Structural Change and Economic Dynamics 71 (2024) 430–443

Contents lists available at ScienceDirect

Structural Change and Economic Dynamics

journal homepage: www.elsevier.com/locate/strueco

Monitoring socioeconomic readiness for the demographic transition: Introducing the Senior Economy Tracker

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ARTICLE INFO

Keywords:
Aging
Demographic transition
Composite indicators
Senior
Older adults

ABSTRACT

Aging constitutes the dominant demographic challenge globally. The demographic transition entails a paradigm shift in the economic model to accommodate economic structures to life-expectancy gains. The socioeconomic implications from this transition remain largely undefined conceptually from an integrated perspective and unrecognized in official statistics. This study introduces a multidimensional and multi-actor reference framework, and a composite indicator, the Senior Economy Tracker (SET), to measure national readiness and progress in adapting to the demographic transition, over time and across countries. We apply our indicator to 27 European countries in 2010-2021. Our study reveals crucial differences in pathways and stages of maturity in addressing the socioeconomic impacts of aging. The proposed indicator aims to guide action to adapt economic structures to longer life spans, assist organizational and individual decision making, facilitate the development of effective policy interventions and raise awareness of the demographic transition.

1. Introduction

For the first time in history, the number of people over 64 has surpassed those below 5 years old globally (UN, 2020). The reversal of the population pyramid -aging[1] and shrinking[2] at an accelerated pace (Bloom & Luca, 2016; Lutz et al., 2008; Partridge et al., 2018)- is universal (Scott, 2021a), and poses a significant structural change globally. The demographic transition not only introduces socioeconomic opportunities from life-expectancy gains (World Health Organization, 2018) but also presents a grand challenge from the potential burden on public expenditures (Bloom et al., 2011; Olshansky, 2021) and intergenerational equity tensions (Amaglobeli et al., 2019; Chen et al., 2018; Harper, 2014).

Economists have debated for long the potential structural effects of the demographic transition on economic growth (i.e. Bloom et al., 2015; Högberg et al., 2018), labor force structure (Gori & Sodini, 2020; Schimke, 2014), and national productivity (Feyrer, 2007; Gittleman et al., 2006). An aging society brings fewer working-age populations and, simultaneously, growing expenses in public health and pensions. However, maximizing the gains from longer lives and minimizing the economic costs may create a longevity dividend (Scott, 2021b) that positively bridges healthier aging with economic benefits. Achieving the longevity dividend requires multi-actor efforts from governments, organizations, and individuals to drive multidimensional structural changes in institutions, markets, and personal behaviors. For example, strategies to offset costs in healthcare and pensions by enhancing productivity and skills among the older adults, aiming to balance age structure and transform potential negative impacts into positive economic outcomes.

To gather empirical evidence on the socioeconomic developments associated with the demographic transition, we require a comprehensive assessment of the gains and costs that it entails and the advancements in the required structural changes. However, the literature analyzing aging from a socioeconomic perspective mostly restricts to demographic structure, focusing on dependency ratios and the relative salience of older cohorts in population pyramids (Siliverstovs et al., 2011). These approaches lack an *integrated* picture of the structural change in economic systems that the demographic transition brings. In particular,

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[1] In 2050 16 % of world inhabitants will be 65+ versus 9 % in 2020 (UN, 2020)

[2] About half of the world population lives in countries where the birth rate is below 2.1 children per woman, thus, at the border of null population growth in the long term (UN, 2019).

https://doi.org/10.1016/j.strueco.2024.08.007
Received 19 December 2023; Received in revised form 11 July 2024; Accepted 13 August 2024
Available online 19 August 2024

extant literature overlooks the multiple dimensions underlying the demographic challenge and the potential for a longevity dividend across various actors. This gap is significant since tackling the demographic transition is pervasive across national agendas and global targets.

