Characterizing Cognitive Dispersion and its Correlates Across the Adult Lifespan in MIDUS

*Laura M. Klepacz, MA

Department of Psychology, North Dakota State University, Fargo, ND, USA

Eric S. Cerino, PhD

Department of Psychological Sciences, Northern Arizona University, Flagstaff, AZ, USA

Jeremy M. Hamm, PhD

Department of Psychology, North Dakota State University, Fargo, ND, USA

*Address correspondence to: Laura M. Klepacz, MA. E-mail: laura.klepacz@ndsu.edu

Abstract

Objectives. Although research has shown that higher levels of within-person variability across cognitive tasks (dispersion) are associated with cognitive decline in clinical samples, little is known about dispersion in comparatively younger, non-clinical, and national samples. A better understanding of dispersion is needed to elucidate for whom and under what circumstances dispersion can be used as a reliable indicator of cognitive health.

Method. We used data from the Midlife in the United States Study (MIDUS; n = 2,229; M_{age} = 56 years, range = 33-83; 56% female) to: (a) characterize dispersion and its cross-sectional correlates in a non-clinical, adult lifespan sample and (b) examine changes in dispersion over time to determine for whom changes in dispersion may reflect better or worse cognitive aging.

Results. Correlations showed higher levels of dispersion were associated with higher levels of mean performance at both waves (*r*s = .28-.29). Autoregressive main effect models showed that increases in dispersion were associated with less decline in mean performance over the two-wave, 9-year follow-up period (β = .17, $p < .001$). Moderation models showed that the link between change in dispersion and change in mean performance was pronounced in comparatively older adults (β = .28), women (β = .27), individuals with less education (β = .23), and those with lower income (β = .23) (all *p*s < .001).

Discussion. Findings suggest that increases in dispersion may not always be maladaptive in normative, adult lifespan samples and may reflect healthier cognitive profiles in individuals who are at greater risk for cognitive impairment.

Keywords: Cognitive aging, Intraindividual variability, Longitudinal change, Lifespan development

Introduction

Intraindividual variability (IIV) refers to short-term dynamic changes within an individual operating on micro timescales (i.e., seconds, minutes, days, or weeks) that can describe people, contexts, or general processes (Cerino & Hooker, 2019). Taking an IIV approach provides investigators with the opportunity to evaluate dynamic fluctuations in cognitive performance beyond the traditionally used measures of central tendency, such as mean performance (e.g., Cerino et al., 2021; MacDonald & Stawski, 2020; Stawski et al., 2019; Halliday et al., 2018). Growing evidence suggests that higher levels of certain forms of IIV in cognitive performance are indicative of cognitive decline and impairment in old age (Malek-Ahmadi et al., 2017). For example, Bangen and colleagues (2019) observed that higher levels of cognitive dispersion, a form of IIV that represents fluctuations across cognitive domains at a single time-point, predicted faster rates of brain structure atrophy as well as functional decline over a two-year period among older adults (n = 451 with mild cognitive impairment, n = 285 cognitively normal). This suggests that cognitive dispersion could be a sensitive marker of neurodegeneration in older adults.

Research has begun to focus on cognitive dispersion as a critical but understudied indicator of IIV. Some dispersion is to be expected in cognitively normal individuals and may not always indicate impairment (Schretlen et al., 2003), and dispersion may normatively increase with age (Christensen et al., 1999). However, recent evidence suggests there may be a link between high levels of dispersion and neurological indicators of cognitive impairment in clinical samples (Gleason et al., 2018). Although past research on dispersion provides valuable insights regarding its potential role in cognitive decline among clinical samples, little is known about dispersion and its correlates in normative, adult lifespan samples. Research on such samples is needed to elucidate for whom and under what circumstances dispersion reflects a reliable indicator of cognitive health. The present study thus used two-wave longitudinal data from the national Midlife in the United States Study (MIDUS) to characterize dispersion and its correlates, in a normative sample that captures an adult lifespan context.

IIV in Lifespan Developmental Research

IIV has been operationalized in several ways, with each providing distinct information into cognitive processes (Cerino & Hooker, 2019). Specifically, IIV has been defined as response time inconsistency (trial-to-trial fluctuations in performance on the same task; e.g., Stawski et al., 2019; MacDonald & Stawski, 2020), performance variability across sessions or days (fluctuations in performance on a particular task across repeated occasions; e.g., Cerino et al., 2021), or dispersion (fluctuations in performance across multiple tasks at a single time-point; e.g., Halliday et al., 2018). It is important to note two caveats prior to summarizing the existing literature in this field. First, many of the IIV studies discussed below were based on samples that are relatively homogenous and tend to be well-educated and White. Second, cross-study comparisons of studies examining IIV are somewhat complicated by the many operationalizations and quantifications of IIV (Stawski et al., 2019).

There is growing evidence to support the assertion that certain forms of IIV provide novel predictive utility beyond measures of central tendency as a marker of cognitive health. Dixon and colleagues (2007) observed in a sample of 304 older adults with or without cognitive impairment, that age and cognitive status groups were more strongly distinguished by measures of response time inconsistency (RTI), than by mean performance on cognitive tasks. Variability in cognitive performance has largely been recognized as reflecting diminished efficiency in cognitive processes. This reduction has been identified as a marker of both normative and pathological cognitive aging (Bielak et al., 2014). It is also noteworthy that recent research investigating dispersion as a form of IIV has shown a possible U-shaped relationship between IIV and age, suggesting that inconsistency in cognitive performance is high in childhood, decreases in younger adulthood and midlife, and then returns to higher levels in older age (Yoneda et al., 2022).

Sociodemographic Correlates of IIV in Cognitive Performance

IIV in cognitive performance has been linked to sociodemographic factors associated with increased risk of cognitive impairment, including sex, age, and socioeconomic status (SES). For example, there is evidence pointing to sex differences in RTI, defined as trial-to-trial fluctuations within a speeded-response time task. Dykiert and colleagues (2012) found that levels of RTI were greater in women in a sample of 1,994 individuals ranging in age from 4 to 75 years. This finding is noteworthy given evidence suggesting that women also tend to have faster age-related declines in global cognition and executive functioning compared to men (Levine et al., 2021).

