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Mid-life employment trajectories and subsequent memory function and rate of decline in rural South Africa, 2000–22

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Abstract

Aim: To investigate mid-life employment trajectories in relation to later-life memory function and rate of decline in rural South Africa.

Methods: Data from the Agincourt Health and Socio-Demographic Surveillance System were linked to the 'Health and Ageing in Africa: A Longitudinal Study of an INDEPTH Community in South Africa' (HAALSI) in rural Agincourt, South Africa ($N = 3133$). Employment was assessed every 4 years over 2000–12 as being employed (0, 1, 2 and ≥ 3 time points), being employed in a higher-skill occupation (0, 1, 2 and ≥ 3 time points) and dynamic employment trajectories identified using sequence analysis. Latent memory z-scores were assessed over 2014–22. Mixed-effects linear regression models were fitted to examine the associations of interest.

Results: Sustained mid-life employment from 2000–12 ($\beta = 0.052$, 95% CI: -0.028 to 0.132, 1 vs 0 time points; $\beta = 0.163$, 95% CI: 0.077 to 0.250, 2 vs 0 time points; $\beta = 0.212$, 95% CI: 0.128 to 0.296, ≥ 3 vs 0 time points) and greater time spent in a higher-skill occupation ($\beta = 0.077$, 95% CI: -0.020 to 0.175, 1 vs 0 time points; $\beta = 0.241$, 95% CI: 0.070 to 0.412, 2 vs 0 time points; $\beta = 0.361$, 95% CI: 0.201 to 0.520, ≥ 3 vs 0 time points) were associated with higher memory scores in 2014/15, but not subsequent rate of memory decline. Moving from a lower-skill to higher-skill occupation was associated with higher memory function, but a faster rate of decline over 2014–22.

Conclusions: Sustained mid-life employment, particularly in higher-skill occupations, may contribute to later-life memory function in this post-Apartheid South African setting.

Keywords: Employment, memory ageing, older adults, South Africa.

Key Messages

- Life-course employment histories may play a role in shaping cognitive function in later life, although there is scarce evidence on this topic from low- and middle-income countries (LMICs), such as South Africa, a middle-income country with one of the highest unemployment rates worldwide.
- This study demonstrated that the duration, order and timing of employment and occupational complexity might contribute to cognitive function in this post-Apartheid South African setting.
- Further longitudinal research from diverse global settings is warranted to investigate life-course employment transitions in relation to subsequent memory decline.

Background

Employment and occupational skill complexity have been associated with cognitive function,[1–7] potentially through engagement in intellectual activities at work that enhance cognitive stimulation and protect against neurodegeneration during ageing.[8,9] Recent studies have measured long-term employment trajectories and have shown that greater time spent in employment, especially in a higher-skill occupation, is associated with higher cognitive function and slower rate of decline, indicating that life-course employment histories may play a role in shaping cognitive function in later life.[10–14]

Nearly all studies on employment trajectories in relation to later-life cognitive health outcomes are based on populations from high-income countries, where long-term unemployment and employment volatility are less common, except during

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periods of financial crisis.[10–13,15,16] There is scarce evidence on this topic from low- and middle-income countries (LMICs), where over 75% of global dementia cases are projected to occur by 2050 and where employment is often informal and volatile in nature.[17,18] Moreover, employment environment, occupational safety regulations and health care benefits could vary across high-income countries (HICs) and LMICs, potentially leading to differential associations between employment and cognitive outcomes across global regions.[19] A comprehensive investigation of mid-life employment trajectories in relation to cognitive ageing is thus particularly important in LMICs, such as South Africa, which has a growing population of working-age adults living in a society with one of the highest unemployment rates worldwide (e.g. ~30% in 2021).[18,20]

We aimed to investigate the association between mid-life employment trajectories over 12 years from 2000–12 and subsequent memory function and rate of decline over 2014–22 among adults aged ≥25 years at baseline in rural Agincourt, Mpumalanga province, South Africa. We hypothesized that: (i) sustained paid employment over 2000–12, particularly in a higher-skill occupation, would be associated with higher memory function at the HAALSI baseline in 2014/15 and a slower rate of decline over time; and (ii) the timing and order of employment status and occupational skills would be associated with these memory ageing outcomes.

