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Cumulative Social Advantage Across the Lifespan: Examining the Convergent and Predictive Validity of a Multidimensional Hierarchical Construct for Health and Longevity

Anthony D. Ong[1, 2] and Frank D. Mann[3]
[1] Department of Psychology, Cornell University
[2] Joan and Sanford I. Weill Department of Medicine, Weill Cornell Medicine
[3] Department of Medicine, Renaissance School of Medicine, Stony Brook University

This study introduces the concept of cumulative social advantage as a hierarchical construct encompassing multiple aspects of social connection, including religious, psychosocial, familial, and emotional dimensions. Using data from the Midlife Development in the United States–II ($n = 4{,}028$) and Refresher ($n = 2{,}586$) cohorts, we assessed the dimensionality, replicability, measurement invariance, and validity of a hierarchical model. Results support measurement invariance across demographic groups and demonstrate the model's convergent and predictive validity. Cumulative social advantage was associated with lower multimorbidity ($\beta = -.17$ [−.22, −.13], $p < .001$), reduced adiposity ($\beta = -.12$ [−.16, −.08], $p < .001$), fewer difficulties with moderate ($\beta = -.18$ [−.22, −.14], $p < .001$) and basic activities of daily living ($\beta = -.20$ [−.24, −.16], $p < .001$), and a decreased hazard rate for all-cause mortality (adjusted hazard ratio = 0.67 [0.47, 0.95], $p < .001$), with a standard deviation increase in cumulative social advantage predicting a 33% reduction in the hazard rate. The ameliorative influence of cumulative social advantage was consistent across sex, race, and education. These findings highlight the complex relationship between social connections and critical health outcomes, emphasizing the importance of considering cumulative social advantage as a potential explanation for understanding individual differences in health across the lifespan.

Public Significance Statement
This study introduces the concept of cumulative social advantage, a multidimensional construct encompassing religious, psychosocial, familial, and emotional support. Findings suggest that individuals with higher levels of cumulative social advantage experience better health outcomes and increased longevity, highlighting the importance of fostering supportive social environments across multiple domains to promote healthy aging and reduce health disparities.

Keywords: social connection, cumulative advantage, health

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Anthony D. Ong https://orcid.org/0000-0002-5032-667X
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Correspondence concerning this article should be addressed to Anthony D. Ong, Department of Psychology, Cornell University, 37 Forest Home Drive, Martha Van Rensselaer Hall, Ithaca, NY 14853-4401, United States. Email: anthony.ong@cornell.edu

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Anthony D. Ong

Social connections are fundamental to health and well-being across the lifespan. An extensive body of research consistently demonstrates that individuals with strong, supportive social relationships experience better physical and mental health, greater resilience in the face of adversity, and ultimately, longer, healthier lives compared to those who lack such connections (Holt-Lunstad, 2018; Holt-Lunstad et al., 2010; Naito et al., 2023; Yang et al., 2016). The significance of social connections for health and well-being is particularly salient in the context of aging. As individuals navigate the challenges and transitions associated with growing older, such as retirement, widowhood, and declining health, the presence of supportive social ties becomes increasingly crucial for maintaining physical and psychological well-being (Antonucci et al., 2014; Carstensen et al., 1999; Cornwell et al., 2008).

Despite the growing body of research on social connection and health, there remains a paucity of comprehensive theoretical models that integrate multiple dimensions of social connection into a single framework (Holt-Lunstad, 2018, 2022). Most extant studies have focused on isolated facets of social connection, limiting our understanding of how diverse social resources collectively influence health outcomes. Here, we introduce the concept of cumulative social advantage as a novel approach to examining the multifaceted influence of social connections on health.

Cumulative Social Advantage as a Multidimensional Construct

Cumulative social advantage refers to the accumulation of social resources across multiple dimensions, including religious, psychosocial, familial, and emotional support. This multidimensional construct acknowledges the tendency for various forms of social connection and support to co-occur and exert a combined influence on health and well-being (Dannefer, 2003; Holt-Lunstad et al., 2017). By considering the cumulative impact of varied forms of social connection and support, the concept of cumulative social advantage provides a more comprehensive understanding of an individual's social resources and their potential influence on health outcomes.

Adopting a cumulative social advantage framework offers several distinct advantages over focusing on isolated dimensions of social connection. First, it acknowledges the complex and interconnected nature of social relationships and the support they provide (Berkman et al., 2000; Umberson & Montez, 2010). Second, it allows for examining the combined impact of multiple forms of social connection, which may have differential effects on health outcomes (Beller & Wagner, 2018; Hakulinen et al., 2016). Third, it posits a broad nomological network (Cronbach & Meehl, 1955), allowing for an extensive multimodal range of potential indicators for what is being measured (Keyes, 1998; Ryff & Singer, 2000). Fourth, it provides a more comprehensive understanding of the distribution of social resources across different demographic groups and how these disparities may contribute to health inequalities (Ajrouch et al., 2005; Uphoff et al., 2013).

Several well-established theoretical frameworks lend credence to cumulative social advantage and its hypothesized impact on health outcomes. The life course perspective (Elder et al., 2003) serves as a foundational theory in understanding cumulative social advantage. This perspective emphasizes the importance of considering the accumulation of social resources and experiences throughout an individual's life in shaping health outcomes. It suggests that early life social advantages can have lasting effects on health in later life, creating a cascade of favorable outcomes over time (Dannefer, 2003, 2020; Ferraro & Shippee, 2009).

Building on this foundation, the convoy model (Antonucci et al., 2014) further supports the concept of cumulative social advantage by highlighting the evolving nature of social networks. This model posits that individuals are embedded in a "convoy" of social relationships that evolve and adapt throughout the lifespan in response to life transitions and shifting social roles. The convoy model's emphasis on the dynamic nature of social networks provides a foundation for understanding how social advantages may accumulate over time. It highlights how life events and developmental transitions reshape the composition and quality of one's social network, potentially influencing the ongoing accrual of social resources. As people navigate different life stages, they may acquire new connections, strengthen existing ones, or experience losses in their social networks, all of which can significantly affect health and well-being. This dynamic perspective enhances our understanding of how early social experiences might influence later social resources and how changes in social networks across the lifespan may contribute to the cumulative nature of social advantage or disadvantage.

Frank D. Mann

Complementing these perspectives, the conservation of resources theory (Hobfoll, 2002) and the stress-buffering and direct effects models (Cohen & Wills, 1985; Thoits, 2011) provide additional theoretical support for the protective effects of cumulative social advantage on health. The conservation of resources theory posits that individuals actively strive to obtain, retain, and protect various resources, including social resources, to cope with stress and maintain well-being. In this context, accumulating social resources across multiple domains creates a reserve of support individuals can draw upon during challenging times (Hobfoll, 2002). The stress-buffering model suggests that social support mitigates the negative impact of stress on health by providing resources to cope with stressful events. Conversely, the direct effects model proposes that social support promotes health independently of stress by fostering a sense of belonging, purpose, and self-worth (Cohen & Wills, 1985). The accumulation of social resources across multiple domains may enhance the stress-buffering and direct effects of social support on health outcomes. This cumulative effect becomes particularly crucial in later life when individuals often face increased stress and challenges related to aging, such as health declines, retirement, or loss of loved ones (Charles, 2010; Charles & Carstensen, 2010).

Despite the strong theoretical foundation supporting cumulative social advantage, significant gaps persist in our empirical understanding and measurement of this construct. The multidimensional nature of cumulative social advantage, with its interrelated components and their tendency to co-occur, has rarely been comprehensively assessed. Furthermore, while establishing measurement invariance across diverse demographic groups is crucial for ensuring the validity and generalizability of findings, this critical step has received insufficient attention in existing research (Vandenberg & Lance, 2000).