Several notable studies have suggested that the oldest adults tend to have the highest levels of IIV (Schretlen, 2003; Hilborn et al., 2009). For example, Hultsch, McDonald, and Dixon (2002) assessed dispersion across cognitive tasks as well as RTI to examine age differences in cognitive variability in a clinically normative sample of 99 younger adults (ages 17-36 years) and 763 older adults (ages 54-94 years). Their findings suggested that IIV in the form of both dispersion and RTI were highest in the older adult group. In a study modeling age differences in performance variability across intensive repeated sessions, Cerino and colleagues examined a sample of 311 older adults (ages 70-90 years) with and without mild cognitive impairment. They found that older age was associated with higher levels of performance variability in memory binding across sessions (Cerino et al., 2021).

It should be noted that some studies have identified possible adaptive qualities to increased levels of IIV in older age. In a study of 36 community-dwelling older adults (ages

60+) that were asked to complete 60 consecutive days of twice a day cognitive assessment, Allaire and Marsiske (2005) found that when practice-related improvement on the tasks was present, higher mean performance was associated with greater cognitive IIV. In this study, IIV was measured by an intraindividual residual index, which reflects variability among multiple domains of cognition across several time-points. The authors suggest that the observation of either adaptive or maladaptive IIV may be dependent upon the cognitive tasks that are utilized. Specifically, they noted that adaptive IIV may be observed when improvement in performance is present as a result of repeated assessments and may reflect active testing of performance strategies by the participant.

The literature is limited regarding the relationship between socioeconomic status (SES) and within-person variability in cognitive performance such as RTI. However, there is information concerning the association between SES and mean cognitive performance, which can in turn be linked to IIV (Hultsch et al., 2002; Li, Aggen, Nesselroade, & Baltes, 2001). In a comprehensive overview of 14 meta-analyses investigating the link between SES and cognitive performance, Korous and Colleagues (2021) reported consistent findings suggesting a small to medium positive association between SES and cognitive performance. This implies that those with lower SES may be more likely to experience greater IIV. Additionally, when examining education level, a key component of SES, Tun and Lachman (2008) found in a sample of 3613 adults (32 - 85 years), that higher education was associated with greater executive efficiency, perhaps resulting in lower levels of IIV (Christensen et al., 2005). In line with this idea, Garrett and colleagues (2012) found that education level was not associated with IIV in the form of RTI in a sample of younger adults (n = 41, 18-34 years), but had a strong and positive association in older adults (n = 57, 60-82 years).

Dispersion as an Understudied Indicator of IIV

Although the implications of more commonly utilized measures of IIV (e.g. RTI, performance variability across sessions, etc.) for cognitive aging are well-established, less is understood about within-person fluctuations across different cognitive tasks that occur at a single time point. Cognitive dispersion is unique to the IIV literature because it represents fluctuations across multiple domains of cognitive functioning (rather than fluctuations in a single domain). Because dispersion reflects an individual's variability in performance across multiple cognitive tasks to capture functioning across domains, it has been suggested to be a sensitive marker of cognitive decline (Watermeyer et al., 2021). Dispersion may be a brief, non-invasive, and cost-effective measure for the early detection of cognitive decline as it provides researchers with a more thorough and inclusive picture of cognitive functioning within the individual (Cherbuin et al., 2010).

Past studies have found that dispersion is sensitive to age differences in older adulthood, specifically suggesting that the old-old (75-92 years) have higher levels of dispersion than the young-old (65-74 years) in a population of 304 individuals without a cognitive impairment (Hilborn, 2009). In addition to being associated with normative cognitive aging (Bangen et al., 2019), dispersion has also been identified as being sensitive to neurocognitive conditions and pathological cognitive decline (Koscik et al., 2016). In a study of 113 younger adults, Rabinowitz and Arnett (2013) found that greater dispersion was linked to post-concussion cognitive dysfunction in college athletes, suggesting that instability in cognitive performance may be associated with certain brain injuries. Additionally, Holtzer and colleagues (2008), found that dispersion was a significant predictor of incident dementia in a sample of 897 older adults (age ≥70 years). Although these studies provide initial evidence that dispersion may be a sensitive indicator of cognitive decline in older clinical populations, they are somewhat limited in their sample sizes and in the indicators of dispersion they employed; as previously mentioned it is possible that the detection of either adaptive or maladaptive dispersion may be dependent on the cognitive tasks included in the analysis.

A coordinated analysis by Yoneda and colleagues (2022) investigating personality correlates of dispersion provides some insight into the characterization of dispersion based on 7 studies: Cognition and Aging in the USA, the English Longitudinal Study of Aging, the Health and Retirement Study, the Long Beach Longitudinal Study, the Swedish Adoption/Twin Study of Aging, MIDUS, and the Wisconsin Longitudinal Study. Their findings point to a possible positive relationship between dispersion and certain protective factors linked to better cognitive health. Yoneda and colleagues found that, across the studies, there was little evidence for a robust negative association between dispersion and mean performance.

Yoneda et al.'s (2022) findings highlight the need to better understand and characterize dispersion in normative samples and how this type of IIV can inform the study of cognitive health and aging. More nuanced investigations of dispersion are required to clarify the extent to which dispersion may or may not reflect maladaptive processes linked to increased risk of cognitive decline. Dispersion reflects a critical form of IIV to study because it can provide an efficient and non-invasive assessment of cognition, it represents an understudied indicator of IIV, and it may provide researchers with a more inclusive picture of cognitive functioning given its capacity to capture cognitive performance across multiple cognitive domains. Thus, the present study systematically examined how dispersion in a younger, clinically normative, and national sample was associated with sociodemographic and cognitive factors whose relationships to healthy cognitive aging have been well-established.

