

residents' experiences with intimacy, directly as relationship partners, and by facilitating or impeding residents' contacts with others. Family members cultivated residents' intimacy opportunities and experiences by direct engagement, resident advocacy, to non-involvement and disengagement. Family members' roles in cultivating intimacy fluctuated over time, increasing at times of health concerns and family change. Perceptive family members considered older adults' intimacy preferences when cultivating their intimate relationships. Family members concerned for the safety of their loved one sometimes acted as "gatekeepers" to intimacy by interfering in intimate relationships. We conclude with a discussion of implications for policy and practice aimed at improving the intimacy process and opportunities for older adults receiving long-term care.

USING THE LIFE STORY BOOK WITH MENTALLY ALERT RESIDENTS OF NURSING HOMES

Theresa Chrisman, *University of Houston, Houston, Texas, United States*

Depression and lack of meaning in life (MIL) are common among residents of nursing homes (NHs) and contribute to a reduction in overall health and well-being. Life Story Book (LSB), a reminiscence intervention, is designed to provide a person with the opportunity to review their past and capture their life stories and photographs into a book. LSB has demonstrated positive outcomes for residents of NHs with dementia, yet little is known for residents without dementia. A switching replication design was used to examine the effects of LSB among 21 mentally alert residents from two NHs (NH-A and NH-B) in Houston, Texas. Participants in NH-A received three weeks of the LSB intervention, while NH-B received three weeks of care-as-usual; the intervention was then switched. The GDS-12R and the MIL questionnaire (MLQ) were used to measure depressive symptoms and MIL respectively. Participants from NH-A ($n = 11$) and NH-B ($n = 10$) had a mean age of 75 years ($SD = 11.34$); 81% female; 52% non-Hispanic white and 33% African American. Results from a one-way MANCOVA found no statistically significant difference on the GDS-12R and MLQ ($F(3, 14) = 2.50$, $p = .102$; Wilks' Lambda = .652; $\eta^2 = .35$). Further analyses comparing the pre-intervention and post-intervention scores for the entire sample ($N = 21$) found a significant reduction in depressive symptoms ($M = 2.67$; $SD = 2.52$) and ($M = 1.67$, $SD = 2.29$); ($t(20) = 2.21$, $p = 0.039$). The potential benefits of LSB for mentally alert residents of NHs warrants further research.

ALL-CAUSE DEMENTIA PREDICTION BY MACHINE LEARNING: THE HEALTH, AGING, AND BODY COMPOSITION STUDY

Chenkai Wu,¹ and Xurui Jin,² 1. *Duke Kunshan University, Kunshan, Jiangsu, China*, 2. *Duke Kunshan University, Kunshan, China*

There are several shortcomings of the currently available risk prediction models for dementia. We developed a risk prediction model for dementia using machine-learning approach and compared its performance with traditional approaches. Data were from the Health, Aging, and Body Composition Study, comprising 3,075 older adults (at least 70 years). Dementia was defined as (1) use of a prescribed

dementia medication, (2) adjudicated dementia diagnosis, or (3) a race-stratified cognitive decline > 1.5 SDs from the baseline mean. We selected 275 predictors collected from questionnaires, imaging data, performance testing, and biospecimen. We used random survival forest (RSF) to build the full model and rank the importance of predictors. Subsequently, we built parsimonious models with top-20 predictors using RSF and Cox regression. A dementia risk score was developed using top-ranked variables. We used the C-statistic for performance evaluation. Over a median of 11.4 years of follow-up, 659 dementias (21.4%) occurred. The RSF model (both including all and top-20 variables) showed a higher C-statistic than the regression model. Digit symbol score, physical performance battery, finger tapping score, weight change since age 50, serum adiponectin, and APOE genotype were the top-6 variables. We created a dementia risk score (0-10) using the top-6 variables. A 1-unit increase in the risk score was associated with an 8% higher risk of dementia. The risk score demonstrated good discrimination (C-statistic=0.75). Machine learning methods offered improvement over traditional approaches in predicting dementia. The risk prediction score derived from a parsimonious model had good prediction performance.

BUILDING, TESTING, AND LEARNING FROM NETWORK MODELS OF HUMAN AGING

Andrew Rutenberg, Spencer Farrell, Arnold Mitnitski, Kenneth Rockwood, and Garrett Stubbings, *Dalhousie University, Halifax, Nova Scotia, Canada*

We have developed computational models of human aging that are based on complex networks of interactions between health attributes of individuals. Our "generic network model" (GNM) captures the population level exponential increase of mortality with age in Gompertz's law together with the exponential decrease of health as measured by the frailty index (FI). Our GNM includes only random accumulation of damage, with no programmed aging. Our GNM allows large populations of model individuals to be quickly generated with detailed individual health trajectories. This allows us to explore individual damage propagation in detail. To facilitate comparison with observational data, we have also developed and tested new approaches to binarizing continuous-valued health data. To extract the most information out of available cross-sectional or longitudinal data, we have also reconstructed interactions from generalized network models that can predict individual health trajectories and mortality.

COMBINING FRONTAL TDCS WITH WALKING REHABILITATION TO ENHANCE MOBILITY AND COGNITION: A PILOT CLINICAL TRIAL

David Clark,¹ Sudeshna Chatterjee,¹ Jared Skinner,² Paige Lysne,³ Samuel Wu,⁴ Dorian Rose,¹ and Adam Woods,⁵ 1. *University of Florida, Gainesville, Florida, United States*, 2. *Appalachian State University, Boone, North Carolina, United States*, 3. *Aging and Geriatric Research, Gainesville, Florida, United States*, 4. *Department of Biostatistics, Gainesville, Florida, United States*, 5. *Clinical and Health Psychology, Gainesville, Florida, United States*