Research Notes / Notes de recherche

A Novel Examination of Successful Aging Trajectories at the End of Life

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RÉSUMÉ

Un indice de vieillissement réussi (SA) a été capturé dans une étude de cohorte longitudinale basée sur la population des personnes de 75 ans et plus, qui a été examiné longitudinalement en utilisant la modélisation d'un mélange de croissance (MMC) pour identifier les groupes ayant des trajectoires similaires utilisant la dernière interview complète de personnes décédées et jusqu'à quatre collections de données précédentes avant la mort. MMC a identifié un modèle avec trois classes. Les classes étaient : haut fonctionnement, pas de déclin (HPD); fonctionnement élevé, baisse progressive (HBP); et un faible fonctionnement, fort baisse (FB). Les individus de la classe HPD étaient significativement plus jeunes à la mort, et à la fin de l'examen, se composait de plus d'hommes, et plus susceptibles d'être mariées, comparativement aux individus HBP et FB. Ces résultats démontrent différentes façons dont les individus peuvent éprouver un vieillissement réussi à la fin de vie. Cette étude fournit le cadre pour la recherche future en ce qui concerne les processus du vieillissement pendant toute la vie, avec des implications importantes pour la politique et la pratique.

ABSTRACT

A successful aging (SA) index was captured in a longitudinal population-based cohort study of individuals aged 75 and older and examined longitudinally using growth mixture modelling (GMM) to identify groups with similar trajectories using decedents' (n = 1,015) last completed interview and up to four previous data collection waves before death. GMM identified a three-class model. Classes were high-functioning, no decline (HN); high-functioning, gradual decline (HG); and low-functioning, steep decline (LS). HN class individuals were significantly younger at death ($p < 0.001$) and at last interview ($p < 0.001$), consisted of more men ($p < 0.001$), and more likely to be married ($p < 0.001$) compared to HG and LS class individuals. These results demonstrate the different ways in which individuals can experience successful aging at the end of life. This study provides the framework for future research into life-course processes of aging, with important implications for policy and practice.

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The ways in which aging has been conceptualised within a positive aging framework has rapidly expanded from humble beginnings. In the early 1960s, Cumming and Henry's disengagement theory (1961) was a popular – albeit, inherently negative – perspective on aging. Within this framework, to age well was to linearly retract from the activities of mid-life. However, in the first issue of *The Gerontologist*, the late Robert Havighurst posited his activity theory (1961), which took cues from positive psychology in contrast to disengagement theory. However, even in those early days, Havighurst suggested that the operationalisation and articulation of successful aging (SA) would be problematic (Havighurst, 1961).

The MacArthur Foundation was formed in 1984 under the leadership of John W. Rowe, with the intent to further articulate SA. A consortium of academics, geriatricians, and gerontologists were gathered to critically examine the ways in which older adults age. From these meetings, one of the most highly cited gerontological papers was produced: the Rowe and Kahn model of SA (1987). In this model, a tripartite conceptualization of aging was suggested, including high physical and cognitive functioning, low probability of disease, and engagement (Rowe & Kahn, 1987). Alongside the many proponents of the Rowe and Kahn model were those who, rightly, acknowledged oversights in the model. For example, Matilda Riley (1998) highlighted the notable absence of social situations. These issues have been acknowledged by Rowe and Kahn and, where possible, improvements have been made.

In the burgeoning SA literature, a number of areas remain that expand beyond the limitations of the Rowe and Kahn model to fundamental conceptual and methodological limitations, notably with respect to the end of life (Cosco, Stephan, & Brayne, 2013). Additionally, the development of a consensus definition of SA has not occurred (Cosco, Prina, Perales, Stephan, & Brayne, 2014a), which has had serious inhibitive effects on cross-study comparisons. Given the inability of SA models to articulate the heterogeneity of aging trajectories at the end of life (Cosco et al., 2013), the implementation of more refined measures and methods of capturing SA across the life course is necessary (Kivimaki & Ferrie, 2011). The conceptual and methodological limitations of extant models have impeded this process, notably with respect to the selection of model components, the use of binary modelling procedures, the nature of the data sets used, and the statistical methods employed in the analysis of these data (Cosco, Stephan, & Brayne, 2014).