The success in addressing the demographic transition varies across countries. Comparative analyses based on composite indicators may bring insights for intra and inter-country assessments, monitoring, cooperation, and development (Biggeri et al., 2019; Greco et al., 2019). However, most works that propose indicators to assess the readiness and progress in tackling the demographic challenge provide fragmented, unidimensional approaches. For example, the active aging index (Zaidi et al., 2017) at an individual level, or the later life workplace index (Finsel et al., 2023) focused on organizational behavior. In contrast to these monothematic analyses, we argue that a comprehensive assessment of the economic implications of aging and the associated opportunities for various stakeholders requires an integrative, multidimensional metric, that offers an easy-to-interpret summary of overall achievements, a challenging task when analyzing multiple indicators separately.

This paper seeks a dual goal: first, to offer a multidimensional composite indicator, the Senior Economy Tracker (SET), designed to measure, examine, monitor, and contrast cross-country readiness and progress along the demographic transition development path. To construct the SET, we introduce a reference framework that systematizes the multiple dimensions underlying the socioeconomic aspects of aging. The SET enables the derivation of an integrative picture of the socioeconomic advancements in addressing the demographic transition, contrasting prior unidimensional efforts. The proposed methodology represents a key contribution to this research. Second, we implement the SET across 27 European countries over the 2010-2021 period to assess country readiness for the demographic transition, explore its evolution within and across regions, and understand the underlying drivers and roadblocks.

Composite indicators simplify complex, multidimensional realities and can significantly influence policy debates and support advocacy discourses (Saltelli, 2007). Despite their widespread use -the paradigm being the Human Development Index (HDI) (Anand & Sen, 2003)- they are subject to academic debate. Critics argue that composite indicators lack statistical significance and exhibit arbitrariness in their construction (Grupp & Mogee, 2004). Conversely, proponents highlight their ability to capture public attention, facilitate understanding of complex issues, and stimulate decision-making processes in both the public and private sectors (Greco et al., 2019) [3]. Therefore, while composite indicators hold substantial potential for social transformation, they can be misleading if not meticulously developed. To mitigate these risks, we constructed the SET according to proven quantitative methodologies (OECD, 2018; Lafortune et al., 2018; Sachs et al., 2018), including normalization, imputation, multivariate analysis, weighting, and aggregation (see Greco et al., 2019 for a review).

The results from the SET show that the most advanced countries in addressing the demographic transition are Denmark and Sweden. These countries exhibit superior progress in the institutional, macroeconomic, and individual dimensions compared to other European nations, even as we impose the need for heightened efforts in regions with more inverted population pyramids. We present different clusters that embed various levels of progress towards a senior economy, finding common and stable patterns and potential areas for improvement, which explain pathways for the development of the senior economy.

We contribute theoretically and empirically to the literature on the change of economic structures (Schimke, 2014; Yu et al., 2023) by providing evidence on regional progress in addressing the demographic transition. Since the SET builds on multiple dimensions, it provides granularity on how these developments unfold. We also extend the literature on the socioeconomic effects of aging and longevity (Bloom et al., 2015; Scott et al., 2021) by providing an integrative reference framework and a multidimensional composite indicator, as compared to valuable yet isolated efforts in the study of aging and its measurement (Finsel et al., 2023; Zaidi et al., 2017). Methodologically, we extend the field of social indicators studies (i.e. Greco et al., 2019; Sachs et al., 2018), particularly in the area of developing composite indicators for the measurement of complex socioeconomic realities.

Effective governance is essential for managing the socioeconomic challenges of the demographic transition, as it ensures the implementation of policies that address the needs of an aging population. Our proposed composite indicator, the SET, is designed to guide sound governance and policymaking by providing a comprehensive measure and monitoring of national progress and readiness to adapt to demographic shifts.