The first objective of this study was to cross-sectionally characterize dispersion and its correlates in an adult lifespan sample from the MIDUS study to provide insight into the relationship between dispersion and important sociodemographic and cognitive factors. Based on past work by Yoneda et al. (2022), we expected to find a null or even positive association between levels of dispersion and average performance across the cognitive tasks. We also expected that in accordance with previous research, dispersion would exhibit null or positive associations with income and education, and a null or negative association with age (Yoneda et al., 2022). Additionally, we recognized that there may exist a curvilinear relationship between dispersion and age: Younger age may be characterized by higher levels of dispersion and, as age increases, these levels may become lower, reflecting more stable cognitive performance in late-middle adulthood, and then increasing again in late adulthood. We thus examined whether there was a curvilinear relationship between age and dispersion.

The second objective was to identify the extent to which (a) changes in dispersion over time were linked to corresponding shifts in mean cognitive performance and (b) examine how such an association may depend on sociodemographic characteristics. Past work indicates that average cognitive performance decreases with age, but the extent to which dispersion increases or decreases across the adult lifespan is unclear (Hilborn et al., 2009; Yoneda et al., 2022). It was thus unclear whether increases in dispersion may be linked to greater or lesser declines in mean performance over the 9-year follow-up. On one hand, increases (or less decline) in dispersion could reflect an adaptive process in the form of maintaining high levels of performance in some cognitive domains with moderate performance in others and could therefore be linked to less decline in mean performance. On the other hand, increases in dispersion could reflect a maladaptive process in the form of significant losses in some cognitive domains while maintaining modest performance in others and could therefore be linked to more decline in mean performance. Moderation models were subsequently conducted to identify the extent to which the link between changes in dispersion and changes in mean cognitive performance differed across key sociodemographic characteristics linked to cognitive aging including age, sex, race, education, and income.

Method

Participants and Procedures

We pursued our research questions using data from the Midlife in the United States National Longitudinal Study of Health and Well-being (MIDUS). A detailed summary of MIDUS can be found elsewhere (Brim et al., 2004; Ryff et al., 2017). MIDUS is an ongoing national study of U.S. adults who were 25-75 years old at baseline (1995-2013). Baseline data were assessed in 1995 (Wave 1; n = 7,108). Willing participants were reassessed in 2004 (Wave 2; n = 4,963) and in 2013 (Wave 3; n = 3,294). Cognitive functioning was only assessed in Wave 2 and Wave 3. Thus, our study employed two-wave data (Waves 2 and 3) that were collected over a 9-year period. Inclusion criteria for this study were that participants provided data on the cognitive functioning tasks at Wave 2 or Wave 3 for the cross-sectional analyses and at Waves 2 and 3 for the longitudinal analyses.

At Wave 2, the analyzed longitudinal sample (2,229) had a mean age of 56±11 years (range = 33-83), was 56% female and 95% white. The sample had a household income of $76,173, and 71% had some postsecondary education. In our analyzed sample, participants were more likely to be younger, female, and have a higher level of education and income (*ps* = .001-.039). The magnitudes of these differences were small (*ds* =.06 -.37; Cohen, 1988)., as with many longitudinal studies (Lindenberger et al., 2001; Radler & Ryff, 2010). Approximately nine years later at Wave 3 of MIDUS, 77% of the sample from Wave 2 was reinterviewed.

Study Measures

Cognitive Functioning. Episodic memory and executive functioning were evaluated at Waves 2 and 3 using The Brief Test of Adult Cognition by Telephone (BTACT) (Lachman & Tun, 2008; Tun & Lachman, 2006). Past studies focused on middle-aged and older adults has shown the BTACT to be a reliable and valid measure of primary dimensions of cognition involving episodic memory and executive functioning; 9-year test-retest reliability of the BTACT has been acceptable (coefficients ranging from .52 to .94); as well as validity checks also supporting the use of this measure across adulthood (coefficients ranging from .42 to .54) (Hamm et al., 2020; Lachman et al., 2014; Tun & Lachman, 2006). A more detailed summary of the BTACT can be found elsewhere (Hughes et al., 2018; Lachman et al., 2010, 2014). It should be noted that the use of telephone assessment is a key distinction between the current study and past studies that have utilized dispersion. Past studies have largely collected cognitive data in-person.

After completing a brief hearing test as inclusion criteria, participants completed two cognitive tests that assessed episodic memory and four tests that assessed executive functioning (Lachman et al., 2014). Episodic memory was assessed with a delayed and immediate recall task (immediate and delayed free recall of 15 words). Executive functioning was assessed using measures of inductive reasoning (completing a pattern in a series of 5 numbers), category verbal fluency (the number of words from the category of animals in 60s), working memory span (the highest span achieved in repeating strings of digits in reverse order), and processing speed (the number of digits produced by counting backward from 100 in 30s). We used T-scores to standardize performance on each task and then generated a mean score to capture average performance across all six tasks at Wave 2 and Wave 3. Wave 3 T-scores were generated using means and standard deviations from Wave 2 to facilitate our longitudinal analyses.

Consistent with prior research (Halliday et al., 2018), we operationalized dispersion as the operant index of intraindividual variability in cognitive performance using an intraindividual/within-person standard deviation. This within-person standard deviation reflects an individual's fluctuations in performance across cognitive tasks (Halliday et al., 2018). We calculated the dispersion scores by first T-standardizing the raw scores on the cognitive tasks (M = 50, SD = 10), after which we generated an intraindividual standard deviation for each participant across tasks. The resulting scores reflect the individual's variability across a battery of cognitive domains relative to the group average performance. Higher levels of dispersion reflect increased variability across cognitive tasks. We generated dispersion scores for each person at both Wave 2 and Wave 3 of the study. A summary of this study's descriptive statistics can be found in Table 1.

