominantly Caucasian and highly educated. 87% our sample was non-Hispanic white, compared to 76% in general population at the age of 65 or older (Administration for Community Living, 2021). Additionally, full-score IQ generated from WAIS IV cognitive assessment for our sample was one standard deviation higher on average than an age-matched normative population. It will be crucial to diversify the sample in the future to gain better understanding of age-related cognitive decline in a more representative sample. In addition, the small sample size leads to low power to detect subtle relationships between variables, especially when there are strong relationships among some of the state of mind variables. The study is still ongoing, and the results should be analyzed again when a larger sample size is achieved.

Lastly, the present study only included older adults. It is unclear, therefore, whether any of the effects we find are unique to older adults or if these relationships are consistent across the lifespan. For example, one of the possible interpretations of motivation finding was the theory of stereotype threat. If that is the correct interpretation, then anxiety about age-related cognitive decline should only affect older adults, and we should only see the negative relationship between motivation and performance in the older group. Future studies should investigate age differences in those effects to further analyze the relationship between state of mind and categorization abilities.

Conclusion

In the proposed study, I tested how similarities between items affect prototype category learning in older adults and the stability of the relationship across multiple categorization tasks. Moreover, I investigated the association between individual older adults' state of mind and category learning abilities. I found that older adults were sensitive to prototype information during both learning and categorization, and that was stable across multiple categorization tasks. Furthermore, there were not robust and consistent effects of state of mind on categorization but some indications that positive affect and motivation may impact categorization abilities. Investigating the association between state of mind and category leaning in older adults is impactful not only because the similar study has not been conducted, but because age differences within each of the state of mind variable has been widely reported, making studies in young adults not generalizable across the lifespan. Future studies should increase time points to further investigate the time-varying variables and collect data from young adults with the same set of experiments and compare the categorization abilities between young and older adults.

Appendix A: Sleep Quality and Subjective Sleepiness Questionnaire

Questions	Answers
At what time did you settle down for the night?	_____hours_____minutes
At what time did you fall asleep last night?	_____hours_____minutes
At what time did you finally wake this morning?	_____hours_____minutes
At what time did you get up this morning?	_____hours_____minutes
Was your sleep...	Very light(1); Light(2); Fairly light(3); Light average(4); Deep average(5); Fairly deep(6); Very deep(7)
How many times did you wake up?	Not at all(0); Once(1); Twice(2); Three times(3); Four times(4); Five times(5); Six times(6); More than six times(7)
How much sleep did you get Last night?	_____hours_____minutes
How much sleep did you get During the day, yesterday?	_____hours_____minutes
How well did you sleep last night?	Very badly(1); Badly(2); Fairly badly(3); Fairly well(4); Well(5); Very well(6)
If not well, what was the trouble?	
How clear-headed did you feel after getting up this morning?	Still very drowsy indeed(1); Still moderately drowsy(2); Still slightly drowsy(3); Fairly clearheaded(4); Alert(5); Very alert(6)
How satisfied were you with last night's sleep?	Very unsatisfied(1); Moderately unsatisfied(2); Slightly unsatisfied (3); Fairly satisfied(4); Completely satisfied(5)
Were you troubled by waking up early and being unable to get off to sleep again?	No(1); Yes(2)
How much difficulty did you have in getting off to sleep last night?	None or very little(1); Some(2); A lot(3); Extreme difficulty(4)
How long did it take you to fall asleep last night?	_____hours_____minutes
Which describes your state of sleepiness?	Feeling active and vital, alert, or wide awake(1); Functioning at high levels, but not at peak, able to concentrate(2); Awake, but relaxed, responsive but not fully alert(3); Somewhat foggy, let down(4); Foggy, losing interest in remaining awake. Slowed down(5); Sleepy, woozy, fighting sleep; prefer to lie down(6); No longer fighting sleep, sleep onset soon, having dream-like thoughts(7)

Appendix B: Positive Affect and Negative Affect Schedule (PANAS)

Indicate the extent you feel this way right now.	Very slightly or Not at all	A little	Moderately	Quite a bit	Extremely
Interested	1	2	3	4	5
Distressed	1	2	3	4	5
Excited	1	2	3	4	5
Upset	1	2	3	4	5
Strong	1	2	3	4	5
Guilty	1	2	3	4	5
Scared	1	2	3	4	5
Hostile	1	2	3	4	5
Enthusiastic	1	2	3	4	5
Proud	1	2	3	4	5
Irritable	1	2	3	4	5
Alert	1	2	3	4	5
Ashamed	1	2	3	4	5
Inspired	1	2	3	4	5
Nervous	1	2	3	4	5
Determined	1	2	3	4	5
Attentive	1	2	3	4	5
Jittery	1	2	3	4	5
Active	1	2	3	4	5
Afraid	1	2	3	4	5

Appendix C: Short Stress State Questionnaire

Not at all = 1; A little bit = 2; Somewhat =3; Very much = 4; Extremely = 5

Questions	Answers
1. I feel dissatisfied.	1 2 3 4 5
2. I feel alert.	1 2 3 4 5
3. I feel depressed.	1 2 3 4 5
4. I feel sad.	1 2 3 4 5
5. I feel active.	1 2 3 4 5
6. I feel impatient.	1 2 3 4 5
7. I feel annoyed.	1 2 3 4 5
8. I feel angry.	1 2 3 4 5
9. I feel irritated.	1 2 3 4 5
10. I feel grouchy.	1 2 3 4 5
11. I am committed to attaining my performance goals	1 2 3 4 5
12. I want to succeed on the task	1 2 3 4 5
13. I am motivated to do the task	1 2 3 4 5
14. I'm trying to figure myself out.	1 2 3 4 5
15. I'm reflecting about myself.	1 2 3 4 5
16. I'm daydreaming about myself.	1 2 3 4 5
17. I feel confident about my abilities.	1 2 3 4 5
18. I feel self-conscious.	1 2 3 4 5
19. I am worried about what other people think of me.	1 2 3 4 5
20. I feel concerned about the impression I am making.	1 2 3 4 5
21. I expect to perform proficiently on this task.	1 2 3 4 5
22. Generally, I feel in control of things.	1 2 3 4 5
23. I thought about how others have done on this task.	1 2 3 4 5
24. I thought about how I would feel if I were told how I performed.	1 2 3 4 5

Appendix D: Situational Motivation Scale

Why are you currently engaged in this activity?	Not at all in agreement	A very little in agreement	Little in agreement	Moderately in agreement	Enough in agreement	A lot in agreement	Exactly
Because I think that this activity is interesting	1	2	3	4	5	6	7
Because I am doing it for my own good	1	2	3	4	5	6	7
Because I am supposed to do it	1	2	3	4	5	6	7
There may be good reasons to do this activity, but personally I don't see any	1	2	3	4	5	6	7
Because I think that this activity is pleasant	1	2	3	4	5	6	7
Because I think that this activity is good for me	1	2	3	4	5	6	7
Because it is something that I have to do	1	2	3	4	5	6	7
I do this activity, but I am not sure if it is worth it	1	2	3	4	5	6	7
Because this activity is fun	1	2	3	4	5	6	7
By personal decision	1	2	3	4	5	6	7
Because I don't have any choice	1	2	3	4	5	6	7
I don't know; I don't see what this activity brings to me	1	2	3	4	5	6	7
Because I feel good when doing this activity	1	2	3	4	5	6	7
Because I believe that this activity is important for me	1	2	3	4	5	6	7
Because I feel that I have to do it	1	2	3	4	5	6	7
I do this activity, but I am not sure it is a good thing to pursue it	1	2	3	4	5	6	7

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