2. A socioeconomic framework to assess the demographic transition

Grand challenges such as the demographic transition span multiple levels of analysis and, therefore, should be examined at various dimensions, facilitating a multistakeholder perspective (Bloom et al., 2011; Buckley et al., 2017). We conceptualize the socioeconomic impacts of the demographic transition and its structural changes through a framework that presents four primary dimensions -demographic, institutional, macroeconomic, and individual-. The dimensions are further divided into several categories to group distinct aspects within them, enhancing the granularity of our framework. Each dimension signifies a specific socioeconomic aspect of adaption to aging populations that contributes to understanding the interplay between demography, the society, and the economy. This comprehensive view captures the progress in addressing the demographic transition, enabling a more nuanced, multidimensional analysis. A positive evolution in these dimensions involves the adaptation to the challenges and beneficial exploitation of the opportunities from the demographic transition.

The *demographic dimension* embeds notions associated with the demographic challenge, such as the proportion of the 65+ population, life expectancy, and life expectancy above 65+. The unprecedented demographic shifts bring additional time and changes in the age structure of the population (Scott, 2023), which demands efforts to support longer lives. Thus, the demographic dimension assesses the advancement in the demographic transition.

The *institutional dimension* represents institutional structures that facilitate or hinder the country adaptation to demographic shifts. The structural changes emanating from the demographic transition demand institutional solutions from policymakers, which we reflect in health and social protection, and pensions and labor protection categories. Institutional advancements to foster healthy lives are crucial to exploit the opportunities of longevity (Scott, 2021b). Longer and healthier lives imply avoiding the economic costs of aging and profiting from longer life spans, maintaining stable consumption patterns, and thus, more incentives to extend working life and/or savings (Bloom et al., 2014; Scott et al., 2021). In turn, the category of pensions and labor protection in the institutional dimension presents the challenge associated with a growing proportion of the population earning retirement pensions for more extended periods. Pensions and labor protections are in intricate connection to the postponement in the retirement age, a phenomenon driven by the widening gap between retirement age and life expectancy. Bloom and colleagues (2014) show that the retirement age should increase, but in a lower proportion as life expectancy improves.

Institutional developments can promote transformations at the *macroeconomic dimension*, which depicts market functioning associated with the senior population, both from the consumption perspective and from their presence in labor markets and senior entrepreneurship. Thus, the macroeconomic dimension depicts the role of companies in

[3] These arguments led Amartya Sen, winner of the Nobel Prize in Economics in 1998, to change his critical stance on composite indicators.

providing goods and services to a growing market segment while facilitating multigenerational labor forces (Beard et al., 2012) and senior-driven economic activities (Azoulay et al., 2020). Extending professional careers to leverage the accumulated social capital can emanate from flexible work and retirement (Maestas et al., 2023), and new models of lifelong learning, mentoring, and reverse mentoring, leading to an intergenerational workforce (Beard et al., 2012).

The progress in the dimensions above are prerequisite for developing the *individual dimension*, which shows households' behaviors that promote, limit, or condition their well-being (Boudiny et al., 2012; Bowling, 2008; Walker & Lowenstein, 2009). A longer life expectancy involves significant personal adaptations and investments in education, savings, and work to manage extended life cycles effectively (Gratton & Scott, 2016; Scott, 2021a). The categories in this dimension cover participation in society, financial security, and active and healthy aging[4], which are crucial for healthy longevity, greater life satisfaction, and well-being (Diener & Seligman, 2004; Gupta, 2018), and, thus, for addressing the challenges of the demographic transition. Some examples of enhancing the individual dimension include life-long learning, technological skills (Niehaves & Plattfaut, 2014), and participation in economic and social life (He et al., 2018; Luiu et al., 2017). According to the bidirectional theory of aging (Scott, 2023), how individuals respond may magnify the impact of institutional and macroeconomic advancements, potentially leading to lower health expenditures and greater consumption (Scott, 2023). In addition, healthy aging can positively influence other dimensions because it facilitates engagement in labour markets, non-paid activities such as caring and volunteering, and social life. This focus maintains the sustainability of social security systems and strengthens social cohesion and inclusion (Zaidi et al., 2017).