Methods

Study setting

Agincourt has a population size of ~120 000 living across 31 villages that cover an area of 450 km^2 in rural northeast South Africa near the Mozambique border.[21] This area was part of the designated 'homeland' where Black South Africans were forcibly re-settled during Apartheid (1948–94) based on their racial and ethnic identities.[22,23] This resulted in racial segregation for the Agincourt population, which purposely limited access to education, employment opportunities and health care services.[22,23] Although the social and economic conditions in Agincourt have improved post-Apartheid, the unemployment rate remains high, partially due to the slow economic growth in rural areas and the long-existing 'Bantu' education system in Apartheid which was designed to 'develop a pool of cheap unskilled manual labor'.[24,25]

Data source

Data were from the Agincourt Health and Socio-Demographic Surveillance System (Agincourt HDSS) over 2000–12 and the 'Health and Ageing in Africa: A Longitudinal Study of an INDEPTH Community in South Africa' (HAALSI) in 2014–22.[21,26] The Agincourt HDSS is a regional census-based platform with nearly 100% population coverage in the Agincourt research site since 1992.[21] HAALSI is a population-representative longitudinal cohort study of 5059 men and women aged 40 and over residing in the Agincourt research site.[26] The HAALSI cohort is embedded in the Agincourt HDSS with a sampling frame identified using the 2013 Agincourt HDSS population.[26]

Study sample

This prospective cohort study measured longitudinal employment exposures in the Agincourt HDSS from 2000 to 2012 and subsequent memory function assessed in HAALSI over 2014–22. Individuals with complete employment status data from 2000 to 2012 and memory test data in 2014/15 (HAALSI Wave 1) were eligible for inclusion ($N = 3133$, as shown in Figure 1).

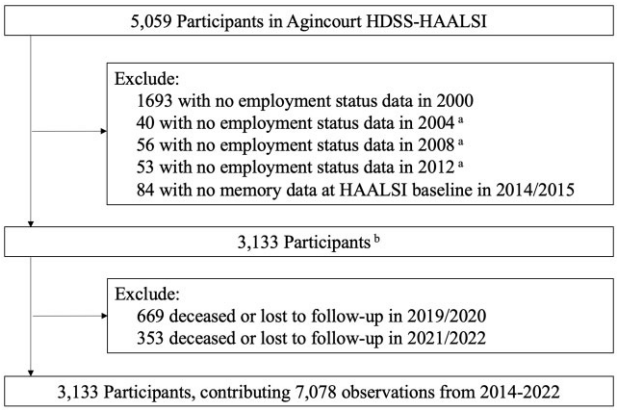


Figure 1. Study flow chart, Agincourt HDSS-HAALSI, Agincourt, Mpumalanga, South Africa, 2000–22. [a]Individuals with no employment data in prior waves were not included. [b]A total of 175 individuals had missing data on job type at 1 or 2 time points, leading to 2958 participants for analyses of the association between experience of employment in higher-skill occupations and memory ageing

Measures

Exposure 1: employment over 2000–12

Current employment status, regardless of part-time or full-time employment, was measured in the Agincourt HDSS in 2000, 2004, 2008 and 2012, defined as 'currently working for pay' (yes; no). We defined employment from 2000 to 2012 as the number of time points at which each participant was working for pay (0, 1, 2 and ≥3 time points).[27] We combined those who were employed at 4 time points ($n = 345$; 11%) with those employed at three time points, because of the limited sample size.

Exposure 2: employment in higher-skill occupations over 2000–12

For those who reported currently working for pay, their primary types of work were recorded in the Agincourt HDSS in 2000, 2004, 2008 and 2012, and were classified as higher-skill occupation vs lower-skill occupation at each time point, based on International Standard Classification of Occupations–08 (ISCO-08).[10,28] Details are provided in the Supplementary Method and Supplementary Table S1 (available as Supplementary data at *IJE* online). We defined employment in a higher-skill occupation over 2000 to 2012 as the number of time points at which each participant was employed in a higher-skill occupation (0, 1, 2 and ≥3 time points). We combined those who had a higher-skill occupation at 4 time points ($n = 85$; 3%) with those who had a higher-skill occupation at 3 time points ($n = 54$; 2%).

Exposure 3: employment trajectories over 2000–12

We identified prototypical employment trajectories from 2000 to 2012 using sequence analysis, which is a multistage process to convert employment histories into sequences and to cluster similar sequences according to the order, timing and duration of four employment states and occupational levels (non-employment; higher-skill occupation; lower-skill

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occupation; unknown occupation).[29,30] First, transition rates (i.e. mean probabilities of transition) between these four employment states were calculated to assign substitution costs, which are used to match each pair of individual employment sequences to one another in the study sample.[29,30] The more common the transitions were between two states, the lower the substitution cost that was assigned (e.g. lower-skill occupation to non-employment was a more common transition than higher-skill occupation to non-employment).[29,30] To minimize the overall cost of matching two similar trajectories, we generated pairwise dissimilarity distances using an optimal matching algorithm that allows substitution of employment states at each time point.[31] We conducted a hierarchical cluster analysis to identify employment trajectories.[32] We used the Duda–Hart stopping rule to help determine the optimal number of clusters (Supplementary Figure S1 and Supplementary Table S2, available as Supplementary data at *IJE* online).[32] We retained the six-cluster solution as it minimized the pseudo-T-squared value and provided detailed information on employment sequence similarity compared with three- or four-cluster solutions. Consistent with prior studies,[11,33] we combined two clusters as they contained qualitatively similar employment trajectory sequences, and had similar associations with cognitive scores in an initial regression analysis, resulting in five prototypical employment trajectories (Figures 2 and 3): (i) consistent non-employment ($n = 1099$), (ii) lower-skill occupation to non-employment ($n = 1437$), (iii) fluctuating higher-skill occupation to lower-skill occupation or non-employment ($n = 247$), (iv) fluctuating lower-skill occupation to higher-skill occupation ($n = 206$) and (v) consistent higher-skill occupation ($n = 144$).

