Education and Successful Aging Trajectories: A Longitudinal Population-Based Latent Variable Modelling Analysis

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ABSTRACT
As the population ages, interest is increasing in studying aging well. However, more refined means of examining predictors of biopsychosocial conceptualizations of successful aging (SA) are required. Existing evidence of the relationship between early-life education and later-life SA is unclear. The Successful Aging Index (SAI) was mapped onto the Cognitive Function and Aging Study (CFAS), a longitudinal population-based cohort (n = 1,141). SAI scores were examined using growth mixture modelling (GMM) to identify SA trajectories. Unadjusted and adjusted (age, sex, occupational status) ordinal logistic regressions were conducted to examine the association between trajectory membership and education level. GMM identified a three-class model, capturing high, moderate, and low functioning trajectories. Adjusted ordinal logistic regression models indicated that individuals in higher SAI classes were significantly more likely to have higher educational attainment than individuals in the lower SAI classes. These results provide evidence of a life course link between education and SA.

RÉSUMÉ
Le vieillissement de la population a non seulement accru l’intérêt pour les études concernant les problèmes de santé, mais aussi pour celles associées au vieillissement en santé. Cependant, il serait nécessaire de définir des mesures plus raffinées liées aux prédicteurs compris dans les conceptualisations biopsychosociales du vieillissement réussi (VR). Les données probantes recueillies à ce jour concernant les liens entre l’éducation à un jeune âge et le VR ne sont pas encore claires. L’indice de vieillissement réussi (IVR) a été cartographié dans le cadre de l’étude Cognitive Function and Aging Study (CFAS), impliquant une cohorte populationnelle étudiée dans une perspective longitudinale (n = 1141). Les scores IVR ont été examinés selon l’approche du growth mixture modelling (GMM) afin d’identifier des trajectoires de VR. Des régressions logistiques ordinaires pondérées (selon l’âge, le sexe, le statut professionnel) et non pondérées ont été réalisées pour évaluer l’association entre les types de trajectoires et le niveau d’éducation. Le GMM a permis d’identifier un modèle à trois classes, comprenant des trajectoires de fonctionnement hautes (TFH), modérées (TFM) et basses (TFB). Les régressions logistiques ordinaires pondérées ont mis en évidence que les individus des classes d’IVR supérieures présentaient une plus forte probabilité d’avoir atteint un niveau de scolarité plus élevé que les individus à IVR inférieur (TFM, TFB) dans cet échantillon (RR 1.44, IC 95 % 1.14-1.82). L’éducation à un jeune âge est associée de manière indépendante à des trajectoires de VR supérieures plus tard dans la vie. Ces résultats recueillis dans une cohorte de sujets britanniques âgés démontrent l’impact du parcours de vie par des liens entre l’éducation et le VR, et révèlent l’influence bénéfique de l’éducation dans le long terme.

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Mots-clés : vieillissement, vieillissement réussi, growth mixture modelling, vieillissement en santé, niveau de scolarité
Background
The number of individuals aged 65 and older is expected to exceed the number of individuals aged below age 15 by 2045, worldwide (United Nations, 2010). Human life expectancy has been increased through advances in medical technology and practice, as well as through changes in social and public health. However, these additional years may not be experienced with good physical health, cognitive functioning, and/or psychosocial well-being. Fostering physiological and psychosocial well-being across the lifespan has important health, policy, and economic implications to mitigate the global demographic shift (United Nations, 2010). In addition to studying specific disorders and the negative aspects of aging, research into the ways in which individuals age particularly well can provide insights into whether and how the latter years of life might be improved.

In the absence of a consensus definition of successful aging (SA) (Cosco, Prina, Perales, Stephan, & Brayne, 2014), researchers have called for more refined measures (Cosco, Stephan, & Brayne, 2014; Kivimaki & Ferrie, 2011). Kivimaki and Ferrie (2011) have identified important shortcomings both in the ability of extant SA metrics to capture SA and in the ways we examine heterogeneity in the aging process. To address these issues, the SA model needs to be grounded in real populations, to be relevant to older people themselves, and to be implemented with sufficient detail to capture the heterogeneity of aging, which includes going beyond biomedical conceptualizations of SA (Bowling & Iliffe, 2006). In addition to improvement in capturing SA, methods of analysis of such measures in populations over time need to be used. Growth mixture modeling (GMM) is a person-centred, longitudinal latent-variable modelling technique used to identify heterogeneous classes of individuals’ responses on a continuous (or ordinal categorical) variable (Muthen et al., 2002), permitting further analysis of the relationship between variables and class membership. GMM has been previously used in the context of disease states, but it has rarely been attempted in the exploration of positive states of aging. In contrast to studies examining individuals’ ill-health, the current study examined the unique characteristics of individuals in the highest functioning longitudinal trajectories.