The Present Study

The present study addresses these critical research gaps by comprehensively examining cumulative social advantage as a hierarchical construct encompassing multiple dimensions of social connection and support. Our objectives are fivefold: (1) assess the dimensionality of cumulative social advantage by identifying the optimal number of dimensions based on available indicators; (2) develop a hierarchical model that captures the correlations among subordinate dimensions of social connection; (3) test the replicability of this hierarchical model across different cohorts; (4) evaluate measurement invariance across age, sex, race, and cohort to ensure the construct's consistency across diverse demographic groups; and (5) examine the convergent and predictive validity of the hierarchical model by investigating its associations with key health outcomes, including multimorbidity, adiposity, physical functioning, and all-cause mortality.

Method

Transparency and Openness

Data and materials from the Midlife Development in the United States (MIDUS) study, including codebooks, survey instruments, and variable descriptions, are publicly available through the MIDUS Colectica Portal (https://midus.colectica.org/). The analysis script is available from the corresponding author upon request. This study meets Level 2 requirements for open science practices.

Procedure and Participants

Data for this study were drawn from the MIDUS-II (2004–2005) and MIDUS Refresher (2008–2009) cohorts of the Midlife Development in the United States (MIDUS) study. These two cohorts provide a unique opportunity to assess the consistency of findings across different samples within a single study while also evaluating the potential impact of an economic recession on cumulative social support. The MIDUS-II cohort data were collected during a period of relative economic prosperity, characterized by a 17.7% increase in gross domestic product and a 14.0% decrease in unemployment. In contrast, the MIDUS Refresher cohort data were collected during the Great Recession, when gross domestic product declined by approximately 3.5%, and the unemployment rate doubled (U.S. Bureau of Economic Analysis, 2024; U.S. Bureau of Labor Statistics, 2024). Despite these differences in macroeconomic conditions, the same study procedures were followed, and identical measures were administered in both cohorts. Only participants with less than 50% missing values for focal variables were included in the present study. Sample characteristics, including age, sex, self-reported race, and level of education, are reported in Table 1.

Table 1
Sample Characteristics for MIDUS-II and Refresher Cohorts

Demographic variable	MIDUS-II development (n = 2,014) *n*	MIDUS-II development (n = 2,014) *M*/%	MIDUS-II holdout (n = 2,014) *n*	MIDUS-II holdout (n = 2,014) *M*/%	MIDUS-II Refresher validation (n = 2,586) *n*	MIDUS-II Refresher validation (n = 2,586) *M*/%
Age	2,014	56.47	2,014	55.94	2,586	52.13
Sex						
Male	893	44.34	904	44.89	1,214	46.95
Female	1,121	55.66	1,110	55.11	1,372	53.05
Race						
White	1,856	92.15	1,831	90.91	2,164	83.68
Black	76	3.77	74	3.67	172	6.65
Other	75	3.72	99	4.92	234	9.05
Missing	7	0.35	10	0.50	16	0.62
Level of education						
Some grade school (1–6)	6	0.30	5	0.25	1	0.04
Junior high school	27	1.34	25	1.24	11	0.43
Some high school	90	4.47	90	4.47	100	3.87
General education diploma	29	1.44	23	1.14	40	1.55
High school diploma	534	26.51	498	24.73	427	16.51
Some college (1–2 years)	348	17.28	342	16.98	365	14.11
Some college (3–4 years)	80	3.97	72	3.57	92	3.56
Associate degree	151	7.50	163	8.09	295	11.41
Bachelor's degree	373	18.52	410	20.36	604	23.36
Some graduate school	61	3.03	67	3.33	64	2.47
Master's degree	214	10.63	220	10.92	439	16.98
PhD, MD, JD, etc.	96	4.77	99	4.92	145	5.61
Missing	5	0.25	0	0.00	3	0.12

Note. n = sample size. MIDUS-II = Midlife Development in the United States–II.

As described in the MIDUS study documentation on the Colectica portal, mortality status has been tracked since MIDUS-II through various methods, including mortality closeout interviews, National Death Index searches, online tracing resources, and routine longitudinal sample maintenance. The MIDUS Core mortality data set, current through 2022, includes mortality status, cause of death, and National Death Index records. Participants with missing mortality data were coded as right censored. Due to the cross-sequential design of the MIDUS study, there is considerable variation in age at each wave of data collection, making time in study, wave of data collection, and calendar date suboptimal time metrics for survival analysis. Therefore, time to event for survival analyses was calculated as either the participants' age at death (Date of Death–Date of Birth) or age at the time of measurement for living/censored participants (Date of Interview–Date of Birth).

Measures

Social Connection Indicators

Twenty-one self-report measures were selected to assess four key theoretical domains of cumulative social advantage (scale details and reliability estimates are available in MIDUS codebooks). These domains include (a) religious and faith-based indicators capturing institutional social integration and community belonging (e.g., "How important is it for you to celebrate religious holidays with your community?" Ellison & George, 1994); (b) parent–child relationship indicators reflecting developmental contexts that shape social capabilities (e.g., "How much love and affection did your mother/father give you?" Eisenberg et al., 2015); (c) community engagement measures assessing social integration and civic participation (e.g., "I feel close to other people in my community" Berkman et al., 2000); and (d) extended emotional support indicators measuring support network utilization (e.g., "How many hours monthly do you receive emotional support from friends/family?" Cohen & Wills, 1985).

To maintain a focused yet comprehensive measure, we excluded certain potential indicators. Scales such as Satisfaction With Relationship to Spouse/Partner were omitted due to their limited applicability across the full sample (i.e., exclusion of unmarried participants). We also excluded measures like Social Potency, which we deemed more reflective of personality traits than social support. These inclusions and exclusions ensured that our construct focused on broadly applicable social connection factors while avoiding conflation with related but distinct psychological constructs.

The selected scales and representative items include (a) *Maternal Affection*: "How much love and affection did she [your mother] give you?" (b) *Paternal Affection*: "How much time and attention did he [your father] give you when you needed it?" (c) *Maternal Generosity*: "How generous and helpful was she [your mother] to people outside the family?" (d) *Paternal Generosity*: "How sociable and friendly was he [your father] to people outside the family?" (e) *Family Support*: "Not including your spouse or partner, how much do members of your family really care about you?" (f) *Friend Support*: "How much can you rely on them [your friends] for help if you have a serious problem?" (g) *Emotional Support—Parent*: "On average, about how many hours per month do you receive informal emotional support (such as getting comfort, having someone listen to you, or getting advice) from each of the following people? Your parents?" (h) *Emotional Support—Child*: "… Your child or children?" (i) *Emotional Support—Other*: "From any other family members or close friends?" (j) *Religious Identification*: "How important is it for you to celebrate or practice on religious holidays with your family, friends, or members of your religious community?" (k) *Religious Practice*: "Read the Bible or other religious literature?" (l) *Religious Support*: "If you had a problem or were faced with a difficult situation, how much comfort would people in your congregation be willing to give you?" (m) *Religious Coping*: "When you have problems or difficulties in your family, work, or personal life, how often do you seek comfort through religious or spiritual means such as praying, meditating, attending a religious or spiritual service, or talking to a religious or spiritual advisor?" (n) *Positive Work–Family Spillover*: "Having a good day on your job makes you a better companion when you get home"; (o) *Positive Family–Work Spillover*: "Talking with someone at home helps you deal with problems at work"; (p) *Social Integration*: "I feel close to other people in my community"; (q) *Meaningfulness of Society*: "I cannot make sense of what's going on in the world (reverse-coded)"; (r) *Social Actualization*: "The world is becoming a better place for everyone"; (s) *Social Contribution*: "I have something valuable to give to the world"; (t) *Social Acceptance*: "I believe that people are kind"; and (u) *Positive Relations With Others*: "Maintaining close relationships has been difficult and frustrating for me (reverse-coded)."

Health Outcomes

Five indicators of aging and physical health were selected to test convergent and predictive validity. (1) *Multimorbidity* was assessed as the count of the total number of chronic conditions participants endorsed in the past 12 months; (2) *Adiposity* was measured by body mass index (BMI), a calculation of weight adjusted for height (kg/m^2); (3) *Basic Activities of Daily Living* (e.g., "Climbing one flight of stairs," "Walking one block") and (4) *Moderate Activities of Daily Living* (e.g., "Climbing several flights of stairs," "Walking several blocks") were assessed via self-reports of physical functional limitations; and (5) *All-Cause Mortality* was operationalized as a binary variable indicating mortality status (0 = no record of death/censored, 1 = deceased).