Outcome: latent memory z-scores over 2014–22

Episodic memory function was assessed in HAALSI 2014/15, 2019/20 and 2021/22 (three waves), incorporating immediate and delayed word recall tests. As the administration of episodic memory tests varied across the HAALSI Waves 1–3, we applied confirmatory factor analysis to create longitudinally harmonized factor scores representing episodic memory at each time point.[34] The method for the longitudinal harmonization of memory scores when test administration changes over time has been demonstrated and validated in prior research.[34] The factor model was of a good fit to the data, and details are provided in Supplementary Table S3 and Supplementary Figure S2 (available as Supplementary data at *IJE* online). The latent memory score was z-standardized to the factor distribution in the HAALSI Wave 1 in 2014/15, such that the scores in the HAALSI Wave 1 had a mean of 0 and standard deviation (SD) of 1, with higher scores indicating higher memory function.

Covariates in 2000

We included the following covariates to reflect baseline demographic characteristics, socioeconomic status and childhood socioeconomic status as potential confounders.[3,5,6,10,22] Demographic characteristics included age (continuous), sex (male; female), marital status (married or partnered; single; separated or divorced; widowed) and country of birth (South Africa; Mozambique or other). Childhood socioeconomic covariates were having parents in a union when the respondent was born (yes; no), having a parent who died before the respondent was aged 18 (yes; no), father's occupation during childhood (lower-skill; higher-skill; other; unknown) and self-rated health in childhood (very good; good; moderate; bad; very bad). Three indicators of socioeconomic status in 2000 were included: the highest level of education (no formal education; some primary (1–7 years); some secondary (8–11 years); secondary or more (12+ years)), self-reported literacy (cannot read and/or write;

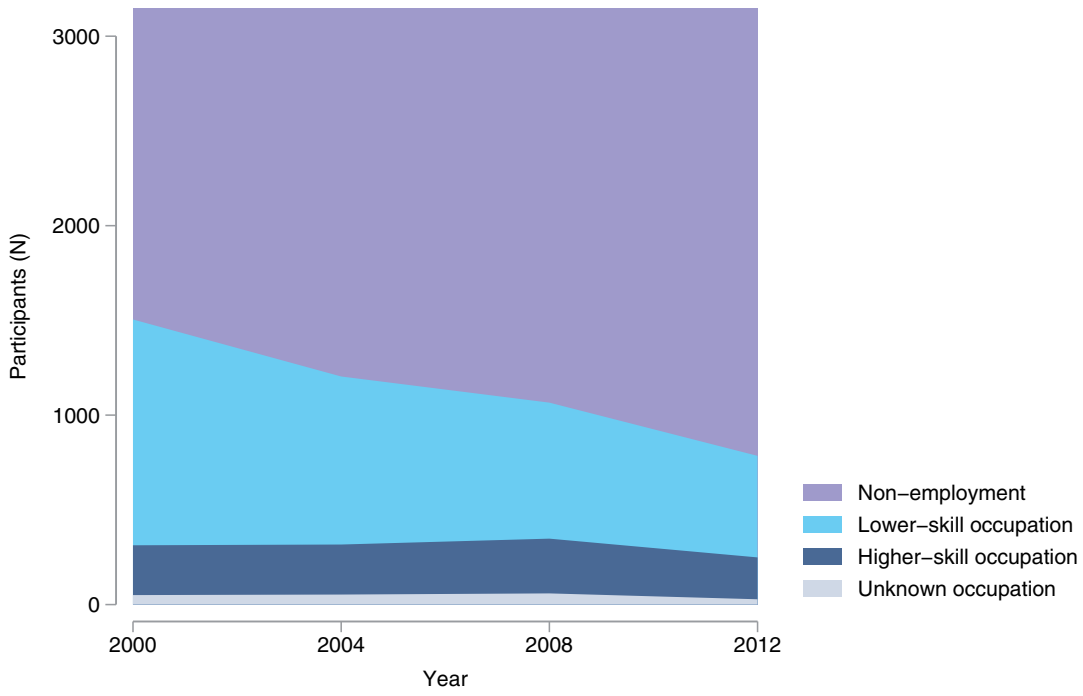


Figure 2. Chronological distribution of employment status and occupation levels over 2000–12, Agincourt HDSS-HAALSI, Agincourt, Mpumalanga, South Africa, $N = 3133$