Several studies to date have examined the relationship between SA and education (Liang et al., 2003; Montross et al., 2006; Palmore, 1979; Strawbridge, Cohen, Shema, & Kaplan, 1996), with mixed results. Using exclusively biomedical SA models, Strawbridge et al. (1996) and Ford et al. (2000) failed to demonstrate a relationship between education and SA. Further, an investigation into self-rated SA and education revealed no significant relationship (Montross et al., 2006). In contrast to these one-dimensional models, Palmore (1979), Vaillant and Mukamal (2001), and Fernandez-Ballesteros Garcia et al. (2011) employed multidimensional models of SA. Palmore identified no significant relationship, Fernandez-Ballesteros Garcia identified one significant relationship among four unique models, and Vaillant found that for each additional year of education the likelihood of an individual’s having poor physical and psychosocial well-being was reduced by 0.85 (95% CI [0.77–0.96]). These studies highlight differences in mapping of SA and the conflicting results between different models of SA and education.

In the current study we used a multidimensional model of SA, developed a priori, to examine the association between education and longitudinal trajectories of SA in later life in a population-representative cohort of adults aged 65 years and older.

Methods
Study Characteristics
The Cognitive Function and Aging Study (CFAS) is a population-based, multicentre cohort study of community-dwelling individuals (n = 13,004) aged 65 years and older. Baseline interviewing began in 1991 in five centres using identical methodology in England and Wales (Newcastle, Nottingham, Oxford, Cambridgeshire, and Gwynedd) (Brayne, 2006). A 20 per cent (n = 2,640) stratified sample (selected based on cognitive ability, age, and centre) completed a more detailed assessment
interview, with re-interviewing approximately every two years. Data from over four years’ follow-up were used in this analysis.

Trained interviewers conducted face-to-face interviews in participants’ place of residence. Questions concerning demographics, cognition (Mini-Mental State Exam: MMSE; Folstein, Robins, & Helzer, 1983), activities of daily living (ADLs), instrumental activities of daily living (IADLs) (Townsend & Ryan, 1991), and psychosocial well-being were included in the interview. Further details of the sampling methods and interview questionnaires are available at www.cfas.ac.uk (Brayne, 2006).

In keeping with the availability of relevant variables and missingness (as outlined in the next section), in this analysis we used data from participants who had completed all of the required components of the successful aging index (SAI) at the second wave of data collection and the two subsequent waves of data collection (data version 9.0) \( (n = 1,141) \). All study centres obtained ethical approval from local research ethical committees.

**Successful Aging**

The Successful Aging Index (SAI) is a validated biopsychosocial measure of healthy aging (Cosco, Stephan, & Brayne, 2015), created using components identified by systematic reviews of lay perspectives – that is, qualitative interviews with members of the general public (Cosco, Prina, Perales, Stephan, & Brayne, 2013) and researchers’ operational definitions (Cosco, Prina, et al., 2014) of SA. The SAI includes measures of cognition (Mini-Mental State Examination), physical functioning (Activities of Daily Living [Townsend & Ryan, 1991]; Instrumental Activities of Daily Living [Lawton & Brody, 1969]), personal resources (e.g., optimism), self-awareness (e.g., self-rated health), and engagement (e.g., interest). The SAI score ranges from 0 to 100 with higher scores indicating greater levels of biopsychosocial SA.

**Education**

Education was captured via a single question asking individuals how many years they had spent in full-time education. Participants were grouped into 0–9, 10–11, and ≥12 years of full-time education reflecting basic, moderate, and high educational attainment in this generation (Collerton et al., 2007).

**Co-variates**

Occupational status was defined using an individual’s occupation at baseline, divided into manual and non-manual occupations. Marital status was grouped into married/cohabiting or not married, including separated, widowed, or single.

**Statistical Procedures**

**Growth Mixture Modelling**

We modelled scores from each participant’s SAI by using GMM to identify groups of individuals with similar SA trajectories, adjusting class-specific trajectory parameters by sex and age at first occasion. Using GMM procedures, we plotted SAI scores from three waves of CFAS data collection (each two years apart) and identified heterogeneous trajectories of SA. Models were estimated using maximum likelihood estimation, with robust estimates under a missing-at-random assumption. Given that only three waves of data were collected, we did not test non-linear trajectories as they require four or more waves of data (Bollen & Curran, 2006). All GMM procedures were conducted in MPlus v7.1 (Muthen & Muthen, 1998–2011).