Over the past several decades, the Rowe and Kahn (1987) model of SA has been cited, examined, and critiqued prolifically (Martinson & Berridge, 2015), collectively moving the field forward. In addition to quantitative analyses of SA, there have been many qualitative studies that have examined what SA means to the layperson. Unfortunately, many of the SA models implemented in quantitative studies have not benefitted from the input of laypersons (Jopp et al., 2014); theory-driven models greatly outnumber lay-informed models (Phelan, Anderson, LaCroix, & Larson, 2004). As a result, the relevance and impact of research conducted using these models to older individuals may be impeded.

Trajectories of aging at the end of life may include some sort of functional decline, be it physical, cognitive, or psychosocial. Unfortunately, the conceptual framework underpinning traditional models of SA cannot accommodate these declines in a meaningful way (Cosco et al., 2013). Once an individual falls below a given threshold, the individual is no longer deemed to be successfully aging, inhibiting the examination of SA from a life course perspective.

In the modelling of SA, data-driven methods of examining the heterogeneity of SA trajectories have not been employed at the end of life. Other areas of research, such as studies of terminal decline in cognition – that is, the decline in cognitive functioning experienced immediately before death – have used modelling techniques similar to those employed in the current study (for example, using time to death as the time metric) – to examine decline at the end of life (Muniz-Terrera, Matthews, Stephan, Brayne, & Group, 2011). However, these models focus on modelling change induced by proximity to death whereas SA is focused on acknowledging and articulating the heterogeneity of aging trajectories.

There is no consensus definition of SA. Further, laypersons and researchers are divided over which components should be included in these models (Cosco, Prina, Perales, Stephan, & Brayne, 2014b). Recent systematic reviews of the literature reveal that laypersons generally suggest psychosocial components (Cosco, Prina, Perales, Stephan, & Brayne, 2013), whereas researchers suggest biomedical components (Cosco et al., 2014a). Additionally, researchers' conceptualisations have generally used binary modelling procedures suggesting that if an individual cannot sustain a high level of functioning across all physiological domains, they can no longer be considered to be "successfully aging". Binary modelling of SA lacks the granularity to articulate the processes of aging, especially in the very old (e.g., persons aged 85 years and older) (Cosco et al., 2014). Finally, the statistical procedures invoked to examine SA at the end of life generally posit absolute measures – for example, thresholds of functioning – to capture heterogeneity in aging rather than relative measures, such as comparing functional capability between study participants.

In order to longitudinally model SA across the life course, statistical procedures that align with the theoretical underpinnings of the SA model must be employed. The SA model was founded on the assertion that the aging process is heterogeneous (Rowe & Kahn, 1987); as such, methods that can examine the characteristics of individuals with similar longitudinal trajectories of a latent variable are advantageous. In contrast to variable-centred approaches, such as structural equation model and factor analysis, which focus on describing the relationships among variables, person-centred approaches, such as growth mixture modelling (GMM), describe relationships among individuals (Ding et al., 2007; Muthén & Muthén, 2000). Through the use of GMM, it is possible to use a data-driven method to extract different classes of individuals with similar SA trajectories and to examine their characteristics at the end of life. To date, these procedures have not been employed at the end of life using a priori SA models that have been informed by layperson perspectives.

The current study aimed to address the conceptual and methodological shortcomings of extant models of SA and to the heterogeneity of SA trajectories at the end of life using data in the Cambridge City over-75 Cohort Study (CC75C).