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Figure 3. Employment trajectories over 2000–12 as identified by sequence analysis, Agincourt HDSS-HAALSI, Agincourt, Mpumalanga, South Africa, $N = 3133$

can read and write) and household asset-based wealth index (in quintiles).[35]

Statistical analysis

We described baseline characteristics of the sample, overall and by employment. Mixed-effects linear regression models with person-specific random slopes and random intercepts were fitted to investigate the associations between each of the three exposure measures with memory scores, adjusted for all covariates described above (Models 1–3). Years of follow-up were identified as the interval between the month of the interview year in HAALSI Wave 1 and the month of the interview year in each of HAALSI Waves 2 and 3 (range: 0–7.25 years). We included statistical interaction terms between years of follow-up and each of the three exposures, to investigate their associations with rate of memory decline. We tested the statistical significance of interaction terms between each covariate and time, observing statistically significant interactions between each of education and gender with time only. These interactions were thus included in the final models. We accounted for practice effects by creating a binary indicator for the first memory assessment, i.e. the 2014/15 HAALSI interview.[36] Missing values of covariates were filled by multiple imputation with chained equations using all variables in the analytical models, with the production of five imputed datasets.

Because the reasons for non-employment and transitions between employment states may differ for men and women, we included three-way statistical interaction terms between each of the three employment exposure variables, years of follow-up and gender. We did not observe evidence for statistically significant gender differences and thus removed the three-way interaction terms.

We conducted several sensitivity analyses. First, we compared baseline characteristics between included and excluded individuals (Supplementary Table S4, available as Supplementary data at *IJE* online). Then, we repeated the analyses restricted to individuals aged under 60 (retirement age in South Africa) in 2012, to calculate an estimate that minimized any potential effects of retirement and eligibility for South Africa's public Old Age Pension beginning at age 60.[37] Third, we repeated the analyses restricted to participants with some formal education to help account for unmeasured confounding bias whereby individuals with lower early-life cognitive development may have been less likely to have worked for pay as adults. Additionally, we repeated the analysis using exposure data over 2004–12 to account for a large proportion of missing exposure data in 2000. The missing data in 2000 mostly came from individuals who lived in villages (e.g. former Mozambican refugees) that were not added to the Agincourt HDSS census region until after 2000.[21] Finally, we incorporated inverse probability weights for study attrition and mortality to account for potential selection bias during the HAALSI follow-up.[38] Statistical analyses were performed with Stata/SE 18.0 (StataCorp).

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Table 1. Baseline characteristics, overall and by employment, Agincourt HDSS-HAALSI, Agincourt, South Africa, 2000–22 ($n = 3133$)