Data Analysis

Analyses were performed using the "psych" (Revelle & Revelle, 2015), "EFAtools" (Steiner & Grieder, 2020), "lavaan" (Rosseel, 2012), "semtools" (Jorgensen et al., 2022), "survival" (Therneau et al., 2024), and "survminer" (Kassambara et al., 2021) packages in RStudio Version 2023.12.0+369. A flowchart summarizing data analytic procedures is depicted in Supplemental Figure S1.

Exploratory and Confirmatory Factor Analyses

MIDUS-II cohort data were randomly and evenly divided into training (n = 2,014) and holdout (n = 2,014) samples for the estimation of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) models. In accordance with methodological recommendations (Auerswald & Moshagen, 2019), different factor extraction techniques were considered to determine a plausible range of factors to retain. These included parallel analysis (Horn, 1965), the Kaiser–Guttman criterion (Guttman, 1954), the empirical Kaiser criterion (Braeken & van Assen, 2017), and the Hull method (Lorenzo-Seva et al., 2011). Model fit was assessed using metrics such as chi-square (model χ^2), root-mean-square error of approximation (RMSEA), and comparative fit index (CFI). These indices, combined with the interpretability and strength of factor loadings, guided the selection of the preferred model.

Due to the indeterminacy of factor scores (Waller, 2023), factor loadings were further analyzed using forest plots, which presented minimum, average, and maximum loadings across 144 EFA models. These models varied by different modeling decisions, including the factoring method (principal axis factoring or maximum likelihood), the calculation of initial communalities, the criteria for optimization in maximum likelihood, and the type of oblique rotation. A decision rule was established to retain the number of factors that minimized RMSEA and maximized CFI while ensuring that each factor had at least three indicators with a minimum loading above .30 and an average loading of .40 or greater across all EFA models. This is consistent with recommendations by Hair et al. (2010) to meet the minimal standards for interpretability. After determining the number of factors to retain, indicators with a minimum loading of less than .30 or an average loading of less than .40 were excluded from subsequent analyses.

In addition to factor loadings (λ), communalities ($h^2 = \sum \lambda_i^2$) for all indicators were examined. A strict communality cutoff (e.g., $h^2 > .50$) was not used for indicator retention. This decision acknowledged the multidimensional nature of cumulative social advantage, recognizing that indicators with lower communalities could still capture theoretically relevant aspects of the hypothesized construct. Instead, communalities were evaluated alongside the strength of primary factor loadings, conceptual coherence of indicators, the relative absence of cross-loadings, and consistency across modeling decisions, to assess the overall quality of indicators and the interpretability of the factor structure.

Following the determination of the optimal factor structure, a hierarchical CFA model was specified and refined using the holdout sample ($n = 2{,}014$). This model was designed to capture the tendency for multiple dimensions of social connection to correlate. The hierarchical CFA model was informed by the factor loadings from the preferred EFA model and compared to an alternative correlated factors model, which allowed latent factors to correlate rather than load onto a common higher order factor. A family identification number was included as a cluster variable in all confirmatory analyses, including invariance testing, convergent validity, and predictive validity. This adjustment accounted for the nonindependence of observations due to siblings being nested within the same family, with standard errors adjusted using a sandwich estimator. Full information maximum likelihood was employed for missing data.

Replicability and Measurement Invariance

The replicability of the hierarchical CFA model was assessed using data from the validation sample ($n = 2{,}568$). Identical CFA models were estimated for both the holdout and validation samples, allowing all parameters to be freely estimated under the assumption of configural invariance. Standardized estimates were then compared with 95% confidence intervals to evaluate the magnitudes of factor loadings across cohorts.

Measurement invariance is essential for ensuring that the construct of cumulative social advantage is consistently measured across different demographic groups, thereby allowing meaningful comparisons without the risk of measurement artifacts or group biases (Vandenberg & Lance, 2000). To evaluate this, measurement invariance was tested across sex (female vs. male), race (White vs. non-White), cohort (MIDUS-II vs. MIDUS Refresher), and age groups (less than 35 years vs. 35–64 years vs. 65 years and older) using a series of nested models with progressively stricter constraints. First, configural invariance was examined to confirm that the factor structure was equivalent across groups. This was followed by an assessment of metric invariance, which tests whether factor loadings are consistent across groups, suggesting that observed variables are equally salient indicators of latent constructs for each group. Scalar invariance was then evaluated, which requires equivalence in item intercepts across groups. Establishing scalar invariance indicates that differences in observed means can be attributed to latent constructs, thus enabling valid comparisons of latent means. Last, strict invariance was tested, assuming equal residual variances across groups, providing the most stringent evidence for measurement equivalence.

Testing these levels systematically allowed for examining the consistency of measurement across groups, ensuring that observed differences were not due to measurement biases. Achieving scalar invariance is crucial for comparing latent means, while strict invariance offers the highest level of evidence that the measurement functions identically across groups. However, scalar invariance is often sufficient for most practical group comparisons (Putnick & Bornstein, 2016). In the event of noninvariant intercepts or factor loadings, interpretation of group differences can proceed under an assumption of partial measurement invariance if noninvariant parameters have only a minor impact on the estimation of latent variables (Byrne et al., 1989).

Following standard procedures (Vandenberg & Lance, 2000), multiple-group models were used to compare configural, metric, scalar, and strict invariance levels across cohorts and demographic groups. Changes in model fit were assessed using ΔRMSEA, ΔCFI, and standardized root-mean-square residual (Chen, 2007; Cheung & Rensvold, 2002). Multiple fit indices were utilized because each captures distinct aspects of model fit, and simulation studies suggest that using several indices can improve the detection of measurement noninvariance (Chen, 2007; Cheung & Rensvold, 2002). The combination of multiple criteria also helps to mitigate Type I and Type II errors in invariance testing (Putnick & Bornstein, 2016).

The decision rules for retaining invariance were as follows: the more parsimonious model was not rejected if $\Delta\text{CFI} > -0.01$, $\Delta\text{RMSEA} < 0.015$, or standardized root-mean-square residual $<0.030/0.015$ for metric or scalar invariance, respectively (Chen, 2007). A model was considered invariant if at least two of the three criteria were met. If any criteria indicated noninvariance, further analyses were conducted to assess practical implications. Specifically, the difference in mean and covariance structures was calculated as an effect size to quantify potential bias in mean scores (Nye & Drasgow, 2011). Additionally, correlations between factor scores derived from invariant and noninvariant models were computed to further assess the practical significance of potential noninvariance.

Convergent and Predictive Validity

To assess the replicability and convergent validity of the hierarchical factor, the same higher order CFA model was estimated in the validation sample ($n = 2{,}568$) before indicators of physical health were simultaneously regressed on the hierarchical factor. These indicators included a count of chronic conditions, BMI, basic activities of daily living, and moderate activities of daily living. Residuals were allowed to correlate to account for potential shared variance unrelated to the hierarchical construct. In this model, to ensure the inclusion of new endogenous variables did not influence the parameters of the measurement model, the first- and second-order loadings estimated from the holdout sample were specified as fixed parameters in the validation sample. This approach preserved the integrity of the original measurement model while testing its associations with health outcomes. Finally, to assess predictive validity, Cox regression analysis was conducted to determine whether higher order factor scores (Thomson, 1935) were predictive of the hazard of all-cause mortality, before and after adjusting for the potentially confounding effects of sex, race, and educational attainment.

Cohort Differences in Cumulative Social Advantage

Finally, to assess cohort differences in cumulative social advantage, a dummy-coded variable indicating cohort membership (0 = MIDUS-II, 1 = Refresher) was included as a predictor of the higher order factor of cumulative social advantage, in addition to demographic covariates. This regression tested whether cumulative social support, on average, was higher or lower during the Great Economic Recession of 2008–2009, holding other demographic variables constant.