For the purpose of examining changes in dispersion and mean performance over time (Objective 2), and as recommended by Cohen, Cohen, West, and Aiken (2013) when using two-wave longitudinal data, we subsequently generated our measures of regressed (residualized) change in dispersion and mean performance by regressing Wave 3 scores on the corresponding baseline (Wave 2) levels of each measure. Residuals from these analyses reflected regressed change that statistically partialed out initial differences due to baseline levels (Maxwell et al., 2017; Tennant et al., 2022). We saved these residuals and used them as indicators of regressed, longitudinal change in dispersion and mean performance (Cohen et al., 2013).

Demographic covariates. Due to their being well-established correlates of cognitive functioning, age, sex, race, education level, and income level were included as correlates, covariates, and moderators in our analyses (Dixon & Lachman, 2019; Hughes et al., 2018; Lachman et al., 2014; Robinson & Lachman, 2018; Tran et al., 2014; Hamm et al., 2024a, 2024b). Age was assessed at Wave 2 (M = 56.62, SD = 11.13), while sex (1 = *male*, 2 =

female; 56% female) and race (0 = *white*, 1 = *non-white*; 95% white) were assessed at Wave 1. Level of education completed (1 = *no school or grade school*, 12 = *doctoral degree*; M = 7.57, SD = 2.51), and total household income (M = 76,173, SD = 60,557) were assessed at Wave 2.

Rationale for Analyses

Preliminary analysis (descriptive models). Bivariate correlations assessed zero-order relationships between the primary study variables. These analyses allowed us to examine the unadjusted relationships between levels of dispersion and central cognitive and sociodemographic factors that are associated with cognitive aging. We then employed paired-sample *t*-tests to assess unadjusted 9-year changes in average levels of dispersion over time (descriptive models). These analyses allowed us to first characterize dispersion cross-sectionally and then to identify the extent to which dispersion levels changed over nearly a decade.

Main analysis (longitudinal predictive models). Our main analyses were conducted in a stepwise fashion. We first employed autoregressive, OLS regression models to examine whether 9-year changes in dispersion across two-waves of data predicted corresponding trajectories of mean cognitive performance. We then expanded the autoregressive models to include interaction terms with sociodemographic moderators to examine whether the relationship between longitudinal changes in dispersion and changes in mean performance depend on age, sex, race, education, and income. All regression models controlled for age, sex, race, education, and income.

Results

Preliminary Descriptive Analysis

Zero-order correlations (unadjusted relationships). Bivariate correlations at Wave 2 showed that higher levels of dispersion were associated with higher levels of mean performance across the cognitive tasks $r = .28$ (see Table 2). There were also small, positive correlations between levels of dispersion and both education and income ($rs = .09, .04$). Higher levels of dispersion were associated with comparatively younger age in this sample ($r = -.08$). A consistent pattern of findings was observed at Wave 3 (see Table 3). Additionally, patterns for the individual cognitive tasks revealed the episodic and working memory domains were most strongly correlated with dispersion (immediate recall $r = 0.25$, delayed recall $r = 0.26$, backward digit span $r = 0.26$).

Curvilinear associations with age (unadjusted relationships). In the interest of examining whether there was a curvilinear relationship between levels of dispersion and age as has been observed in other studies, we ran an OLS regression model that predicted Wave 2 dispersion from age and quadratic age. Results showed no evidence of a significant relationship between quadratic age and dispersion ($\beta = -.24$, $b = -.001$, $SE = .0004$, $p = .117$).

Paired-sample *t*-tests (9-year change). Paired sample *t*-tests revealed no significant changes in average levels of dispersion between waves, suggesting that levels of dispersion were relatively stable over time ($M_{\text{diff}} = 0.04$, $t(2515) = 0.63$, $p = .265$, Cohen's $d = .01$). Results also revealed significant 9-year declines in average cognitive performance ($M_{\text{diff}} = -1.37$, $t(2515) = 14.45$, $p < .001$, Cohen's $d = .29$).

Main Analysis (Longitudinal Predictive Models)

Main effect models. Autoregressive OLS regression models assessed the extent to which regressed change in dispersion predicted corresponding 9-year regressed change in mean performance across the cognitive tasks, while controlling age, sex, race, education level, and income (see Table 4). Results showed that increases in dispersion over time were associated with less decline in mean performance ($\beta = .20$, $b = .34$, $SE = .032$, $p < .001$). Sensitivity analyses that controlled for differences in the time lag between Wave 2 and Wave 3 assessments were consistent with our main analyses ($\beta = .12$, $b = .33$, $SE = .032$, $p < .001$)

Moderation models. We subsequently tested whether key sociodemographic characteristics moderated the relationship between dispersion and mean performance (see Table 5). Results of the autoregressive OLS regression models revealed that age ($\beta = .09$, $b = .01$, $SE = .002$, $p < .001$) and sex ($\beta = .08$, $b = .28$, $SE = .065$, $p < .001$) moderated the positive association between change in dispersion and change in mean performance. Income ($\beta = -.03$, $b = -.01$, $SE = .005$, $p = .064$) and education ($\beta = -.03$, $b = -.02$, $SE = .013$, $p = .080$) marginally moderated the link between change in dispersion and change in mean performance. Race did not moderate the association between change in dispersion and change in mean performance ($\beta = .01$, $b = .05$, $SE = .135$, $p = .78$).

Simple slope analyses probed the interactions to assess the influence of dispersion on mean performance at low (-1 SD) and high (+1 SD) levels of the moderator variables (see Figure 1; Cohen et al., 2013; Hayes, 2017). Results showed that increases in dispersion over time were most strongly associated with shallower 9-year declines in cognitive performance among comparatively older adults (+1 *SD* or 68 years: $\beta = .28$, $b = .46$, $SE = .044$, $p < .001$) versus comparatively younger adults (-1 *SD* or 48 years: $\beta = .12$, $b = .19$, $SE = .047$, $p < .001$). The association was also strongest in women ($\beta = .26$, $b = .45$, $SE = .042$, $p < .001$)

compared to men (β = .10, b = .17, SE = .049, p < .001). Simple slopes analysis further showed the association between change in dispersion and change in mean performance was stronger for those with lower (β = .23, b = .39, SE = .045, p < .001) compared to those with higher levels of education (β = .17, b = .28, SE = .046, p < .001). Lastly, the association was strongest for those with lower income (β = .23, b = .39, SE = .045, p < .001) compared to higher income (β = .17, b = .27, SE = .046, p < .001). Sensitivity analyses that controlled for differences in the time lag between Wave 2 and Wave 3 assessments were consistent with our main analyses in documenting that age moderated (β = .09, b = .01, SE = .003, p < .001), and income and education marginally moderated (βs = -.04 & -.04 , bs = -.01 – -.03, SEs = .005 - .013, ps = .053 - .042), the association between change in dispersion and change in mean performance.