Baseline characteristic	Total ($n = 3133$)	Employment from 2000 to 2012			
		0 time points ($n = 1099$)	1 time point ($n = 676$)	2 time points ($n = 557$)	≥3 time points ($n = 801$)
Episodic memory, mean (SD)[a]	8.16 (3.58)	7.16 (3.40)	7.85 (3.37)	8.71 (3.31)	9.39 (3.71)
Age, years, mean (SD)	47.81 (12.76)	53.45 (13.96)	47.85 (12.36)	44.63 (10.70)	42.23 (8.90)
Age, years, median (range)	47 (25–96)	55 (25–91)	48 (25–89)	45 (25–96)	42 (25–74)
Sex, *n* (%)					
Female	1728 (55.15)	779 (70.88)	398 (58.88)	281 (50.45)	270 (33.71)
Male	1405 (44.85)	320 (29.12)	278 (41.12)	276 (49.55)	531 (66.29)
Country of birth, *n* (%)					
South Africa	2328 (74.35)	812 (74.02)	494 (73.08)	411 (73.79)	611 (76.28)
Mozambique and other	805 (25.69)	287 (26.11)	182 (26.92)	146 (26.21)	190 (23.72)
Parents were in a union when participant was born, *n* (%)	2931 (93.58)	1034 (94.17)	630 (93.20)	519 (93.18)	748 (93.38)
Parent died before participant was 18 years old, *n* (%)	2727 (87.04)	963 (87.63)	580 (85.80)	490 (87.97)	694 (86.64)
Father's occupation when the participant was a child, *n* (%)					
Lower-skill occupation	2283 (72.87)	772 (70.25)	494 (73.08)	413 (74.15)	604 (75.41)
Higher-skill occupation	186 (5.94)	58 (5.28)	38 (5.62)	38 (6.82)	52 (6.49)
Other	356 (11.36)	135 (12.28)	79 (11.69)	52 (9.34)	90 (11.24)
Unknown	308 (9.83)	134 (12.19)	65 (9.62)	54 (9.69)	55 (6.87)
Self-rated childhood health, *n* (%)					
Very good	2196 (70.14)	766 (69.83)	471 (69.67)	404 (72.53)	555 (69.29)
Good	542 (17.31)	186 (16.96)	116 (17.16)	87 (15.62)	153 (19.10)
Moderate	192 (6.13)	66 (6.02)	45 (6.66)	34 (6.10)	47 (5.87)
Bad	105 (3.35)	40 (3.65)	23 (3.40)	18 (3.23)	24 (3.00)
Very bad	96 (3.07)	39 (3.56)	21 (3.11)	14 (2.51)	22 (2.75)
Education, *n* (%)					
No formal education	1351 (43.23)	625 (57.08)	299 (44.36)	212 (38.06)	215 (26.91)
Some primary (1–7 years)	1149 (36.77)	372 (33.97)	269 (39.91)	213 (38.24)	295 (36.92)
Some secondary (8–11 years)	357 (11.42)	71 (6.48)	73 (10.83)	81 (14.54)	132 (16.52)
Secondary or more (12+ years)	268 (8.58)	27 (2.47)	33 (4.90)	51 (9.16)	157 (19.65)
Self-reported literacy, *n* (%)					
Can read and/or write	1885 (60.20)	483 (43.99)	379 (56.15)	386 (69.30)	637 (79.53)
Cannot read or write	1246 (39.80)	615 (56.01)	296 (43.85)	171 (30.70)	164 (20.47)
Marital status					
Married/cohabiting	2079 (66.42)	649 (59.05)	419 (61.98)	392 (70.50)	619 (77.47)
Separated/divorced	272 (8.69)	79 (7.19)	76 (11.24)	53 (9.53)	64 (8.01)
Widowed	244 (7.80)	81 (7.37)	64 (9.47)	36 (6.47)	63 (7.88)
Single	535 (17.09)	290 (26.39)	117 (17.31)	75 (13.49)	53 (6.63)
Household asset-based wealth index, *n* (%)					
1 (poorest)	534 (17.38)	196 (18.18)	117 (17.57)	111 (20.18)	110 (14.14)
2	614 (19.99)	216 (20.04)	148 (22.22)	124 (22.55)	126 (16.20)
3	628 (20.44)	230 (21.34)	141 (21.17)	108 (19.64)	149 (19.15)
4	638 (20.77)	232 (21.52)	134 (20.12)	103 (18.73)	169 (21.72)
5 (richest)	658 (21.42)	204 (18.92)	126 (18.92)	104 (18.91)	224 (28.79)

[a] Raw episodic memory scores included immediate word recall scores (range 0–10) and delay word recall scores (range 0–10) at HAALSI baseline.
Missing rate: 2.0% for household asset-based wealth index, 0.3% for education, 0.1% for marital status, 0.06% for self-rated childhood health and 0.03% for having parents in a union when the respondent was born.

Results

Characteristics of the sample

This study included 3133 participants [mean age in 2000 (SD): 48 (12.76), range: 25–96] and 55.15% were female ($n = 1728$) (Table 1). A total of 1099 participants (35.07%) were never employed over 2000–12, and 676 (21.58%), 557 (17.78%) and 801 (25.57%) participants were employed at 1, 2, and 3 time points, respectively.

Employment and memory function and decline

Results from Model 1 (Table 2) suggest that employment over 2000–12 was associated with higher mean latent memory z-scores in 2014/15 ($\beta = 0.052$, 95% CI: -0.028 to 0.132, 1 vs 0 time points; $\beta = 0.163$, 95% CI: 0.077 to 0.250, 2 vs 0 time points; $\beta = 0.212$, 95% CI: 0.128 to 0.296, ≥3 vs 0 time points), indicating a dose-response relationship (Figure 4a). The interaction terms between employment and years of follow-up in Model 1 suggested a null association between employment and rate of memory decline (Figure 4a).

Employment in a higher-skill occupation and memory function and decline

Employment in a higher-skill occupation over 2000–12 was associated with higher latent memory z-scores in 2014/15 (Model 2 in Table 2: $\beta = 0.077$, 95% CI: -0.020 to 0.175, 1 vs 0 time points; $\beta = 0.241$, 95% CI: 0.070 to 0.412, 2 vs 0 time points; $\beta = 0.361$, 95% CI: 0.201 to 0.520, ≥3 vs 0 time

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Table 2. Mixed-effects linear regression analyses of the association between employment trajectories from 2000 to 2012 and latent memory z-scores from 2014 to 2022, Agincourt HDSS-HAALSI, Agincourt, Mpumalanga, South Africa