Results

Dimensionality of Social Connection

Pearson's and Spearman's correlations between indicators of social connection are reported in Supplemental Tables S1–S3. In the training, holdout, and validation samples, Bartlett's test (p values < .001) and Kaiser–Meyer–Olkin index (>.75) indicated that data were suitable for factor analysis (Table 2). Different factor extraction techniques in the training sample yielded a wide range of factors to retain (minimum = 1, maximum = 6, mode = 6; Supplemental Figure S2 Panel A). Among these, the four-factor solution demonstrated superior model fit compared to one-factor, two-factor, and three-factor solutions. Specifically, compared to the three-factor solution, the four-factor solution significantly improved model fit ($\Delta\chi^2 = 614.73$, $df = 13$, $p < .001$). Additionally, the four-factor solution maintained three or more indicators per factor with average loadings ≥.40 and minimum loadings ≥.30.

Although the model fit statistics indicated further improvement with a five-factor solution, this model included a factor with no indicators that met the loading criteria (average loading ≥.40 and minimum loading ≥.30; Supplemental Figure S7A). Moreover, although model fit statistics also improved with a six-factor solution, 75% of the six-factor solutions contained Heywood cases, indicating potential overfit and model instability. Based on the above considerations, the four-factor solution was selected as the preferred model. This decision balanced parsimony with model fit alongside the strength and interpretability of factor loadings.

Table 2
Descriptive Statistics for Measures of Psychosocial Support

	MIDUS-II training (n = 2,014)			MIDUS-II holdout (n = 2,014)			MIDUS-II Refresher validation (n = 2,586)		
Indicator of psychosocial support	n	M	SD	n	M	SD	n	M	SD
1. Maternal Affection	1,931	3.12	0.68	1,954	3.14	0.67	2,497	3.18	0.70
2. Paternal Affection	1,853	2.72	0.78	1,885	2.72	0.79	2,253	2.86	0.78
3. Maternal Generosity	1,930	3.36	0.71	1,951	3.37	0.72	2,493	3.37	0.73
4. Paternal Generosity	1,846	3.24	0.79	1,876	3.23	0.81	2,246	3.28	0.81
5. Family Support	2,003	3.29	0.65	1,995	3.28	0.67	2,571	3.26	0.67
6. Friend Support	2,003	3.29	0.65	1,995	3.28	0.67	2,571	3.26	0.67
7. Emotional Support—Parent	1,873	0.46	0.84	1,876	0.47	0.90	2,451	0.60	1.05
8. Emotional Support—Child	1,888	1.01	1.32	1,871	1.02	1.39	2,462	0.88	1.39
9. Emotional Support—Other	1,892	0.94	1.01	1,883	0.96	1.10	2,476	0.95	1.10
10. Religious Identification	2,001	19.88	5.43	1,995	19.42	5.70	2,565	18.70	6.11
11. Religious Practice	1,995	9.90	4.37	1,991	9.57	4.33	2,561	9.13	4.35
12. Religious Support	1,223	13.98	1.74	1,183	13.96	1.77	1,373	13.76	1.84
13. Religious Coping	1,987	5.65	2.13	1,984	5.51	2.14	2,565	5.34	2.21
14. Positive Work–Family Spillover	1,350	11.64	2.96	1,375	11.67	2.94	1,580	11.16	2.89
15. Positive Family–Work Spillover	1,343	13.54	3.18	1,372	13.41	3.15	1,580	12.96	3.02
16. Social Integration	2,003	14.71	3.97	1,997	14.72	4.01	2,567	14.19	3.96
17. Meaningfulness of Society	2,003	9.22	3.11	1,995	9.19	3.05	2,566	9.37	3.07
18. Social Actualization	2,003	12.64	4.02	1,995	12.67	3.93	2,568	11.68	3.96
19. Social Contribution	2,003	15.61	3.70	1,995	15.71	3.63	2,566	15.72	3.56
20. Social Acceptance	2,003	14.08	3.32	1,997	14.00	3.28	2,568	13.26	3.37
21. Positive Relations With Others	2,009	40.64	6.88	2,005	40.52	7.04	2,571	39.52	7.16
Statistical index	χ^2	df	p	χ^2	df	p	χ^2	df	p
Bartlett's test for indicators (Kaiser–Meyer–Olkin)	11873.28	210	<.001 (.78)	12495.67	210	<.001 (.78)	15931.81	210	<.001 (.78)

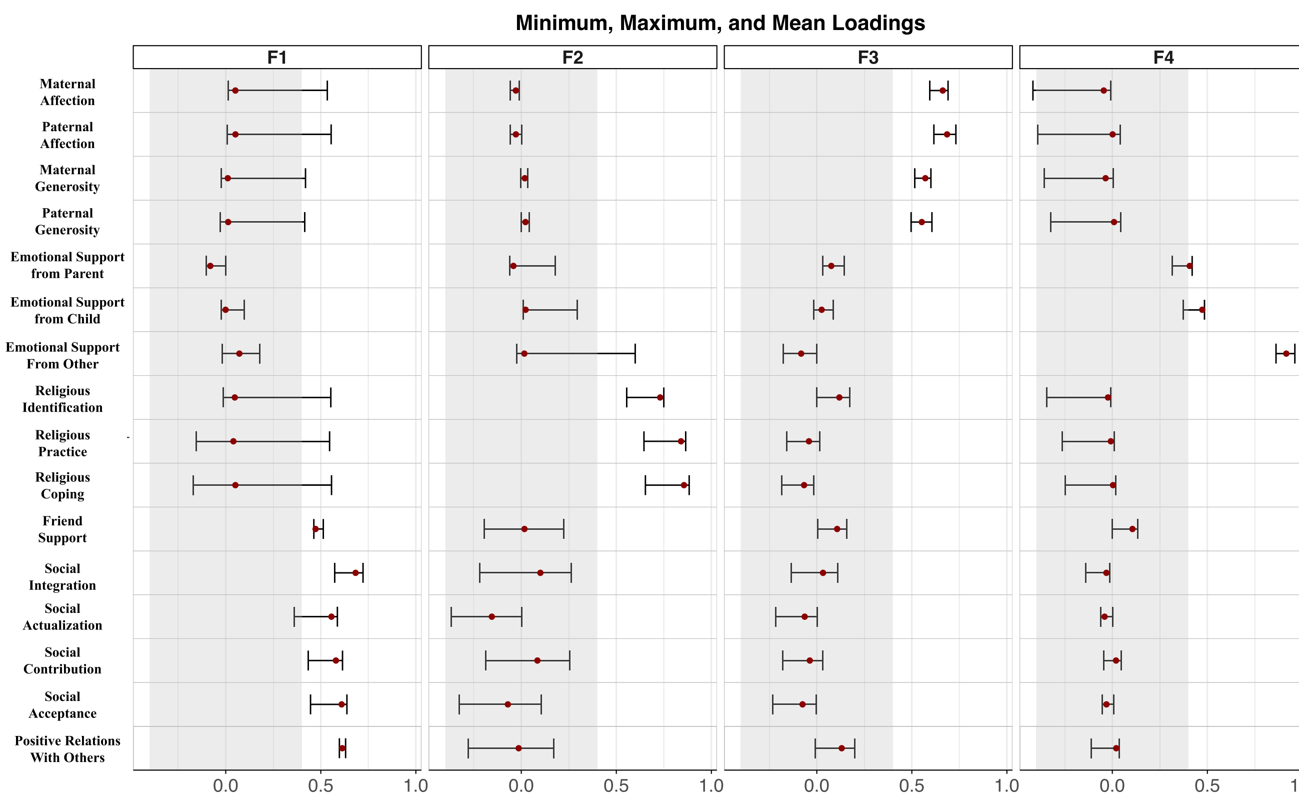
Note. MIDUS-II = Midlife Development in the United States–II; n = sample size; χ^2 = chi-square test statistic for Bartlett's test; p = p value for Bartlett's test.