Recommended model selection procedures involve the examination of fit indices – for example, Bayesian Information Criterion (BIC) (Raftery, 1995), interpretation of classes, and classification properties. As the number of classes is not known a priori, we fitted models with an increasing number of classes and chose the model with the lowest BIC (Schwarz, 1978). In addition to the standard BIC, the sample-adjusted BIC (SABIC) (Sclove, 1987) and Akaike Information Criterion (AIC) (Akaike, 1973) were assessed to provide supporting evidence of the fit of the model, with lower SABIC and AIC scores indicating better model fit. Models that include particularly small portions (e.g., <1%) of the sample have limited practical applicability, a criterion that is also used to evaluate model fit.

The model requires a stage of interpretation of classes since spurious classes may be identified (Bauer & Curran, 2003) resulting from the nature of the model, which has been designed to fit non-normal data. Classification is assessed via evaluation of the entropy, an index that takes values between 0 and 1 with high values indicating a clear classification of individuals in classes (Celeux & Soromenho, 1996).

**Analysis of Education and SAI Trajectory**

Once we had identified the best fitting model, we performed an a posteriori analysis of the data to examine differences in education group and trajectory membership. We used chi-square and t-tests to examine group differences in demographic variables including age, marital status (married or not married), occupational status (manual employment or non-manual employment), and sex (female or male). We examined the differences in educational level between individuals in...
the highest SA trajectory and the lower SA groups in the total sample and by gender using the OLOGIT command in Stata 14. To accomplish this, we used unadjusted and adjusted (age, sex, marital status, occupational status) ordinal logistic regressions (back-weighted to adjust for over sampling of individuals aged 75 years or older and sampling to the diagnostic interview at baseline). We further examined interaction/efffect modification by conducting age, sex, and occupational status and multicollinearity via variance inflation factor analysis (with values greater than 10 identified as problematic).

Missingness

Given that the SAI is an average of all the constituent components, we excluded individuals with missing component values and conducted a complete case analysis. This was done as missing data on one or more component variables would skew calculation of the SAI variable, providing an unrepresentative score for those individuals without complete data. Missingness at random for demographic variables in the multivariate modelling was assessed using a chi-square test examining the association between missingness and years in full-time education.

Results

Sample Characteristics

The sample included 1,141 individuals, with a mean age at baseline of 76.39 (standard deviation [SD] = 6.47). The sample was primarily female (63.37%), not married (51.89%), had manual occupations (70.20%) and 0–9 years of fulltime education (64.25%) (Table 1). At the first follow-up wave, 619 participants (54.3%) remained in the study, and at the second follow-up, 144 (12.4%) remained. Missingness was significantly associated with sex (greater missingness in women: $n = 360$ [33.24%], compared to men: $n = 151$ [26.54%]; $\chi^2 = 7.84$, $p = .005$), older age (mean age for missing participants 83.05; mean age for participants in sample 76.39; $t[1,650] = -17.99$, $p < .001$), marital status (missing if married: 143 [20.61%]; missing if not married, 284 [32.57%]; $\chi^2 = 35.76$, $p < .001$) and education (missing if 0–9 years education: 295 [28.89%]); missing if 10–11 years education: 76 [23.24%]; missing if ≥12 years education: 36 [19.05%]; $\chi^2 = 10.18$, $p = .006$). No significant differences were identified between missingness and occupational status (missing if in manual occupation: 333 [29.68%]; missing if in non-manual position: 173 [34.06%]; $\chi^2 = 3.13$, $p = .08$).

Trajectory Analysis

The GMM procedure revealed three distinct SA classes: the highest functioning trajectory (HFT; $n = 125$), moderate functioning trajectory (MFT; $n = 458$), and low functioning trajectory (LFT; $n = 558$). The HFT class had the highest intercept and flattest slope; the MFT had a moderate intercept and slope; and the LFT had the lowest intercept and steepest slope (Figure 1). The three-class model was selected according to the AIC and BIC fit indices in combination with the entropy and theoretical relevance of these findings (Table 2); this model presented the greatest entropy (0.66) in combination with the lowest BIC (1525.880). Although the four-class model presented a lower AIC and SABIC, the inability of the model to converge and the much lower entropy and higher BIC suggested that this model was a poorer fit when compared to the three-class model.

Demographic Characteristics

When compared to the MFT and LFT classes, individuals in the HFT class were significantly younger,
composed of more men, had higher occupational status, and were more likely to be married (Table 1).