Characteristics	β (95% CI)	*P*
Model 1: Employment (*n* = 3133)		
Years of follow-up	−0.005 (−0.026 to 0.017)	0.661
Employment		
0 time points	ref.	
1 time point	0.052 (−0.028 to 0.132)	0.201
2 time points	0.163 (0.077 to 0.250)	<0.001
≥3 time points	0.212 (0.128 to 0.296)	<0.001
Employment X years of follow-up		
1 time point	0.009 (−0.008 to 0.027)	0.293
2 time points	−0.005 (−0.024 to 0.013)	0.570
≥3 time points	−0.005 (−0.023 to 0.012)	0.547
Model 2: Employment in a higher-skill occupation (*n* = 2958)[a]		
Years of follow-up	−0.008 (−0.027 to 0.012)	0.437
Employment in a higher-skill occupation		
0 time points	ref.	
1 time point	0.077 (−0.020 to 0.175)	0.121
2 time points	0.241 (0.070 to 0.412)	0.006
≥3 time points	0.361 (0.201 to 0.520)	<0.001
Employment in a higher-skill occupation X years of follow-up		
1 time point	−0.006 (−0.027 to 0.015)	0.569
2 time points	−0.025 (−0.062 to 0.012)	0.188
≥3 time points	−0.029 (−0.064 to 0.005)	0.093
Model 3: Dynamic employment trajectories (*n* = 3133)		
Years of follow-up	−0.007 (-0.029 to 0.014)	0.503
Dynamic employment trajectories		
Consistent non-employment	ref.	
Lower-skill occupation to non-employment	0.109 (0.040 to 0.177)	0.002
Fluctuating higher-skill to lower-skill occupation or non-employment	0.087 (−0.028 to 0.203)	0.139
Fluctuating lower-skill to higher-skill occupation	0.264 (0.139 to 0.390)	<0.001
Consistent higher-skill occupation	0.349 (0.189 to 0.509)	<0.001
Dynamic employment trajectories X years of follow-up		
Lower-skill occupation to non-employment	0.004 (−0.011 to 0.018)	0.614
Fluctuating higher-skill to lower-skill occupation or non-employment	0.008 (−0.017 to 0.033)	0.546
Fluctuating lower-skill to higher-skill occupation	−0.028 (−0.055 to −0.001)	0.045
Consistent higher-skill occupation	−0.011 (−0.046 to 0.023)	0.521

Models adjusted for age, sex, country of birth, marital status, whether parents were in a union when the respondent was born, having a parent who died before the respondent was 18, father's occupational skill level during childhood, self-rated health in childhood, highest level of education, self-reported literacy, household asset-based wealth index in 2000, interaction between years of follow-up and sex and interaction between years of follow-up and education.

[a] A total of 175 individuals had missing data on job type at 1 or 2 time points, leading to 2958 participants for analyses of the association between experience of employment in higher-skill occupations and memory ageing.

points; Figure 4b). The 95% CIs of slope estimates for employment in a higher-skill occupation crossed the null, indicating that greater time spent in a higher-skill occupation was not associated with rate of memory decline (Figure 4b).

Dynamic employment trajectories and memory function and decline

Table 2 (Model 3) and Figure 4 show the results for the association between dynamic employment trajectories and memory function and decline. First, transition from a lower-skill occupation to non-employment (β = 0.109, 95% CI: 0.040 to 0.177; $P = 0.002$) was associated with higher memory z-scores compared with consistent non-employment. Second, the regression coefficient for fluctuation from lower-skill occupation to higher-skill occupation (β = 0.264, 95% CI: 0.139 to 0.390; $P < 0.001$) was stronger in magnitude than that for fluctuation from higher-skill occupation to lower-skill occupation or non-employment (β = 0.087, 95% CI: −0.028 to 0.203; $P = 0.094$), indicating that the order of occupation complexity over the life course may be associated with memory function (Figure 4c). However, compared with consistent non-employment, fluctuating from lower-skill to higher-skill occupations (β = −0.028, 95% CI: −0.055 to −0.001; $P = 0.045$) was associated with a faster rate of memory decline over 2014–22. Results from sensitivity analyses were similar to our main findings (Supplementary Tables S5–S8, available as Supplementary data at *IJE* online).

Discussion

In this large, population-based cohort of middle-aged and older adults in rural South Africa, we found that paid employment in mid-life, particularly in a higher-skill occupation, was associated with better later-life memory function. These findings indicate that the duration, order and timing of employment and occupational complexity might contribute to memory function during ageing in a low-income, post-Apartheid South African setting.