As depicted in Supplemental Figure S6A, religious affiliation, identification, and coping measures loaded onto the first factor (range of average λ = .77–.87), representing individual differences in religious and faith-based social support. The second latent factor captured individual differences in prosocial relations and community engagement, as measures of social well-being, friend support, and positive relations with others loaded onto this factor (range of average λ = .46–.64). Measures of parental affection and generosity loaded on the third factor (range of average λ = .53–.67), interpreted broadly as individual differences in parental warmth and social modeling. The number of hours that family, friends, and others provided emotional support loaded onto the fourth factor (range of average λ = .42–.86), identifying another dimension of extended interpersonal-emotional support.

Conversely, indicators such as social meaning, family support, religious support, work–family spillover, and family–work spillover were excluded from subsequent analyses due to low loadings (average loading <.40 or minimum loading <.30). Factor extraction techniques and EFA models were then reestimated in the training sample using the reduced pool of indicators (k = 16), which yielded a smaller plausible range of factors to retain (minimum = 1, maximum = 4, mode = 4; Supplemental Figure S2 Panel B). The resulting four-factor solution demonstrated strong psychometric properties, with high average loadings (.41–.86) and minimum loadings >.30 across all factors. Communalities for retained indicators spanned a wide range (h^2 = .18–.74), reflecting the complex, multidimensional nature of cumulative social advantage. In line with our theoretically driven approach, indicators with communalities less than .50 were retained based on their conceptual importance and satisfaction with other statistical criteria. Figure 1 depicts each factor's average, minimum, and maximum oblique rotated loadings across 144 EFA models. Supplemental Figures S3A–S8B depict the average, minimum, and maximum oblique rotated loadings for one-factor through six-factor solutions of the original (k = 21) and reduced pool of indicators (k = 16).

Figure 1

Loadings From the Preferred EFA Model



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Note. EFA models were estimated using data from the MIDUS-II training sample (n = 2,014). The mean rotated factor loading was calculated across 144 EFAs, varying the factoring method (principal axis factoring and maximum likelihood), the calculation of the initial communalities in principal axis factoring, the criterion type, the specification of starting values for maximum likelihood, and the type of oblique rotation, including promax, oblimin, quartimin, simplimax, bentlerQ, geominQ, and bifactorQ. The error rate was 0%, 100% converged, 0% contained Heywood cases, and 100% were admissible. Shaded regions of forest plots encompass −.40 to .40. F = forest plot; EFA = exploratory factor analysis; MIDUS-II = Midlife Development in the United States–II. See the online article for the color version of this figure.

A Hierarchical Model of Social Connection

Average factor correlations in the training sample were uniformly positive (see Supplemental Table S4), indicating a general tendency for dimensions of social support to co-occur. A hierarchical model of cumulative social advantage was the best-fitting model, with a general "a-factor" capturing the tendency for subordinate dimensions of social advantage to correlate. To empirically justify this second-order model, we conducted a nested model comparison between the correlated first-order and second-order CFA models. This comparison involved a correlated factors model, which freely estimated correlations between latent factors, and a higher order model that introduced a superordinate factor. Both models assumed a simple structure, with each indicator loading onto only one latent factor and residual correlations fixed to zero (Supplemental Figure S9). Analysis of factor loadings revealed significant results across both levels of the model. Lower order factor loadings ranged from $\lambda = .35$ to .86, while higher order factor loadings spanned from $\lambda =$ .18 to .68 (all p values <.001). The comparison favored the more parsimonious higher order model, which did not significantly worsen fit compared to the correlated factors model ($\Delta\chi^2 = 4.67$, $\Delta df = 2$, $p = .097$, ΔBayesian information criterion = −9.80).

Despite this comparative advantage, the initial higher order model's absolute fit statistics fell short of conventional thresholds for good model fit ($\chi^2 = 1181.33$, $df = 100$, $p <$ .001, RMSEA = 0.073, 90% CI [.070, .077], CFI = 0.864). To address this, modification indices were consulted, and residual correlations were strategically added to improve model fit (Mueller & Hancock, 2008; see Supplemental Figure S10). The resulting modified higher order CFA model (Figure 2) demonstrated good fit ($\chi^2 = 351.52$, $df = 90$, $p <$ .001, RMSEA = 0.038, 90% CI [0.034, 0.042], CFI = 0.970). This modified model also maintained its advantage over the correlated factors model with identical residual correlations ($\Delta\chi^2 = 5.10$, $\Delta df = 2$, $p = .078$, ΔBayesian information criterion = −9.46).

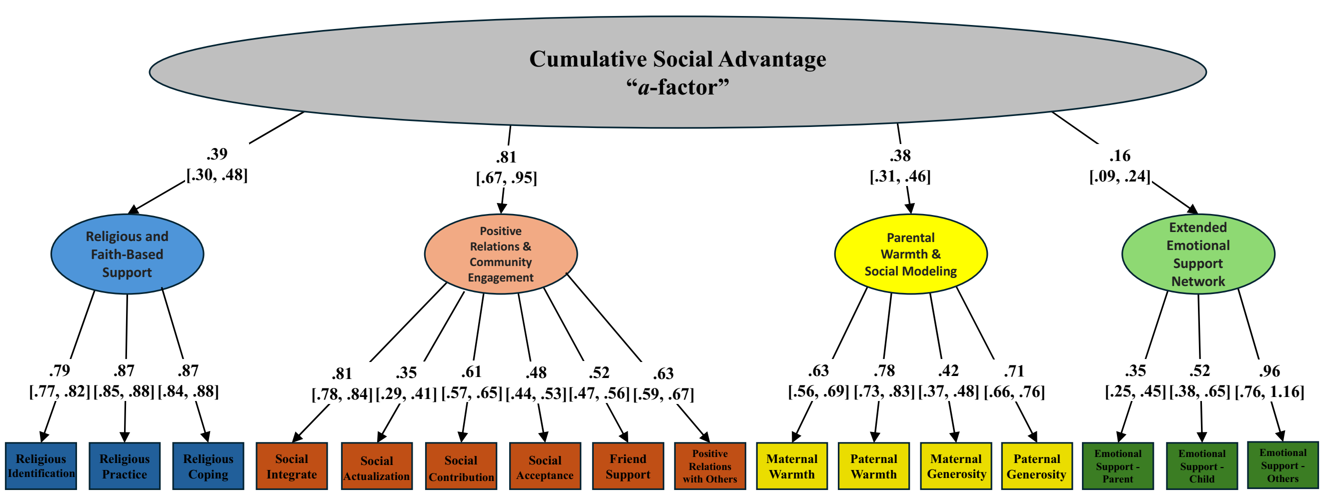
To assess generalizability, the higher order CFA model with residual correlations was validated in the MIDUS Refresher cohort. The model exhibited good fit in this independent sample ($\chi^2 = 377.65$, $df = 90$, $p < .001$, RMSEA = 0.035, 90% CI [0.032, 0.039], CFI = .975). Importantly, standardized factor loadings were consistent across the holdout and validation samples, with point estimates showing overlapping 95% confidence intervals (Table 3). These results provide evidence for the replicability of our higher order model across different samples.

Measurement Invariance and Cohort Differences

Results of measurement invariance models are reported in Supplemental Table S5. For sex, race, and cohort, all fit statistics favored either scalar or strict measurement models, providing consistent evidence for invariance. For age groups (<35 years vs. 35–64 years vs. 65+ years), two out of three fit statistics favored the metric, scalar, and strict models, providing mixed support for measurement invariance. However, the difference in mean and covariance structures indicated that

Figure 2

Standardized Factor Loadings From a Higher Order Model of Cumulative Social Advantage



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Note. Standardized loadings are reported with 95% CIs in brackets for the depicted higher order CFA model fit to data from the MIDUS-II holdout sample. The superordinate "a-factor" represents this general tendency for various forms of social advantage to accumulate across multiple domains. Model $\chi^2 =$ 351.520, $df = 90$, $p < .001$, CFI = 0.97, RMSEA = 0.038, 90% CI [0.034, 0.042], p value Ho: (RMSEA ≤ 0.050) = 1.000, SRMR = 0.038. Correlations among residuals are omitted to ease visualization (see Supplemental Material). CFA = confirmatory factor analysis; MIDUS-II = Midlife Development in the United States–II; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; CI = confidence interval; SRMR = standardized root-mean-square residual. See the online article for the color version of this figure.