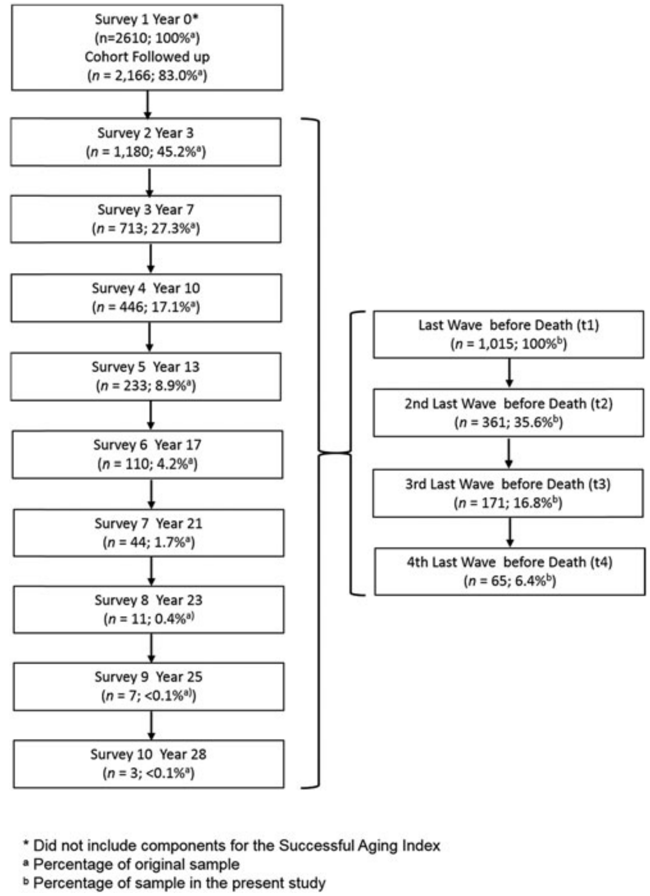

Figure 1: Study participant inclusion flowchart

Methods

Study Participants

CC75C is a longitudinal population-based cohort study (n = 2,610) founded in 1985 and designed to measure the prevalence and incidence of dementia at very old age (Fleming, Zhao, O'Connor, Pollitt, & Brayne, 2007). In the baseline wave of data collection, all men and women aged 75 years or older were sampled from five primary care practices, and one in three from a sixth practice in Cambridge (U.K.). A 95 per cent response rate was achieved. Follow-up interviews were conducted with surviving respondents at 3, 7, 9, 10, 13, 17, 21, 23, 25, and 28 years (Figure 1) capturing data on physical functioning, cognitive functioning, and psychosocial well-being.

SA Index

An SA index was created using components identified by operational definitions (Cosco et al., 2014a) and layperson perspectives (Cosco et al., 2013) of SA. The SA index includes seven items: (a) maintenance of interest, (b) absence of loneliness, (c) optimism, (d) self-rated health, (e) cognitive functioning (i.e., Mini-Mental State Examination (MMSE) (Folstein, Robins, & Helzer, 1983), (f) instrumental activities of daily living (IADLs) (Lawton & Brody, 1969), and (g) activities of daily living (ADLs) (Katz, 1983). Using a procedure similar to the Frailty Index (Searle, Mitnitski, Gahbauer, Gill, & Rockwood, 2008), ordinal variables were assigned a value from 0 to 100 based on their reported level of functioning. For example, participants were asked "How do you feel about the future?", to which a response of "optimistic" would receive a score of 100; "empty expectations", a score of 50; and "pessimistic", a score of 0. The one non-ordinal item, MMSE scores, was categorized using a procedure similar to that of Searle et al. (2008): that is, scores of 26–30 would receive a score of 100; 22–25, a score of 67; 18–21, a score of 33; and 0–17, a score of 0 based on established cut-points for cognitive functioning. The scores from the seven constituent components were averaged to get a score between 0 and 100, with increasing scores indicating more SA (a more detailed description of the methods for constructing the SA index are available in Cosco, Stephan, & Brayne, 2015). In contrast to binary models that are unable to articulate the processes of aging with the necessary granularity needed for GMM (Cosco et al., 2014), the indexing procedure provides a novel method of longitudinally quantifying SA.

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Participant Classification

Individuals who had died between each wave were identified using their date of death and date of interview. The SA index was calculated for each individual at their last interview before death (t1) and at up to three previous waves of data collection (t2–t4) (Figure 1). Variables necessary to create the SA index were not available in the baseline interview of the CC75C study; therefore, we used only scores from subsequent waves.

Co-variates

Self-reported survey data was collected for all co-variates. Socioeconomic status was indicated by the individual's employment before retirement according to the United Kingdom's Registrar General's occupational classification and grouped into manual or non-manual, as per Lawlor, Smith, and Ebrahim (2004). Marital status was grouped into married or not married at the last wave of data collection. Education was captured using the individuals' self-reported age at which they left school.