Comparison with existing studies

Our findings are consistent with prior studies,[10,11,13,14] indicating that long-term, consistent paid employment in adulthood could help to delay the onset of cognitive impairment

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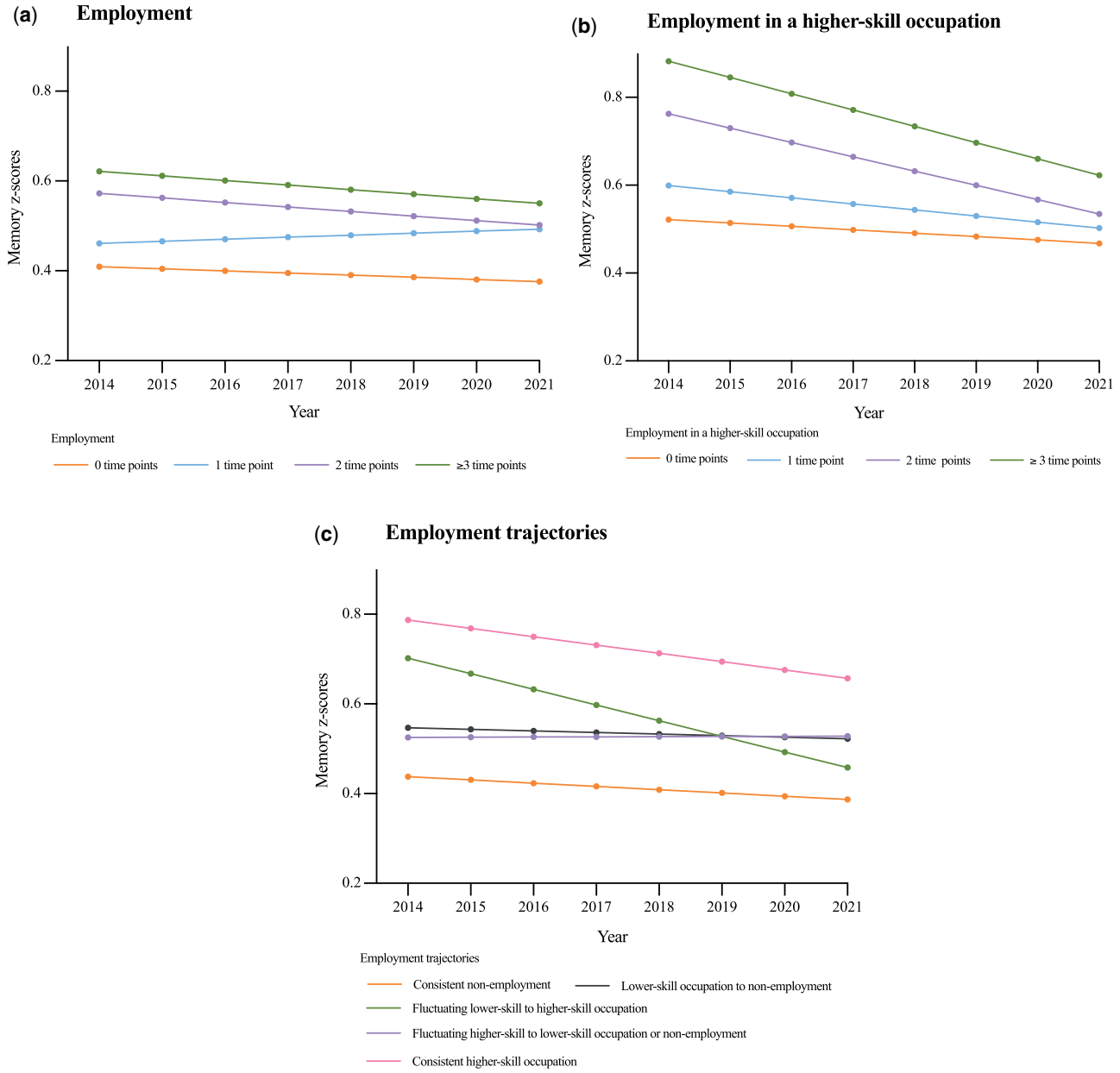


Figure 4. Estimated latent memory z-scores over 2014–22 by employment trajectories over 2000–12, ADHSS-HAALSI, Agincourt, Mpumalanga, South Africa. (a) Estimated memory z-scores over 2014–22 by employment experience over 2000–12. All covariates were held at their mean values or at the first category-level, as in Model 1 in Table 2. (b) Estimated memory z-scores over 2014–22 by the experience of employment in higher-skill occupation over 2000–12. All covariates were held at their mean values or at the first category-level, as in Model 2 in Table 2. (c) Estimated memory z-scores over 2014–22 by dynamic employment trajectories over 2000–12. All covariates were held at their mean values or at the first category-level, as in Model 3 in Table 2

and dementia.[1–3] Sustained employment and its associated benefits may facilitate socioeconomic material accumulation (such as wealth), promote social status and social relationships and reduce psychosocial distress, resulting in healthier lifestyle coping behaviours (such as non-smoking) and decreased risk of cardiovascular diseases.[16,39–42] All of these are important predictors of cognitive health during ageing.[43] Similar to existing studies that measured occupation complexity, job control and job demand,[6,9,10,13,44] we observed that long-term employment in occupations that involve a range of complex tasks and require upper-level educational qualifications was associated with higher cognitive function in later-life. Sustained employment in these cognitively demanding occupations could bolster cognitive stimulation that protects individuals from abnormal neurodegeneration, such as increasing nerve degeneration and dysregulated axongenesis.[9,45–47]