**Education and Successful Aging**

In the total sample, individuals with more education were significantly more likely to be in higher functioning classes in unadjusted (OR 1.38, 95% CI [1.13–1.69]) and adjusted models (age, occupational status, marital status, sex) (OR 1.44, 95% CI [1.14–1.82]). Among men, a relationship between education and successful aging class existed in an unadjusted (OR 1.54, 95% CI [1.09–2.18]) but not in an adjusted model (OR 1.31, 95% CI [0.90–1.92]). Among women, a relationship between education and successful aging class existed in unadjusted (OR 1.60, 95% CI [1.24–2.07]) and adjusted models (OR 1.50, 95% CI [1.11–2.03]). Men were significantly more likely to be in higher functioning classes if they had more education in unadjusted models; however, this relationship was attenuated by age, sex, and marital status in adjusted models.

Women were significantly more likely to be in higher functioning classes in unadjusted and adjusted (age, occupational status, marital status) models if they had higher levels of educational attainment. The relationship between education and functional class membership was, however, attenuated by 14.9 per cent when controlling for age, occupational status, and marital status. In the full sample, fully adjusted models indicated that higher education was associated with higher functioning classes.

No statistically significant interactions were observed between education and sex (men as reference group; 10–11 years’ education: OR 0.86, 95% CI [0.48, 1.55]; ≥12 years’ education: OR 1.37, 95% CI [0.65, 2.88]), age (10–11 years’ education: OR 1.19, 95% CI [0.67, 2.11]; ≥12 years’ education: OR 1.00, 95% CI [0.50, 1.99]), occupational status (manual occupation as reference group; 10–11 years’ education: OR 1.21, 95% CI [0.65, 2.25]; ≥12 years’ education: OR 0.68, 95% CI [0.32, 1.44]), or marital status (married participants as reference group; 10–11 years’ education: OR 1.01, 95% CI [0.57, 1.77]; ≥12 years’ education: OR 1.74, 95% CI [0.88, 3.44]). Further, variance inflation factor (VIF) analysis revealed no evidence of multicollinearity with respect to education (VIF = 1.15), age (VIF = 1.11), sex (VIF = 1.09), occupational status (VIF = 1.15), or marital status (VIF = 1.18).

**Discussion**

Using GMM procedures, we identified high, moderate, and low SA trajectory classes. Individuals in the HFT

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**Figure 1: Estimated mean trajectories of Successful Aging Index scores (HFT: high functioning trajectories; MFT: moderate functioning trajectories; LFT: low functioning trajectories).**

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**Table 2: Model selection criteria**

<table>
<thead>
<tr>
<th>Class</th>
<th>AIC</th>
<th>BIC</th>
<th>SABIC</th>
<th>Entropy (% of sample)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>14491.776</td>
<td>14557.291</td>
<td>14515.999</td>
<td>0.57</td>
</tr>
<tr>
<td>3</td>
<td>14420.047</td>
<td>14525.880</td>
<td>14459.178</td>
<td>0.66</td>
</tr>
<tr>
<td>4*</td>
<td>14400.269</td>
<td>14556.499</td>
<td>14458.034</td>
<td>0.59</td>
</tr>
</tbody>
</table>

*Note: *Did not converge; AIC: Akaike Information Criteria; BIC: Bayesian Information Criteria; SABIC: Sample-adjusted Bayesian Information Criteria.
the degree to which a model can delineate between

class were primarily men, married, and of high occupa-
tional status. After adjusting for age, sex, and occupa-
tional status, a significant and independent association
between higher education and better SA trajectories in
later life was demonstrated in the total sample. These
results suggest that early-life education is an indepen-
dent marker of SA in later life.

Limitations include a substantial degree of missing
data and model fit. As highlighted in the methods, our
study used a complete case analysis. We made this
decision to ensure that the integrity of the SAI was
maintained, that is, that respondents’ subjective inter-
pretation of components was captured. Further, as in
any longitudinal study of older adults, there is a sig-
nificant level of attrition via death. This attrition pre-
disposes the sample to having a survivor bias in which
only individuals who are healthier are included (Young,
Powers, & Bell, 2006). Given the association between
longevity and indicators of socioeconomic advantage,
such as education, this may also result in more edu-
cated individuals staying in the sample (Young et al.,
2006), as was the case in the current study. Although
individuals who were less healthy and less educated
may not have been included in the sample, one pur-
pose of this study was to examine the association
between the educational attainment of individuals in
the best functioning successful aging trajectory relative
to other individuals in the sample, even if they were
part of a particularly healthy and well-educated group.
As a result of this attrition, subsequent waves of the
CFAS (e.g., beyond four years’ follow-up) could not be
used because of the inability of the models to converge.
However, GMM uses maximum likelihood estimation,
with robust estimates under a missingness-at-random
assumption.