The multidimensional framework facilitates a comprehensive analysis of the demographic transition by incorporating into multi-actor interactions, be they governments and NGOs (demographic and institutional dimension), companies and trade unions (macroeconomic dimension), or households (individual dimension), to make the necessary adjustments (e.g., infrastructure deployment, technological developments, enabling regulation, savings behavior, investing in own human capital all-life-long and healthy habits). Therefore, the framework reflects the integrated nature of the demographic grand challenge, linking public, private, and social agents (Gallouj et al., 2015).

Our framework to assess the socioeconomic implications of the demographic transition comprises four dimensions, nine categories, and 67 base indicators. Table 1 lists the selected base indicators. Four principles have guided the criteria for indicator selection: Comparability, ensuring indicator availability for many countries to facilitate cross-country comparisons; Historical availability, covering an extended time horizon for longitudinal analysis; Reliability, sourcing from public and open access databases such as Eurostat and OECD; and Specificity, providing data across age cohorts to focus on the senior population.

The following section displays the methods to summarize these inputs into a single aggregate measure, the SET, which can be further decomposed if needed.

Table 1
Base indicators to construct the SET, organized by dimensions and categories.

Demographic Dimension (A)	
A1.1 Population average age *	A1.4 Quality of life span *
A1.2 Senior population (% total population) *	A1.5 Life expectancy above 55 *
A1.3 Life expectancy **	A1.6 Dependency ratio *
Institutional Dimension (B)	
Health and social protection (B1)	***Pensions and labor protection (B2)***
B1.1 Health expenditure per capita **	B2.1 Average annual pension *
B1.2 Health expenditure government **	B2.2 Number of pensions *
B1.3 Health and social workers (density) **	B2.3 Replacement rate *
B1.4 Proportion of health expenditure government funded **	B2.4 Average retirement age **
	B2.5 Length of retirement **
	B2.6 Expenditure on private pension plans by individuals **
	B2.7 Expenditure on private pension plans by companies **
	B2.8 Poverty risk across pensioners *
Macroeconomic Dimension (C)	
Goods and services market- seniors (C1)	***Labor market- seniors (C2)***
C1.1 Mean consumption expenditure *	C2.1 Length of working life *
	C2.2 Labor transition (ratio) *
	C2.3 Senior remote working *
	C2.4 Senior employment rate *
	C2.5 Senior self-employment *
Individual Dimension (D)	
Participation in society (D1)	***Financial security (D2)***
D1.1 Inability to allocate small amounts for weekly personal expenses *	D2.1 Relative average income *
D1.2 Inability to participate regularly in leisure activities *	D2.2 Absence of risk of poverty *
D1.3 Inability to meet with family or friends in a hotel or restaurant at least once a month *	D2.3 Absence of severe material deprivation *
D1.4 Income inequality (80-20 Ratio) *	D2.4 Absence of energy poverty (households:1 senior) *
D1.5 No internet connection for personal use *	D2.5 Absence of energy poverty (households:2 adults and at least 1 senior) *
D1.6 Independent and autonomous living (one senior) *	D2.6 Senior workers at risk of poverty *
D1.7 Independent and autonomous living (two or more senior) *	D2.7 Inability to meet unforeseen financial expenses (households: 1 senior) *
D1.8 Life-long learning *	D2.8 Inability to meet unforeseen financial expenses (households: 2 adults and at least 1 senior) *
D1.9 Technological skills *	D2.9 Ratio of housing cost to disposable income (households: 1 senior) *
Healthy and active aging (D3)	D2.10 Ratio of housing cost to disposable income (households: 2 adults and at least 1 senior) *
D3.1 Access to health services *	D2.11 Indebtedness for primary residence *
D3.2 Self-perceived health status (very good or good) *	D2.12 Percentage of home ownership (households: 1 senior) *
D3.3 People with long-term illnesses or health problems *	D2.13 Percentage of home ownership (households: 2 adults and at least 1 senior) *
D3.4 Self-perceived absence of limitations in daily activities due to health problems *	
D3.5 Self-perceived absence of lack of medical care *	
D3.6 Healthy life expectancy at age 65 *	
D3.7 Premature deaths due to exposure to fine particulate matter*	