Table 3

Factor Loadings From the Higher Order Confirmatory Factor Analysis Model Across Holdout and Refresher Samples

	Cumulative social advantage							
Factor loading	Holdout	Refresher	Holdout	Refresher	Holdout	Refresher	Holdout	Refresher
Higher order loading	0.39 [0.30, 0.48]	0.37 [0.31, 0.44]	0.81 [0.67, 0.95]	0.75 [0.65, 0.85]	0.38 [0.31, 0.46]	0.45 [0.38, 0.53]	0.16 [0.09, 0.24]	0.18 [0.10, 0.25]

	Religious and faith-based support		Community engagement and social support		Parent–child relationship support		Extended emotional support network	
Factor loading	Holdout	Refresher	Holdout	Refresher	Holdout	Refresher	Holdout	Refresher
Lower order loading								
Religious Identification	0.79 [0.77, 0.82]	0.80 [0.78, 0.82]						
Religious Practice	0.87 [0.85, 089]	0.86 [0.85, 0.88]						
Religious Coping	0.87 [0.85, 0.88]	0.89 [0.87, 0.90]						
Social Integration			0.81 [0.78, 0.84]	0.80 [0.77, 0.83]				
Social Actualization			0.35 [0.29, 0.41]	0.28 [0.23, 0.34]				
Social Contribution			0.61 [0.57, 0.65]	0.63 [0.59, 0.66]				
Social Acceptance			0.48 [0.44, 0.53]	0.51 [0.47, 0.54]				
Friendship Support			0.52 [0.47, 0.56]	0.44 [0.40, 0.48]				
Positive Relations With Others			0.63 [0.59, 0.67]	0.61 [0.58, 0.65]				
Maternal Affection					0.63 [0.56, 0.69]	0.69 [0.63, 0.74]		
Maternal Generosity					0.78 [0.73, 0.83]	0.75 [0.71, 0.79]		
Paternal Affection					0.42 [0.37, 0.48]	0.46 [0.41, 0.51]		
Paternal Generosity					0.71 [0.66, 0.76]	0.77 [0.73, 0.81]		
Emotional Support—Parent							0.52 [0.38, 0.65]	0.51 [0.42, 0.60]
Emotional Support—Children							0.96 [0.76, 1.16]	0.76 [0.66, 0.87]
Emotional Support—Others							0.35 [0.25, 0.45]	0.52 [0.43, 0.62]

Note. Standardized loadings are reported with 95% confidence intervals reported in brackets below the corresponding point estimate.

potentially noninvariant parameters across age groups had no practical significance, with the expected bias in mean total score approximating zero (<.001). The high correlation between factor scores estimated from strict and configural invariance models (Pearson's $r = .98$, $p < .001$; Spearman's $\rho = .98$, $p < .001$) confirmed that potentially noninvariant parameters across age groups had a negligible impact on the estimation of factor scores.

Next, the impact of the Great Recession of 2008–2009 on cumulative social advantage was assessed by regressing the higher order factor on a binary variable that indicated whether participants were from the MIDUS-II or Refresher cohorts (0 = MIDUS-II, 1 = Refresher). This regression indicated that, on average, cumulative social advantage was −.17 *SD*s lower for participants in the Refresher cohort (95% CI [−0.25, −0.10], $p < .001$) during the midst of the Great Recession, compared to participants in the MIDUS-II cohort, who participated during a time of relative economic prosperity. Results also indicate a small but significant positive association between age and cumulative social advantage ($\beta = 0.19$, 95% CI [.14, .23], $p < .001$), suggesting that older adults tend to report slightly higher levels of cumulative social advantage, such that a 1-year increase in age is associated with a .03 *SD* increase in cumulative social advantage. Compared to females, on average, males had lower levels of cumulative social advantage ($\beta = -0.46$, 95% CI [−.66, −.26], $p = .007$), while higher levels of education were associated with higher levels of cumulative social advantage ($\beta = 0.24$, 95% CI [.17, .30], $p < .001$).

Convergent Validity

To evaluate convergent validity, the higher order CFA model was extended to include four correlated health outcomes: multimorbidity, BMI, basic activities of daily living, and moderate activities of daily living. These outcomes were simultaneously regressed on demographic variables and the higher order factor of cumulative social advantage, while first- and second-order loadings were specified as fixed parameters, specifically the unstandardized coefficients corresponding to the standardized loadings reported in Table 3.

In this highly constrained model ($\chi^2 = 1704.99$, $df = 235$, $p < .001$, RMSEA = 0.049, 90% CI [0.047, 0.051], CFI = 0.911), higher levels of cumulative social advantage were concurrently associated with lower multimorbidity ($\beta = -0.18$, $SE = .03$, $p < .001$), lower BMI ($\beta = -011$, $SE = 0.03$, $p < .001$), and fewer physical functional limitations, including moderate activities ($\beta = -0.20$, $SE = .02$, $p < .001$) and basic activities of daily living ($\beta = -0.17$, $SE = 0.03$, $p < .001$). As depicted in Figure 3A, these findings provide evidence that the higher order factor is significantly associated with physical health and age-related outcomes, supporting the convergent validity of cumulative social advantage.

Predictive Validity

To evaluate predictive validity, higher order factor scores were saved and included in Cox regressions to predict all-cause mortality before and after adjusting for the potentially confounding effects of demographic covariates. Cox models were estimated using maximum likelihood with robust standard errors, and the Breslow method (Hertz-Picciotto & Rockhill, 1997) was used for tied survival times. Results are reported in Table 4. Providing evidence for the predictive validity of the higher order factor of social advantage, a standard deviation increase in social advantage was significantly predictive of a 34% decrease in the hazard rate of all-cause mortality (unadjusted hazard ratio [unadjusted HR] = 0.66, 95% CI [0.47, 0.94], $p = .025$). This effect remained statistically significant after adjusting for demographic covariates (see Table 4). Compared to females, males had a significantly higher hazard rate of mortality (adjusted HR = 1.14, 95% CI [1.02, 1.29], $p = .026$), as did Black adults (adjusted HR = 1.85, 95% CI [1.32, 2.58], $p < .001$) compared to White adults. Higher educational attainment was associated with a reduction in the mortality hazard rate by approximately 6% (adjusted HR = 0.94, 95% CI [0.88, 0.99], $p = .045$).