Discussion

This study sought to identify (a) how dispersion was related to cognitive and sociodemographic factors implicated in cognitive aging using a cross-sectional lens and (b) how longitudinal changes in dispersion were linked to trajectories of mean cognitive performance and for whom this association was most pronounced. We observed in our cross-sectional analysis that higher levels of dispersion were associated with higher levels of mean performance, younger age, higher education, and higher income. When the data were examined from a longitudinal perspective (across two waves), we observed that increases in dispersion over the 9-year period were associated with slower declines in mean cognitive performance. Our analysis revealed that the association between longitudinal change in dispersion and change in average performance across tasks was moderated by age and sex, and marginally moderated by education and income level. Results suggest the link between dispersion and mean performance was strongest for older adults, women, and for those with a lower education and income level. Findings advance the literature by providing initial evidence that dispersion may not reflect a risk factor for age-related cognitive decline or impairment in community-dwelling, adult lifespan samples.

Cross-Sectional Characterization of Cognitive Dispersion

Our first objective was to cross-sectionally describe how dispersion was related to established correlates of cognitive health that included average performance, age, sex, race, education level and income level. Our results indicated that higher levels of dispersion were associated with higher mean performance across cognitive tasks. This result is somewhat surprising given that previous investigations have shown that higher variability in response times (RTI), for example, tends to be associated with worse cognitive performance (Bielak et al., 2014). However, this finding is relatively in line with results from Yoneda and colleagues' (2022) coordinated analysis. They found little evidence for a strong negative association between dispersion and mean performance across tasks and observed a small positive association between dispersion and average performance for MIDUS participants. It is notable that, contrary to the present study, Yoneda et al. did not include delayed recall or processing speed in their dispersion index. However, they did include the stop-and-go switch task (SGST; a measure of task switching and inhibitory control), which we omitted due to the larger amount of missing or invalid data on the SGST (9% of SGST data were missing due to technical problems or failure to carry out the task as instructed; Tun & Lachman, 2008). This difference is important given the results from our analysis showing that immediate and delayed recall, and the backward digit span tasks were the strongest performance correlates of dispersion.

One potential explanation for the result showing that greater dispersion is linked to better cognitive performance can be found in MIDUS's sample characteristics. Compared to the other datasets examined by Yoneda and colleagues, MIDUS contained the youngest (M_{age} = 56) sample which was approximately a decade younger than participants from the other studies. Additional results from the cross-sectional analysis revealed noteworthy associations between age, education, and income. The finding that greater dispersion was associated with younger age is especially interesting given past literature suggesting that older age may be associated with higher dispersion in a study that contrasted a sample of young adults (aged 17-36) with old and very old adults (aged 54-94) (Hultsch et al., 2002). However, this finding was not dissimilar to Yoneda and colleagues who did not observe consistent negative associations between age and dispersion.

In recent years, dispersion has been identified as a potentially non-invasive tool that can detect early cognitive changes associated with neuropathology (Halliday et al., 2018). The results of the current study point to boundary conditions and suggest that dispersion may not be sensitive to these early changes in samples of comparatively healthy and younger adults and instead could even reflect processes linked to healthy aging. Several studies have discussed the potential for certain forms of IIV to be adaptive in specific contexts. In a study exploring the potential adaptive qualities of IIV, Cañigueral and colleagues (2023) found among a sample of 208 children (age 6-13 years) that a target training program resulted in increased RTI in performance on a task where greater flexibility in cognitive processing was required for better task performance. Given the potential for dispersion to reflect adaptive processes in younger adults, the cross-sectional results of the current study highlight the importance of a lifespan developmental approach to studying variability in cognitive performance. One explanation for our results showing a positive correlation between dispersion and mean performance is that adults in midlife and early old age may be more efficient at employing flexible cognitive processes, causing them to have higher levels of performance on some tasks but not others and thus have higher variability (dispersion) across tasks.

Results from our preliminary correlational analysis provide additional insight into why dispersion may be linked to better average cognitive performance. Correlations assessing the relationship between dispersion and individual cognitive domains showed the strongest relationships were between dispersion and the immediate recall, delayed recall, and backward digit span tasks. These findings suggest that the positive association between dispersion and average mean performance appears to be driven by individuals who are performing especially well in the domains of the episodic memory (immediate and delayed recall) and working memory (backwards digits), but who may have more modest performance on the other cognitive tasks.

Characterizing Change in Cognitive Dispersion Over Time

Our second objective was to identify how change in dispersion over time was associated with trajectories of cognitive performance and assess possible sociodemographic moderators of this relationship. Findings suggest that increases in dispersion over time are associated with slower declines in mean cognitive performance across a two-wave, 9-year follow-up. These findings point to the possibility that increases in dispersion may be linked to the preservation of cognitive functioning in certain relatively healthy adult lifespan samples. This is somewhat contrary to recent findings indicating that increases in dispersion, calculated as the difference between scores at baseline and at a relatively brief 12-month follow up, were associated with reductions in entorhinal and hippocampal cerebral blood flow in individuals who tested positive for biomarkers for Alzheimer’s disease (Holmqvist et al., 2022). However, this study included a more clinical sample compared to the current study.