Statistical Procedures

Latent variable modelling is a burgeoning area of interest with a ubiquitous presence in scientific research, allowing for the examination of unobserved, or latent, phenomena. As a result of advancements in statistical techniques and the increasing availability of relevant statistical software, latent variable modelling has become widely used in recent years (Loehlin, 2009). Latent variable modelling includes a number of methods – for example, factor analysis, path analysis, structural equation modelling, and GMM – using observed variables to draw inferences about latent phenomena. Trajectories of SA were modelled in MPlus 7.0 (https://www.statmodel.com/) using GMM, a person-centred longitudinal latent variable analysis technique (Ding et al., 2007; Muthén & Muthén, 2000). In GMM, models are estimated under the maximum likelihood estimation, with robust estimates under a missing-at-random assumption. The objective of GMM is to group similar individuals into separate classes, that is, to identify homogenous subpopulations within a larger heterogeneous population (Jung & Wickrama, 2008; Muthén & Muthén, 2000), enabling the identification of disparate trajectories – for example, of cognitive decline (Muniz-Terrera, Matthews, Dening, Huppert, & Group, 2009) or depression (Norton, Sacker, Young, & Done, 2011) – when repeated-measure longitudinal data sets are employed, such as with CC75C. The SA paradigm was founded on the acknowledgement that aging is a heterogeneous process (Rowe & Kahn, 1987); therefore, the theoretical underpinning of the SA model aligns closely with the person-centred approach used in GMM.

As a result of issues of convergence in waves with < 10 per cent of the original sample, it was possible to use only four waves of data collection in the GMM analysis. Sex and age at death were included as co-variates. Various permutations of the co-variate relationships with the intercept and slope were used to find the best model fit once the appropriate number of trajectories had been identified.

The number of trajectories identified – that is, model fit – we assessed by using the Akaike information criteria (AIC) (Akaike, 1987), Bayesian information criterion (BIC), and sample-adjusted Bayesian information criterion (SABIC) (Nylund, Asparoutiov, & Muthén, 2007), with the lowest values on each measure chosen to identify the best-fitting model (Schwarz, 1978). Additionally, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMRLR) (Lo, Mendell, & Rubin, 2001) and parametric bootstrapped likelihood ratio test (BLRT) (McCutcheon, 1987) were used to inform model selection, with models reaching significance rejecting the null hypothesis that the current number of classes are a better fit than fewer classes. Because of the nature of the model, which has been designed to fit non-normal data, the model must be interpreted within a theoretical framework; otherwise, spurious classes may be identified (Bauer & Curran, 2003). We assessed classification 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).

Demographic characteristics (sex, socioeconomic status [SES], education) across classes were compared using, χ^2 tests for categorical variables and *t*-tests for continuous variables. These analyses were performed using Stata 12 (https://www.stata.com/).

Missingness

The SA index calculates an average of components derived equally from layperson perspectives and researcher perspectives; therefore, missing components' values would skew these data. Individuals who did not have complete data for the SA index were subject to listwise deletion during the creation of the index – that is, if any component of the index was missing for a study participant, such as ADL score, he/she was excluded from the study. Further, individuals who were still alive in the study were listwise deleted. Missingness at random for demographic variables, physical function (i.e., presence of disability in activities of daily living or instrumental activities of daily living), and cognitive function (Mini-Mental State Examination [Folstein et al., 1983] $\geq$ 27) was assessed via χ^2 tests or *t*-tests.

Table 1: Fit indices used in growth mixture modelling model identification

Class	AIC	BIC	SABIC	Entropy	Smallest Class (% of sample)	LMRLRT	BLRT
2	11105.707	11179.5447	11131.906	0.58	0.33	< 0.001	< 0.001
3	10993.565	11101.863	11031.989	0.61	0.20	< 0.001	< 0.001
4*	10963.828	11116.43	11017.972	0.64	0.07	0.23	< 0.001

*** Did not converge**
AIC: Akaike information criteria; BIC: Bayesian information criteria; BLRT: parametric bootstrapped likelihood ratio test; LMRLRT: Lo-Mendell-Rubin adjusted likelihood ratio test; SABIC: sample-adjusted Bayesian information criteria

In GMM, models are estimated using maximum likelihood estimation, with robust estimates under a missing-at-random assumption (Jung & Wickrama, 2008).

Results

Of the 1,180 participants interviewed at Survey 2, 1,015 had SA index scores at t1, 361 at t2, 171 at t3, and 65 at t4; mean number of waves participated in was 1.43 (*SD* 0.77). Individuals missing SA index scores (n = 157) were significantly more likely to be women ($\chi^2 = 8.74$, $p = .003$), less likely to be married ($\chi^2 = 16.16$, $p < .001$), and to be older when they died (t[1,172] = –6.03, $p <$ .001) and at their last interview (t[1,178] = –9.1911, $p < .001$), compared to included participants. No differences were observed between missing individuals' SES, education, and presence of cognitive/physical disability at Survey 2.