* Indicator source: Eurostat; ** Indicator source: OECD

3. Methods

3.1. Construction of the SET

Based on the socioeconomic framework to assess the demographic transition, we propose a composite indicator -the SET- to monitor regional readiness and progress in addressing demographic challenges. The SET score ranges from 1 to 100, where lower values denote weak or critically insufficient efforts to meet the needs and capitalize on the opportunities of an aging society, and higher values indicate substantial advancement or even role models. The steps followed for its construction are detailed in the paragraphs below.

We start with the normalization of base indicators to homogenize measurement units (Capelle-Blancard & Petit, 2017; OECD, 2018) at a normalized value in the 1-100 interval, with 1 meaning the worst possible result and 100 the technical optimum. We apply the min-max method due to its simplicity, efficiency, and widespread use among the different normalization methods (Freudenberg, 2003; Jacobs et al., 2004; OECD, 2008). For the min-max normalization of each base indicator, we use the historical minimum and maximum values throughout

[4] Active aging has been an increasing focus by national governments (Boudiny, 2013) and the WHO, understood as a 'continued participation in social, economic, cultural, spiritual and civic life, as well as social, mental and physical well-being, autonomy and independence' (Zaidi et al., 2017:139).

the time frame and regions observed.

The SET construction process continues with the imputation of the missing observations in the base indicators using standard regression methods (Jadhav, 2019). In particular, we apply a multivariate linear regression imputation to the whole set of base indicators (no restrictions were applied to the number of predictors used). Other imputation methods, such as the Expectation-Maximization (EM), the Modified Akima cubic Hermite interpolation, and the Shape-preserving piecewise cubic spline interpolation[5], were assessed and compared through the computation of the Root Mean Square Error (RMSE), providing worse results than the selected technique. All imputed values below the minimum value registered are set to 1.

We then perform a multivariate analysis to examine the correlations between base indicators within each category. A high level of correlation would imply the existence of collinearity and the potential for "double counting" issues in weighting methods (OECD, 2018). The results from the analysis demonstrate that significant correlations are absent in most instances (see Annex A for the correlation matrices of each category). This absence of strong correlations suggests robustness in the selected base indicators within categories, as each one predominantly offers supplementary information concerning the others. Besides, we address the potential issues of double counting emanating from specific cases with high correlations[6] using weighting techniques based on statistical methods, as explained below.

In the following stage, we apply the weighting and aggregation techniques. While these are distinct processes, they are closely interconnected, as aggregation relies on the weights derived from weighting. For this reason, weighting and aggregation are implemented simultaneously at the three levels defined within the conceptual framework (base indicators, categories, and dimensions -see *Table 1*). We follow a bottom-up process where *i)* all base indicators within a category are aggregated into a "category index" (first level); *ii)* all category indexes within a dimension are aggregated into a "dimension index" (second level); and *iii)* the indexes associated with the institutional, macroeconomic and individual dimensions are aggregated into the SET score (third level). This structured approach follows a hierarchical aggregation methodology (Szopik-Depczyńska et al., 2018) that ensures the availability of more granular measures (i.e., category and dimensions indexes) and improves traceability and transparency. Therefore, the weighting and aggregation techniques depend on the specific level considered.

We apply statistical methods to determine the base indicators' weights within each category (first level). Particularly, we obtain these weights from the factorial analysis (OECD, 2008) of the existing correlations between the base indicators of each category (see Annex B for details). This approach serves two primary purposes. Firstly, it effectively addresses the potential issues related to "double counting" among highly correlated base indicators, eliminating the need to disregard any of them[7]. Secondly, given the substantial number of base indicators in some categories (up to 13), other methods, such as expert criteria, become challenging due to the potential for significant cognitive strain (OECD, 2008), while our proposal assigns unbiased weights with a statistically driven approach. We apply equal weighting for the second and third levels since the variables in these levels are limited in number, equally significant, and conceptually uncorrelated. Table C1 (Annex C) shows the results for weight allocations in the three levels.