Findings from our moderation analyses suggested that the positive associations between change in dispersion and change in mean performance was strongest among older adults, women, and for those with lower education and lower income. Thus, we not only observed that increases in dispersion were associated with shallower declines in cognitive performance, but we also found this association was pronounced in individuals who were at greater risk for declines in cognitive functioning. This points to the possibility that dispersion could be indicative of healthier cognitive aging profiles that involve preserved episodic and working memory in these populations. Future studies should prioritize the formal examination of the mechanisms that might explain the associations revealed in our moderation analysis. For example, investigating individual differences in lifestyle (e.g., engagement in cognitively stimulating activities) may provide insights to further characterize changes in dispersion in adult lifespan samples.

Our findings can also be interpreted from the perspective of past work that has proposed a U-shaped relationship between age and IIV. Specifically, our results showing that the younger (vs. older) adults in our sample have higher levels of dispersion may be due to the fact that MIDUS is a relatively younger sample. Perhaps in another sample, representing lifespan data from early childhood to advanced old age, we would see the pattern discussed by Williams et al. (2005) that found IIV in the form of RTI was high in younger age, lower in midlife, and increased again in later adulthood. What is less intuitive, however, is our finding that even though our adult lifespan sample was younger on average than many other national studies, the oldest adults seem to experience the largest benefits of dispersion in relation to slower declines in mean cognitive performance. In fact, the moderation analysis revealed that the link between increases in dispersion and attenuated declines in mean performance was twice as large in older versus younger adults. It may be valuable for future studies to examine dispersion's link to psychobehavioral correlates of healthy cognitive functioning to better understand how dispersion may be contributing to less decline in cognitive performance as individuals grow older.

Our results that showed increases in dispersion over time were associated with less decline in mean performance are also notable when considered within the context of cognitive aging frameworks. Theories related to behavioral trajectories of cognitive flexibility suggest that as age increases, flexibility in cognition, often measured using task-switching tests, steadily declines (Schwarze, Fandakova, & Lindenberger, 2024). Perhaps our results suggesting an adaptive quality to increases in variability over time, point to the possible utilization of compensatory strategies that make up for cognitive losses associated with aging through increased cognitive flexibility. It would be valuable for future studies to investigate possible links between levels of cognitive dispersion and performance on tasks of cognitive flexibility (e.g., task switching) to examine an additional potential mechanism driving the association between changes in dispersion and change in mean performance. It is possible that increases in dispersion in this sample could additionally point to an adaptive process associated with aging that functions to maintain high levels of performance on some tasks (e.g., in the domains of episodic and working memory) and moderate performance on others, thereby leading to less decline in cognitive functioning in general over time. In other words, perhaps in younger samples cognitive dispersion may be reflecting the level of cognitive adaptability an individual displays in response to specific tasks. Thus, in our study, higher levels of dispersion across tasks may reflect more efficient cognitive accommodation or responsiveness on specific tasks.

Several limitations of this study should be noted. First, although extensive work has been conducted on the reliability and factor structure of the BTACT which has shown it to be an efficient tool for neuropsychological assessment and for monitoring trajectories of cognitive aging (Hughes et al., 2018; Lachman et al., 2014; Tun & Lachman, 2008), there are some limitations to telephone testing. For example, testing over the phone restricts the types of cognitive measures to those that are auditory in nature, while in-person testing can allow for assessing visual and tactile domains. Thus, future research should formally evaluate whether associations between changes in dispersion scores and cognitive functioning vary as a function of assessment modality (i.e., telephone administration, in-person clinic assessments, mobile cognitive test performance in naturalistic settings). Further, this study advanced understanding of correlates of dispersion as one operant index of IIV in a national adult lifespan sample. Future work should use other longitudinal studies of cognitive aging to characterize changes in other indices of IIV (e.g., RTI in speeded response time tasks, performance variability across intensive repeated measurement sessions) and how they may differ or match the pattern of findings in the current study. In this way, a more comprehensive picture of adaptive and maladaptive markers of cognitive aging can be drawn for samples across the adult lifespan. Our study may also be limited by the specific domains of cognition assessed by MIDUS; subsequent studies using dispersion should consider how the tasks included in the generation of the dispersion index may impact the observed relationships.

Conclusion

The present findings provide initial evidence that increased levels of dispersion may not always be maladaptive. This finding has meaningful implications for the study of healthy cognitive aging. Results showed that in a comparatively younger and unimpaired sample, higher levels of within-person variability across cognitive tasks were associated with higher average performance, or better cognitive functioning. Findings also suggest that from a longitudinal perspective, increases in dispersion over time were linked to slower declines in cognitive functioning, and this association was strongest in those who are generally at higher risk for future cognitive impairment. Our results highlight the importance of examining dispersion in non-clinical, normative, adult lifespan samples that are more representative of the population to better describe its links to both healthy and unhealthy cognitive aging.

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Conflicts of Interest

The authors have no conflicts of interest to declare.

Ethics Approval

MIDUS data collection was reviewed and approved by the Education and Social/Behavioral Sciences and the Health Sciences Institutional Review Boards at the University of Wisconsin-Madison.

Consent to Participate

Written consent was obtained for all participants prior to beginning the study.

Data Availability

Participants in the present study were drawn from MIDUS. Data and study materials for MIDUS are publicly available from the Inter-University Consortium for Political and Social Research after registration (https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/203). The design, hypotheses, and analytic plan were not preregistered.

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Table 1

Descriptive Characteristics of the Participants

Variable	*M* ± *SD*	*n* (%)	Range
Age[b]	55.62 ± 11.13		33 - 83
Sex[a]			
Male		979 (43.9%)	
Female		1,250 (56.1%)	
Race[a]			
White		2,119 (95.1%)	
Black		53 (2.4%)	
Native American		5 (0.2%)	
Asian or Pacific Islander		9 (0.4%)	
Other		27 (1.2%)	
Multiracial		16 (0.7%)	
Income[b]	76,173 ± 60,557		0 – 300,000
Education[b]	7.57 ± 2.51		1 - 12
Dispersion[b]	7.48 ± 3.06		0.42 – 35.49
Mean performance[b]	49.96 ± 6.81		27.63 – 73.04
Dispersion[c]	7.34 ± 2.91		1.09 – 19.41
Mean performance[c]	49.89 ± 7.00		21.89 – 72.44

Note. SES = socioeconomic status.