Missingness in the dataset was assessed with respect
to age, sex, education, and marital status; we noted
that individuals missing from the current study but in-
cluded in the broader CFAS were significantly older
and had significantly fewer years of full-time edu-
cation. An additional purpose of the current study was to
identify individuals who were aging particularly well
within the sample rather than to present trajectories
that are representative of the general population. It is
important to note that only a relatively small propor-
tion of individuals in such a large study met the crite-
reria for the high functioning HA trajectory. Further,
given the observational nature of the study, we were
unable to establish the underpinning causative mecha-
nisms that were driving the relationships observed.

The best-fitting model was selected for further analysis;
however, limitations in the model fit must be acknowl-
edged, notably regarding entropy. Entropy refers to
the degree to which a model can delineate between
classes, with lower levels of entropy indicating a higher
probability of misclassification of individuals into
classes. The model we chose for further analysis had
the highest level of entropy of all the possible model
permutations; however, by absolute standards, rather
than relative standards, this level of entropy was rela-
tively low. Therefore, we have used the best fitting
model in these analyses given the possibility of mis-
classification of individuals based on the entropy of
the model.

Previous studies that have examined the relation-
ship between SA and education have used mixed
models and have subsequently produced contradic-
tory results (Liang et al., 2003; Montross et al., 2006;
Palmore, 1979; Strawbridge et al., 1996). Studies that
employed unidimensional models (for example, only
physical functioning) did not demonstrate a signifi-
cant relationship between education and SA (Ford et al.,
2000; Strawbridge et al., 1996). However, in three of
six studies that invoked a multidimensional model
of SA, including both psychosocial and biomedical
components, researchers observed significant rela-
tionships (Fernandez-Ballesteros Garcia et al., 2011;
Hamid, Moltz, & Ibrahim, 2012; Vaillant & Mukamal,
2001). Of note, in the Fernandez-Ballesteros Garcia
et al. (2011) models, the only model that reached signif-
cance was the one with the greatest number of psy-
chosocial components, including subjective health and
satisfaction. These studies used models that were pri-
marily researcher-driven in their constituent com-
ponents and in their thresholds.

Our current study used an a priori model of SA and
a data-driven method for extraction of SA trajec-
tories. The components included in the SAI have been
informed by lay perspectives, given the SAI relevance
to older people. A key strength of GMM models is the
ability to articulate SA in relative, rather than absolute,
terms. In models of SA that posit researcher-driven
thresholds if individuals cannot fulfill these criteria,
the opportunity for further analysis is inhibited. Con-
versely, in GMM, individuals’ performance is group-
based using similar trajectories – that is, GMM models
do not employ an absolute threshold; therefore, these
data are able to articulate heterogeneous trends.

Occupational status and education are closely linked,
as demonstrated in the current study by the attenua-
tion of the relationship between SA and education when
adjusted for occupational status. In the total sample,
however, education was a statistically significant, inde-
dependent marker of membership in higher SA classes
after adjusting for age, sex, and occupational status
in the full sample and in a subsample of women. This
relationship approached significance in men, but was
not observed. Given the much lower sample size of

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men (n = 418), this may have been a function of the attenuation of statistical power. Although there were sex differences in the relationships between SA classes and education, these interactions did not reach statistical significance. These results provide support for the independent influence of education on SA. However, the practical implications of these results must be interpreted with caution. Although we demonstrated a statistically significant association, the application of these findings in real-world settings will require further research into the causative mechanisms that underpin this association. Another area for further research is into the relationship between occupational status and gender in aging populations. Although research into the implications of increased gender equity have suggested trends towards more positive women’s health outcomes (Moss, 2002), this relationship has not been explored across cohorts or in the context of aging trajectories.

These results suggest that education is a statistically significant, independent marker of SA. Although the mechanisms underpinning this association require further investigation – as educational attainment will be a reflection of innate ability and childhood circumstances – the potential modifiability of educational attainment may permit societies to influence the future trajectory for their populations through policies implemented in early life. These findings are consistent with research looking at the negative elements of aging, notably dementia (Stern et al., 1994) and terminal decline (Batterham, Mackinnon, & Christensen, 2011), highlighting the long-term benefits of higher education attainment in older samples.

References


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