A three-class model provided the best fit to the data (Table 1) capturing high-function, no decline (HN) (n = 333, 32.8%); high-function, gradual decline (HG) (n = 483, 47.5%); and low-function, steep decline (LS) (n = 199, 19.6%) classes (Table 2). This model had low AIC, BIC, and SABIC values; sufficient entropy; reasonable class sizes; and the trajectories were theoretically sound. LMRLRT values suggested a four-class model; however, this model failed to converge.

The HN class exhibited virtually no decline, with individuals clustered at a high level of sustained functioning. The HG class had the highest initial level of functioning; however, in contrast to the HN class, it exhibited a marked decline in SA index score towards death. The LS class exhibited the lowest initial functioning and the steepest decline in SA index score as individuals approached death (Figure 2).

When compared with the HG class, the HN class contained significantly more men, married participants, individuals who died earlier, and who had a longer interval between their last interview and death. When compared to the LS class, the HN class contained significantly more men, married individuals, fewer manual labourers, and individuals who died earlier and had a longer interval between the last interview and death. No differences were observed in educational attainment (i.e., school-leaving age) across the three classes.

Discussion

The trajectories captured by the SA index scores demonstrate three separate end-of-life trajectories. Individuals in the HN class were predominately married men of high SES. These results suggest that individuals may have very different end-of-life trajectories within an SA framework, highlighting limitations in previous conceptualisations of SA through the use of novel indexing and modelling procedures.

Limitations in the creation of the SA index include missing values resulting from both the listwise deletion

Table 2: Characteristics of study participants and trajectories, by successful aging class

Sample Group		*n*	Intercept	Slope	Women (%)	Married (%)	Manual Work (%)	Age Left School (years) mean	Age at Last Interview mean	Age at Last Interview *SD*	Age at Death mean	Age at Death *SD*	Time between Last Interview and Death (years) Mean	Time between Last Interview and Death (years) *SD*
Total		1015			63.94	31.72	61.36	14.80	84.60	4.32	89.47	5.04	2.73	2.29
	HN†	333	95.64	–0.31	48.05	50.75	56.31	14.98	82.94	3.59	88.29	4.90	3.03	2.74
Class	HG	483	96.98	–2.47	68.94***	23.86***	63.11	14.74	85.03***	4.24	89.88***	4.96	2.68*	2.07
	LS	199	90.04	–4.25	78.39***	18.78***	65.63*	14.65	86.29***	4.70	90.47***	5.10	2.37**	1.91

† Reference group * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

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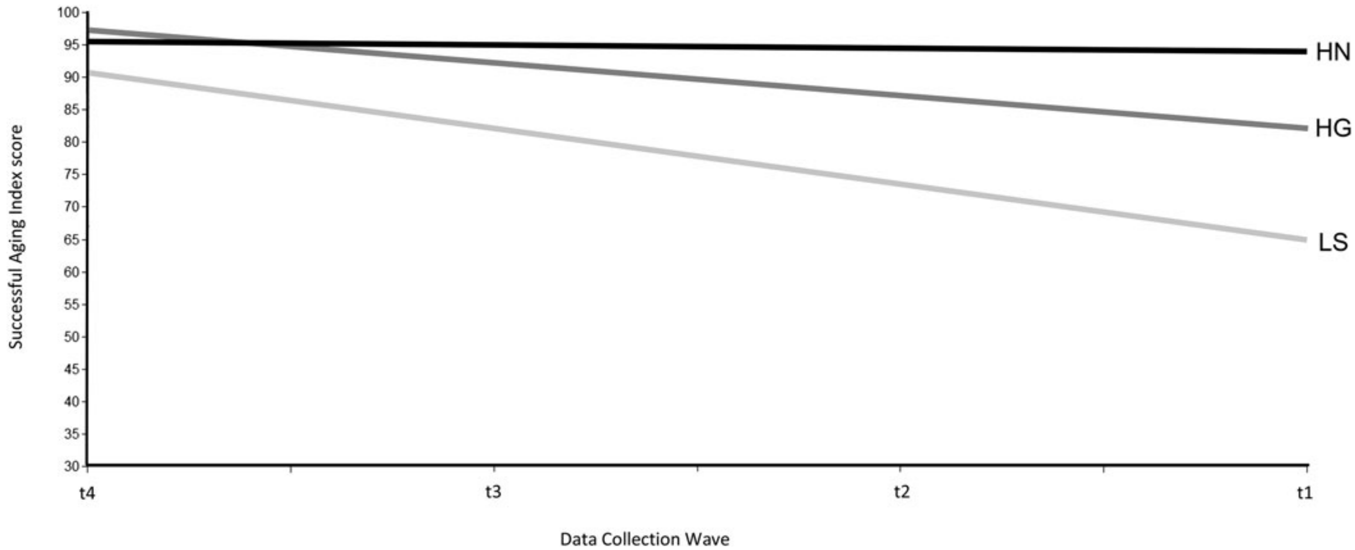