[a] Wave 1; [b] Wave 2; [c] Wave 3.

Table 2

Zero-Order Correlations for the Main Study Variables and Wave 2 Cognitive Tasks

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Age[b]	–																
2. Sex (female)[a]	.004	–															
3. Race (minority)[a]	-.05	.03	–														
4. Education[b]	-.14	-.10	-.01	–													
5. Income[b]	-.29	-.12	-.06	.35	–												
6. Immediate recall[b]	-.32	.21	-.05	.21	.16	–											
7. Delayed recall[b]	-.32	.21	-.05	.19	.14	.79	–										
8. Backwards counting[b]	-.43	-.14	-.13	.29	.28	.29	.25	–									
9. Category fluency[b]	-.31	-.07	-.06	.34	.22	.31	.26	.42	–								
10. Backwards digits[b]	-.17	.03	-.03	.20	.13	.35	.33	.30	.21	–							
11. Number series[b]	-.26	-.11	-.12	.41	.28	.29	.26	.48	.38	.34	–						
12. Dispersion[b]	-.08	.02	.03	.09	.04	.25	.26	.16	.12	.26	.14	–					
13. Mean performance[b]	-.44	.03	-.11	.40	.29	.74	.71	.68	.64	.62	.68	.28	–				
14. Dispersion[c]	-.10	-.01	-.01	.08	.06	.15	.16	.14	.13	.19	.09	.34	.22	–			
15. Mean performance[c]	-.50	.04	-.11	.36	.30	.47	.46	.61	.48	.42	.54	.19	.75	.29	–		
16. Δ Dispersion[bc]	-.09	-.01	-.004	.06	.04	.07	.09	.09	.08	.13	.04	.00	.12	.94	.24	–	

17. Δ Mean performance[bc]	-.35	.04	-.02	.09	.16	-.10	-.09	.17	.03	-.08	.05	-.04	.00	.19	.66	.22	–

Note. SES = socioeconomic status. All rs ≥ .05 are significant at $p < .05$.

[a] Wave 1; [b] Wave 2; [c] Wave 3.

Table 3

Zero-Order Correlations for the Main Study Variables and Wave 3 Cognitive Tasks

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Age[b]	–																
2. Sex (female)[a]	.004	–															
3. Race (minority)[a]	-.05	.04	–														
4. Education[b]	-.15	-.10	-.01	–													
5. Income[b]	-.29	-.11	-.05	.35	–												
6. Immediate recall[c]	-.32	.21	-.05	.22	.16	–											
7. Delayed recall[c]	-.32	.21	-.05	.19	.14	.79	–										
8. Backwards counting[c]	-.43	-.14	-.13	.29	.28	.25	.25	–									
9. Category fluency[c]	-.31	-.07	-.06	.34	.22	.26	.26	.42	–								
10. Backwards digits[c]	-.17	.03	-.03	.20	.13	.33	.33	.30	.21	–							
11. Number series[c]	-.26	-.11	-.12	.41	.28	.26	.26	.48	.38	.34	–						
12. Dispersion[b]	-.08	.02	.03	.09	.04	.26	.26	.16	.12	.26	.14	–					
13. Mean performance[b]	-.45	.03	-.10	.41	.30	.71	.71	.68	.64	.62	.68	.28	–				
14. Dispersion[c]	-.11	-.004	.004	.07	.05	.16	.16	.16	.13	.19	.08	.35	.22	–			
15. Mean performance[c]	-.52	.04	-.09	.37	.30	.46	.46	.61	.49	.42	.54	.19	.75	.29	–		
16. Δ Dispersion[bc]	-.09	-.01	-.004	.05	.04	.08	.08	.11	.08	.13	.03	.00	.13	.94	.24	–	
17. Δ Mean performance[bc]	-.35	.03	-.02	.09	.16	-.09	-.09	.17	.04	-.08	.05	-.04	.00	.19	.66	.21	–

Note. SES = socioeconomic status. All rs ≥ .05 are significant at $p < .05$

[a] Wave 1; [b] Wave 2; [c] Wave 3.

Table 4

Main Effect Model Regression Coefficients for 9-Year Regressed Changes in Mean Performance

Variable	Model 1	
	β	*b* (*SE*)
Age[b]	-.40**	-.16 (.009)
Sex[a]	.06*	.58 (.179)
Race[a]	-.06*	-1.23 (.403)
Education[b]	.11**	.19 (.040)
Income[b]	.09**	.07 (.016)
Dispersion[b]	.00	.00 (.032)
Mean performance[b]	-.26**	-.19 (.017)
Δ Dispersion[bc]	.20**	.34 (.032)

Note. SES = socioeconomic status.

[a] Wave 1; [b] Wave 2; [c] Wave 3.

* *p* < .05; ** *p* < .01.

Table 5

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	*b* (*SE*)	*β*	*b* (*SE*)	*β*	*b* (*SE*)	*β*	*b* (*SE*)	*β*	*b* (*SE*)
Age[b]	-.39**	-.16 (.009)	-.40**	-.16 (.009)	-.40**	-.16 (.008)	-.40**	-.16 (.008)	-.40**	-.16 (.008)
Sex[a]	.06**	.62 (.178)	.06**	.60 (.178)	.06**	.56 (.177)	.06**	.54 (.177)	.06**	.55 (.177)
Race[a]	-.06**	-.20 (.398)	-.06**	-1.24 (.397)	-.06**	-1.21 (.399)	-.06**	-1.24 (.398)	-.06**	-1.25 (.399)
Education[b]	.10**	.18 (.039)	.11**	.19 (.039)	.11**	.19 (.039)	.10**	.19 (.039)	.10**	.19 (.039)
Income[b]	.09**	.00 (.000)	.09**	.07 (.015)	.09**	.07 (.015)	.09**	.07 (.015)	.09**	.07 (.015)
Dispersion[b]	.00	.01 (.031)	-.00	.00 (.031)	.00	.00 (.031)	.00	.00 (.031)	.00**	.00 (.031)
Mean performance[b]	-.26**	-.19 (.017)	-.26**	-.19 (.017)	-.26**	-.18 (.016)	-.26**	-.18 (.016)	-.26**	-.18 (.016)
Δ Dispersion[bc]	.19**	-.30 (.161)	.19**	-.08 (.107)	.20**	.32 (.033)	.20**	.49 (.101)	.19**	.39 (.050)
Δ Dispersion[bc] x age[b]	.08**	.01 (.003)								
Δ Dispersion[bc] x sex[a]			.08**	.27 (.064)						
Δ Dispersion[bc] x race[a]					.01	.05 (.135)				
Δ Dispersion[bc] x education[b]							-.03	-.02 (.012)		
Δ Dispersion[bc] x income[b]									-.04	-.01 (.005)