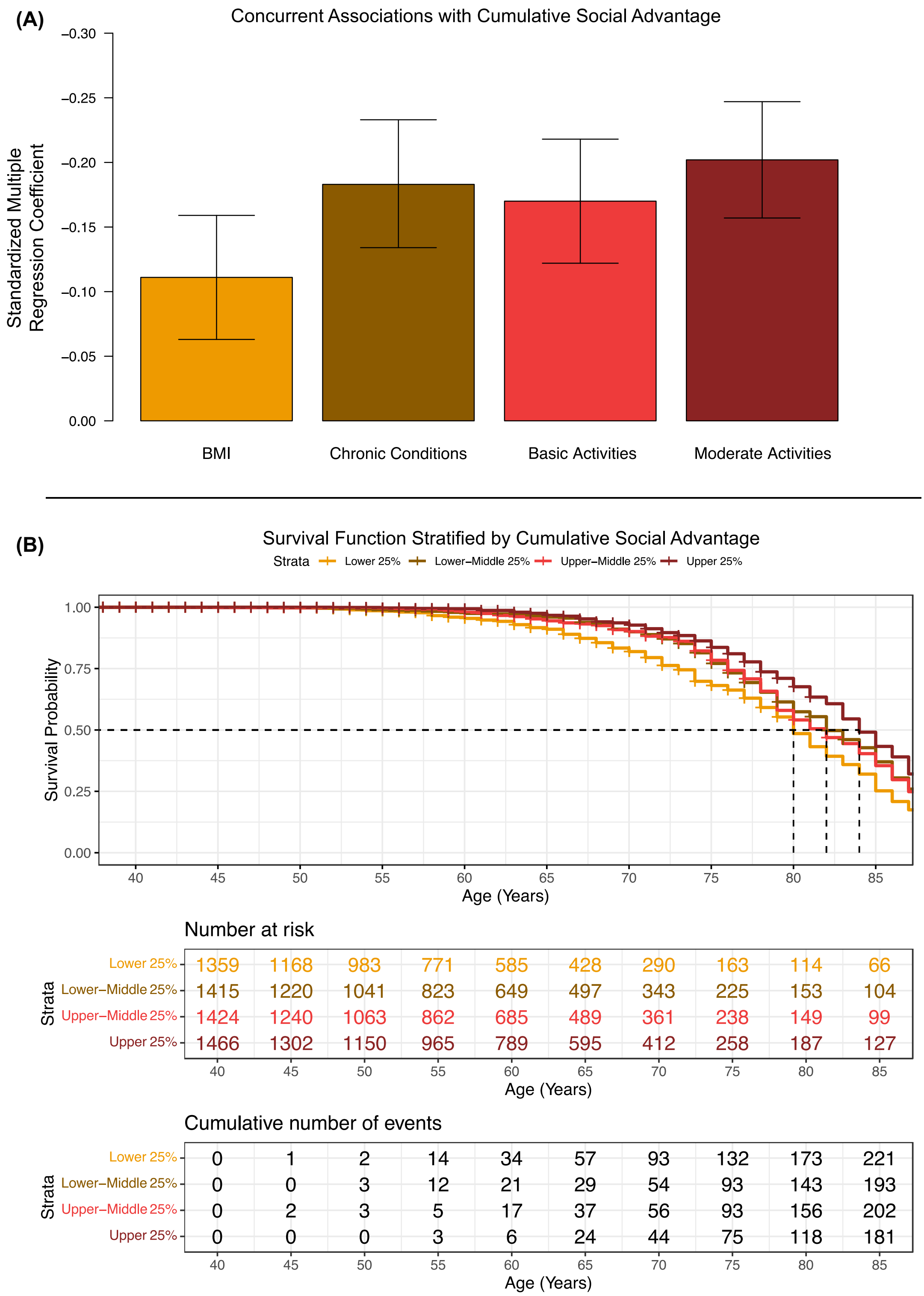
To help visualize findings and determine clinical significance, Kaplan–Meier survival functions were stratified by quartiles of cumulative social advantage (Figure 3B). For individuals with scores in the lower quartile of cumulative social advantage, the median survival time (80 years, 95% CI [79 years, 81 years]) was 2–6 years younger than individuals with scores in the upper quartile (84 years, 95% CI [83 years, 85 years]). Differences in survival curves from the stratified Kaplan–Meier model were statistically significant ($p < .001$), according to regular log-rank, Gehan–Breslow, Peto–Peto, and modified Peto–Peto tests.

Discussion

The present study introduces the concept of cumulative social advantage as a hierarchically structured construct encompassing multiple dimensions of social connection and examines its associations with health outcomes and all-cause mortality in a large sample of adults from the MIDUS study. As noted by Dannefer (2003) and Willson et al. (2007), cumulative advantage is a key mechanism through which inequality is generated across the life course, with early advantage setting in motion a series of cascading socioeconomic, psychosocial, and health outcomes. Our findings provide robust evidence for the multidimensional nature of cumulative social advantage; its replicability across different cohorts; measurement invariance across sex, age groups, and racial groups; and its convergent and predictive validity in relation to key health indicators, mortality risk, and impact from an economic recession.

The exploratory and confirmatory factor analyses revealed a four-factor structure of cumulative social advantage,

Figure 3
Evidence for the Convergent and Predictive Validity of Cumulative Social Advantage



Note. Panel A depicts cross-sectional associations between cumulative social advantage and health outcomes, plotting standardized multiple regression coefficients with 95% confidence intervals adjusted for age, sex, race, and education. Panel B depicts Kaplan–Meier survival functions of all-cause mortality stratified by quartiles of cumulative social advantage. Dashed lines denote median survival times. BMI = body mass index. See the online article for the color version of this figure.

Table 4
Results of Cox Proportional Hazard Model Predicting All-Cause Mortality

Variable	*b*	*SE*	*p*	aHR [95% CI]
Main effects model				
Cumulative social advantage factor score	−0.40	0.18	.025	0.67 [0.47, 0.95]
Male sex	0.13	0.06	.026	1.14 [1.02, 1.29]
Black race	0.61	0.17	<.001	1.85 [1.32, 2.58]
Other race	−0.19	0.23	.414	0.83 [0.53, 1.30]
Education	−0.06	0.03	.045	0.94 [0.88, 0.99]
Interaction effects model				
Cumulative social advantage factor score	−0.43	0.65	.024	0.65 [0.45, 0.95]
Male sex	0.14	0.06	.021	1.15 [1.02, 1.29]
Black race	0.61	0.17	<.001	1.84 [1.32, 2.56]
Other race	−0.22	0.24	.364	0.80 [0.49, 1.30]
Education	−0.06	0.03	.045	0.94 [0.88, 0.99]
Male Sex × Cumulative Social Advantage	0.01	0.06	.899	1.01 [0.89, 1.14]
Black Race × Cumulative Social Advantage	0.23	0.16	.148	1.26 [0.92, 1.73]
Other Race × Cumulative Social Advantage	−0.08	0.17	.634	0.92 [0.65, 1.30]
Education × Cumulative Social Advantage	0.04	0.03	.144	1.05 [0.98, 1.11]

Note. Baseline hazards were stratified by deciles of cumulative social advantage. For the main effects model, BIC = 8973.54. For the interaction model, BIC = 8997.67. $\Delta\chi^2 = 3.99$, $df = 4$, $p = .406$. Test of proportional hazards assumption for the main effects model: $\chi^2 = 3.37$, $p = .640$. b = unstandardized coefficient from Cox model; *SE* = robust standard error; aHR = adjusted hazard ratio with 95% CIs in brackets; p = probability of the estimated association if the null hypothesis is true (i.e., $b = 0$); CI = confidence interval; BIC = Bayesian information criterion.

comprising religious and faith-based support, community engagement and work–family balance, parental warmth and social modeling, and extended emotional support networks. These findings align with previous research highlighting the diverse sources and types of social support individuals may draw upon throughout their lives (Berkman et al., 2000; Dannefer, 2003; Holt-Lunstad et al., 2017; Willson et al., 2007). The higher order factor structure of cumulative social advantage, which captures the intercorrelations among these dimensions, suggests that individuals who benefit from one form of social support are likely to have access to other forms as well. This underscores the importance of considering the cumulative impact of multiple dimensions of social support on health outcomes rather than examining isolated aspects of social connection (Dannefer, 2020; Hakulinen et al., 2016; Willson et al., 2007).

Replicability, Measurement Invariance, and Validity

The replicability of the hierarchical model across the MIDUS-II and MIDUS Refresher cohorts, along with the demonstration of measurement invariance across sex, age groups, and racial groups, provides strong evidence for the robustness and generalizability of the cumulative social advantage construct. These findings suggest that the structure and meaning of cumulative social advantage are consistent across different population subgroups and time periods, enhancing confidence in the validity and utility of this construct for understanding social determinants of health.

The convergent validity of cumulative social advantage was supported by its significant associations with multiple health indicators, including lower multimorbidity, reduced adiposity, and fewer physical functional limitations. These results align with extensive research demonstrating the protective effects of social support on physical health outcomes (Holt-Lunstad, 2018; Holt-Lunstad et al., 2010). Furthermore, the predictive validity of cumulative social advantage was further supported by its association with a decreased hazard rate for all-cause mortality, with a standard deviation increase in cumulative social support predicting an 33% reduction in the hazard rate of mortality.

Our analyses also revealed significant associations between demographic factors—sex, education, and race—and mortality risk, consistent with findings from population-based studies (e.g., Ross et al., 2012; Wu et al., 2021). The higher mortality risk observed among males, individuals with lower educational attainment, and Black participants is consistent with previous findings, including those from the MIDUS-II cohort (Turiano et al., 2014). Notably, the significant effect of cumulative social advantage on mortality, independent of these demographic factors, suggests that the benefits of cumulative social support likely extend across these diverse demographic groups.