Figure 2: Estimated mean successful aging index trajectories. HN: high-function, no decline class; HG: high-function, gradual decline class; LS: low-function, steep decline; t4-1: data collection waves from death (i.e., t1 is the last data collection wave before death).

of individuals that did not complete all components of the measure and from attrition. Given that the index calculates an average value for all of the constituent components, individuals with missing data would not have a score comparable to those with complete data. Individuals excluded from the study differed from study participants in sex, marital status, and age; however, no differences were identified in individuals' SES, education, physical functioning, and cognitive functioning at Survey 2, which is the first survey with all SA index components (Figure 1). The methods used in this longitudinal analysis employed time to death, rather than chronological age, as the time metric and used maximum likelihood estimation under a missing-at-random assumption, which are better able to accommodate attrition. Whether attrition resulting from death was truly missing at random is debatable and, therefore, is a limitation of the current study. Further, individuals' information was included at their last wave of data collection, which is as close to death as possible. However, the interval between the last interview and the time of death varied across individuals, ranging from only a few days to several years.

The three identified trajectories differed not only in their intercepts, but also in their slopes, highlighting the different ways in which individuals can successfully age at the end of life. The HN class and HG class began with a similar level of functioning but had vastly different slopes of decline; the HG class declined at a much faster pace than the HN class, which experienced very little decline. This is an important relationship to explore, particularly with regards to protective factors that permit individuals in the HN to maintain their high level of functioning. Through the examination of why individuals in the HG class started at the same level of functioning but declined much more rapidly, we find it is possible that this decline can be staved off or attenuated. Further, by examining modifiable lifestyle behaviours and social mechanisms that explain the differences in slope between HG and LS classes, researchers will be provided important insights to the end-of-life process.

The trajectories modelled in the current study benefitted from the use of a metric of SA that has improved granularity over binary models and longitudinal latent variable modelling techniques that allow the identification of different classes of SA. Previous studies have faced conceptual challenges in the creation of SA models that are relevant to researchers and older adults; these issues have been addressed through the use of an index that is informed by systematic reviews of layperson perspectives and operational definitions of SA. Methodologically, extant models have not been able to articulate SA due to the use of binary models, which have inhibited the accommodation of decline. Through the use of time to death as the time metric, individuals' data from the end of life can be modelled using latent variable modelling procedures, combatting these issues. These results have important implications for further research, highlighting alternative and novel means with which to model processes, such as SA, using indexing procedures and longitudinal latent variable modelling. Further, these results highlight the potential for important research possibilities into the provision of resources and care in the dying process. If these procedures can elucidate different SA trajectories towards the end of life, the relationship between modifiable lifestyle behaviours and these classes can be identified, with the potential for implementing policies and interventions to facilitate these outcomes.

As highlighted by the trajectories identified via GMM, SA is not an all-or-nothing state. Rather, there are many ways in which individuals experience SA and the dying process. Further work investigating risk and protective factors for SA will have important implications for policy implementation and intervention trials focused on the fostering of better biopsychosocial functioning at the end of life.

The current study provides a novel framework and method with which to examine heterogeneous trajectories of SA at the end of life. These results provide a step forward in the conceptualisation and examination of the disparate ways in which individuals can age well, highlighting the potential for future research to examine factors that foster more positive end-of-life experiences. Further research is required to unpick the specific mechanisms behind these different SA trajectories; however, the current study establishes the conceptual and methodological framework for the advancement of these areas of research into the processes of SA at the end of life.

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