Moderated Effect Model Regression Coefficients for 9-Year Regressed Changes in Mean Performance

Note. SES = socioeconomic status.

[a] Wave 1; [b] Wave 2; [c] Wave 3.

* $p < .05$; ** $p < .01$.

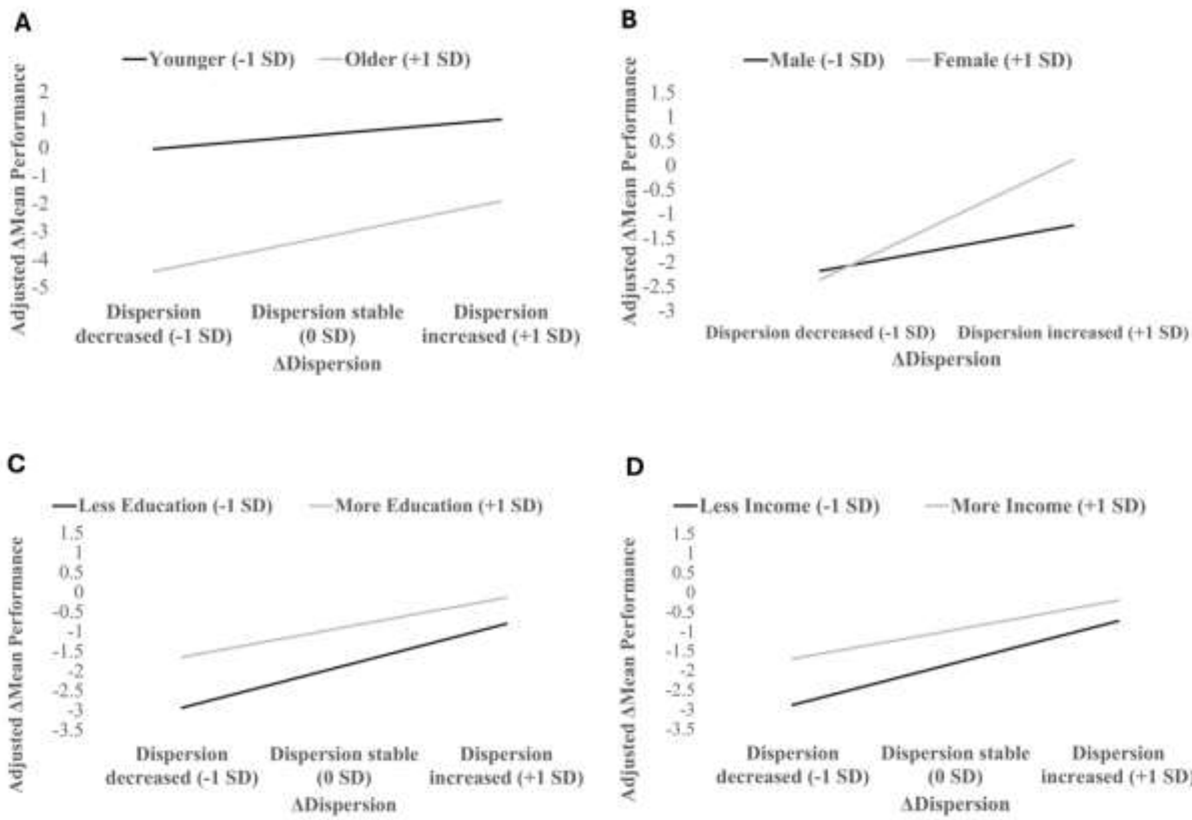
Figure 1. Predicted values adjusted for average sample declines of -1.37 units in mean performance.

Notes. SD = standard deviation. Mean performance is represented as T-scores. Regressed changes in dispersion predicting regressed change in (A1) mean performance at younger (-1 SD) and older (+1 SD) ages; (B) mean performance for men and women; (C) mean performance at lower (-1 SD) and higher (+1 SD) levels of education; and (D) mean performance at lower (-1 SD) and higher (+1 SD) income.

Alt Text:

Graph of study results showing that the positive relationship between change in average performance and change in cognitive dispersion is most prominent in (A) older adults; (B) for females; (C) for those with less education; (D) for those with lower income.

Figure 1


A
Younger (-1 SD)
Older (+1 SD)
Adjusted ΔMean Performance
2
1
0
-1
-2
-3
-4
-5
Dispersion decreased (-1 SD)
Dispersion stable (0 SD)
Dispersion increased (+1 SD)
ΔDispersion
B
Male (-1 SD)
Female (+1 SD)
Adjusted ΔMean Performance
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
Dispersion decreased (-1 SD)
Dispersion increased (+1 SD)
ΔDispersion
C
Less Education (-1 SD)
More Education (+1 SD)
Adjusted ΔMean Performance
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
Dispersion decreased (-1 SD)
Dispersion stable (0 SD)
Dispersion increased (+1 SD)
ΔDispersion
D
Less Income (-1 SD)
More Income (+1 SD)
Adjusted ΔMean Performance
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
Dispersion decreased (-1 SD)
Dispersion stable (0 SD)
Dispersion increased (+1 SD)
ΔDispersion