Theoretical and Methodological Implications

The present study's findings have important theoretical implications, as they integrate multiple conceptual frameworks to provide a more comprehensive understanding of the multidimensional nature of social support and its cumulative impact on health outcomes. The life course perspective (Elder et al., 2003) and the convoy model of social relations (Antonucci et al., 2014) provide a foundation for understanding how social advantages accumulate across life stages and relationship domains to shape health trajectories in later life. Our findings support these theoretical perspectives by demonstrating the multidimensional structure of cumulative social advantage and its associations with health outcomes across the life course.

Furthermore, theories such as the conservation of resources theory (Hobfoll, 2002) and the stress-buffering and direct effects models (Cohen & Wills, 1985; Thoits, 2011) help elucidate the mechanisms through which cumulative social advantage may promote health and well-being by providing a reserve of social resources that individuals can draw upon to cope with stress and maintain a sense of meaning and purpose in life. Our findings provide empirical support for these theoretical mechanisms, as the cumulative impact of multiple dimensions of social support was associated with better health outcomes and reduced mortality risk.

From a methodological standpoint, the present study demonstrates the value of using advanced statistical techniques, such as EFA and CFA, hierarchical modeling, and multiple-group analysis, to thoroughly assess the dimensionality, replicability, and measurement invariance of complex constructs like cumulative social advantage. Establishing measurement invariance across sex, age, and racial groups is particularly important for ensuring that the construct is being measured consistently across diverse populations, enhancing the validity and generalizability of the findings (Vandenberg & Lance, 2000).

Our analyses also revealed an age-related trend in cumulative social advantage, indicating a small but significant positive association between age and cumulative social advantage, with older adults in our sample reporting slightly higher levels of social resources and support. However, the modest effect size suggests that factors beyond age contribute considerably to an individual's level of cumulative social advantage. The relative invariance of our higher order model across age groups further supports its utility in life course research, enabling meaningful comparisons of cumulative social advantage across different life stages. It is important to note, however, that while our study includes a wide age range, our analyses of age group differences are cross-sectional. This limitation underscores the need for longitudinal studies to disentangle age effects from cohort effects and to examine how cumulative social advantage may change within individuals over time.

These findings also highlight the potential for interventions targeting cumulative social advantage to promote healthy aging and mitigate health disparities. Programs aimed at strengthening family relationships, promoting community engagement, religious practice, and enhancing access to emotional support networks might be particularly effective in promoting cumulative social advantage and its associated health benefits (Antonucci et al., 2014; Berkman et al., 2000; VanderWeele, 2017). Such interventions align with Keyes's (2007) call for a paradigm shift in mental health research and services, emphasizing the importance of fostering supportive social environments across multiple domains.

Limitations and Future Directions

Despite its strengths, the present study has several limitations that point to important directions for future research. A key consideration is the inherently dynamic nature of cumulative social advantage, which evolves throughout the life course. Our cross-sectional data, though informative, cannot capture these temporal dynamics. The concept of cumulative social advantage suggests that resources in one life domain can foster advantages in others—for example, strong early family relationships might develop skills that later enhance community engagement, initiating self-reinforcing cycles of positive social experiences that potentially confer long-term health benefits (Dannefer, 2003, 2020; Ferraro & Shippee, 2009). To fully understand these complex, interconnected pathways, longitudinal research is essential. Such studies would allow us to observe how various dimensions of social support interact and accumulate over time, shaping individual health trajectories (Antonucci et al., 2014; Hobfoll, 2002). This would enable researchers to differentiate between true cumulative effects and potential selection effects, determining whether healthier individuals are more likely to accrue social advantages over time or if the accumulation of social advantages itself leads to improved health.

Our findings on cumulative social advantage should be interpreted within the broader context of socioeconomic inequalities. Factors such as educational attainment, income, and occupational status are well-established drivers of health disparities and cumulative advantage processes (Kuh et al., 2004; Marmot, 2005). This relationship is exemplified by differences observed between the MIDUS-II and MIDUS Refresher cohorts, with the latter collected during the 2008 financial crisis. While our data do not allow for detailed analysis of income inequality metrics such as Gini coefficients (Crystal et al., 2017), the observed cohort differences likely reflect, in part, the economic challenges faced by the MIDUS Refresher participants. Future research should aim to develop more comprehensive models that integrate both social and economic dimensions of cumulative advantage, including more detailed economic data to examine how economic trends and income inequality interact with accumulating social advantages over time. Such integrated approaches could provide a more complete understanding of how various forms of advantage accumulate over the life course to influence health and longevity.

While we strived for a comprehensive representation of cumulative social advantage, we acknowledge that the available data in the MIDUS study constrained our measure selection. Although this limitation is common in secondary data analysis, the MIDUS study's thorough assessment of social relationships and support across multiple domains provided a strong foundation for examining our construct of interest through key theoretical domains, including religious and faith-based support, community engagement, parent–child relationship quality, and extended emotional support networks. These domains align well with established theoretical frameworks of social support and connection across the lifespan (Antonucci et al., 2014; Berkman et al., 2000), allowing us to examine how different types of social resources co-occur across multiple dimensions. The validity of our measurement model is supported by robust associations between cumulative social advantage and multiple health outcomes; the consistent relationships with multimorbidity, BMI, physical functioning, and mortality persisted after controlling for demographic covariates, suggesting that our model captures meaningful variance in social advantage with important implications for health and longevity.

The hierarchical structure of our model demonstrates how different domains of social support tend to co-occur and collectively influence health outcomes, reflecting the multidimensional nature of social advantage (Dannefer, 2003; Ferraro & Shippee, 2009). While our study established the validity of this hierarchical model, future research should examine both differential associations between specific support domains and health outcomes and expand measurement to include emerging dimensions of social connection. Such dimensions include digital networks, workplace social capital, neighborhood resources, extended family networks, and broader cultural capital—additions that would deepen our understanding of social connections' impact on health while identifying new intervention targets.

From an analytical perspective, while our latent variable modeling approach provided valuable insights into cumulative social advantage by examining how measured variables manifest as constructs through patterns of covariation, we acknowledge certain methodological considerations. Our approach emphasized theoretical interpretability and demonstrated strengths through replicability across samples, measurement invariance across demographics, and robust associations with health outcomes. Alternative analytical strategies, such as machine learning algorithms (e.g., random forest, elastic net, extreme gradient boosting), might identify additional complex relationships in our data and potentially enhance the prediction of health outcomes, though often at the cost of reduced interpretability. Future research might explore whether such complementary approaches could enhance prediction while maintaining the theoretical clarity that our current framework provides.

A significant limitation of our study is the predominantly White composition of our sample (~90%). This demographic characteristic limits the generalizability of our findings to more diverse populations. While our measurement invariance results provide some initial evidence for the construct's applicability across broad racial categories, specifically White compared to non-White, the limited representation of specific racial and ethnic minority groups prevents us from making strong claims about the invariance of the cumulative social advantage construct across more specific racial and ethnic categories. Given the well-documented racial and ethnic disparities in health outcomes and social support structures in the United States (Williams et al., 2019), future research should prioritize the validation of the cumulative social advantage construct in more diverse samples. Additionally, future studies should explore how cumulative social advantage may apply to other demographic groups, such as individuals from different socioeconomic backgrounds, sexual orientations, or cultural contexts.

Conclusion

This study introduces a novel, comprehensive approach to understanding the multidimensional nature of social connection and its cumulative impact on health outcomes and mortality risk. By integrating multiple theoretical frameworks and using advanced statistical techniques, we provide robust evidence for the reliability, validity, and generalizability of the cumulative social advantage construct across diverse population subgroups and time periods. Our findings enhance understanding of how cumulative social support influences health and well-being, informing public health policies that prioritize social connectedness as a critical strategy for improving population health and promoting healthy aging across the lifespan (Holt-Lunstad, 2022, 2024). Future research addressing the limitations identified in this study will further elucidate the complex relationships between social advantage, health, and well-being throughout the life course, ultimately contributing to more effective strategies for promoting healthy aging and reducing health disparities.

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