Compared with employment trajectories identified in existing research in the USA,[10] we observed a higher proportion of consistent non-employment (4% in the US study vs 35% in our study) in this rural South African region. There are likely to be different reasons for non-employment between countries (e.g. earlier retirement in the USA and unemployment in South Africa), which require further investigation. A point of caution is that our estimates are relatively imprecise, with overlapping 95% CIs for several employment trajectory categories. Further research with larger sample sizes is warranted.

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Contrary to our hypothesis, sustained employment and employment in a higher-skill occupation were not associated with rate of memory decline. Our findings are consistent with a recent study suggesting that primary lifetime occupation complexity may contribute to higher-level cognitive function but not subsequent rate of decline in later-life.[48] Our results contradict other evidence in the USA, where a study found that working for pay over the life course may attenuate memory decline among women.[11] We also observed that transitions from lower-skill to higher-skill occupations were associated with a faster rate of memory decline, inconsistent with our hypothesis. This counterintuitive result may be subject to the regression to mean fallacy, measurement error in occupation patterns due to high fluctuation in employment or interval censoring in this cohort, or random error due to the limited length of follow-up for memory function. It may also be that employment in this South African setting, where the predominant job industries were mining and industrial farming, involved hazardous exposures such as to neurotoxic chemicals at work, insufficient occupation safety, psychosocial stressors and lack of benefits, all of which may have counteracted any protective benefits of employment for cognitive health.[19] Further longitudinal research on this topic from diverse global settings is warranted.

Limitations and strengths

As we only had employment data at 4 time points, our exposure measures may be subject to measurement error if there are unobserved employment status changes between these time points. In addition, employment trajectories as identified by sequence analysis can be subjective, as the investigator is required to select the best-fitting cluster solution based on model fit, theory and subject matter knowledge.[49] Therefore, the differences in memory function that were observed between trajectories of fluctuating employment skill level should be viewed with caution. Due to data limitations, we were unable to distinguish between different job types within each skill level and did not differentiate the reason for non-employment (e.g. retirement, disability or sick leave), informal vs formal employment, part-time vs full-time employment and employment benefits, all of which could plausibly modify the observed associations or lead to misclassification bias.[50] Finally, there could be residual confounding from early-life cognitive function and time-varying confounders over the exposure period, such as depressive symptoms. We were unable to control for these factors, as they were not measured in the Agincourt HDSS. Therefore, the observed associations should be cautiously interpreted and require further investigation.

To the best of our knowledge, this is one of the first studies to investigate longitudinal employment trajectories in relation to later-life cognitive health in a low-income, rural, sub-Saharan African context. We analysed data from a rural region of South Africa, a country with one of the highest unemployment rates worldwide. Future studies should investigate the forms of cognitive stimulation involved in various occupations, the different types of financial and social benefits provided by work and potential heterogeneity in memory ageing among different types of non-workers in low- and middle-income settings.

Conclusion

Sustained mid-life employment, particularly in higher-skill occupations, may contribute to later-life memory function but not to decline over time in this rural, low-income post-Apartheid South African setting.

Ethics approval

Ethical approval was granted by the University of the Witwatersrand Human Research Ethics Committee (M110138, M180585, M960720 and M081145 for the Agincourt HDSS; M141159 for HAALSI; M200556 for the present analysis), the Harvard T.H. Chan School of Public Health Office of Human Research Administration (C-13-1608-02 for HAALSI) and the Mpumalanga Provincial Research and Ethics Committee. The University of Michigan Health Sciences and Behavioral Sciences Review Board (HUM00181917) and the Indiana University Human Research Protection Program (2002584956) provided ethical approval for the present analysis. Informed consent is obtained at every Agincourt HDSS surveillance update visit, from the head of the household or another eligible adult in the household, and from all HAALSI study participants.

Data availability

The de-identified HAALSI data are publicly available at: [https://haalsi.org/data]. The de-identified Agincourt HDSS data may be accessed through completion of an online data request form and data use agreement at: [https://www.agincourt.co.za/?page_id=1883].

Supplementary data

Supplementary data are available at *IJE* online.

Author contributions

X.Y., M.R., and L.K. designed the study. X.Y. performed data analysis and drafted the first version of the manuscript. All authors provided critical review for important intellectual content of the manuscript and approved the final manuscript for submission.

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Conflict of interest

None declared.

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