To select the aggregation technique for each level, we draw on the concept of substitutability (Lafortune et al., 2018), which refers to the extent to which trade-offs or compensations among indicators are permitted. In the first level, compensation among base indicators within a category is permissible[8], leading us to adopt a stance of absolute substitutability and to employ linear aggregation. At the second and third levels, however, substitutability is more restricted[9], and consequently, we chose geometric aggregation as the most appropriate method.

In the third aggregation level, we use the demographic dimension as an adjustment factor to accommodate the demographic pressure. Because the demographic dimension involves exogenous demographic trends, it serves as an adjustment factor to require further efforts to countries that present more advanced stages in the demographic transition. In other words, we argue that the institutional, macroeconomic and individual efforts need to be strengthened as the population pyramid becomes more inverted to fulfil the pressing needs imposed by the demographic challenge. We compute the demographic adjustment according to Eq. (1).

$$fadj_i(t) = \frac{I_{i,\ B}(t) + I_{i,\ C}(t) + I_{i,\ D}(t)}{I_{i,\ A}(t) + I_{i,\ B}(t) + I_{i,\ C}(t) + I_{i,\ D}(t)} \tag{1}$$

where $fadj_i(t)$ is the adjustment factor for country *i* at time *t* and $I_{i,\ X}(t)$ is the index obtained for dimension *X* at time *t*.

Eq. (2) exhibits the $SET_i(t)$ for country *i* at time *t*.

$$SET_i(t) = \left(I_{i,\ B}(t)^{1/3} \cdot I_{i,\ C}(t)^{1/3} \cdot I_{i,\ D}(t)^{1/3}\right) \cdot fadj_i(t) \tag{2}$$

The SET score enables the monitoring of a country's progress over time and facilitates comparisons among nations. We apply two supplementary analytical techniques to enhance the SET analytical depth and broaden the results insights: discriminant analysis and clustering.

3.2. Application of discriminant analysis and clustering to the SET

3.2.1. Discriminant analysis

The discriminant analysis draws on the computation of the discriminant coefficients (DC) (Ivanovic, 1974) for the SET score and its dimensions to determine which countries differ most from the rest.

DC coefficient is significantly more sensitive than the coefficient of variation to measure the discriminating capacity of an indicator: while the coefficient of variation restricts to the relative dispersion concerning the mean, the DC considers all the relative distances between every pair of different values of the indicator (Zarzosa, 1994; Zarzosa and Somarriba, 2013). The DC ranges between 0 and 2, where 0 denotes the extreme case of null discriminant power (all countries present the same value in the SET or dimension studied), and 2 stands for the extreme case of full discriminant power (all countries present null value in the SET or dimension studied except one country). Thus, the more heterogeneous countries' values within the SET or dimension, the higher the DC obtained. To examine countries' disparities, we measured country contribution to the total DC value for the SET or for each dimension according to Eq. (3) - note that $\sum_{i=1}^{m} DC_i(t) = DC(t)$. The greater the value of $DC_i(t)$, the greater the differentiation of country *i*.

[5] We have applied the regression and EM methods with the software IBM SPSS statistics https://www.ibm.com/docs/en/SSLVMB_27.0.0/pdf/en/IBM_SPSS_Missing_Values.pdf, and the Modified Akima cubic Hermite interpolation and the Shape-preserving piecewise cubic spline interpolation with Matlab software https://es.mathworks.com/help/matlab/ref/fillmissing.html

[6] We consider a high correlation when the Pearson coefficient (in absolute value) is above 0.6 (Fox et al., 1993)

[7] As OECD (2008) notes, factor analysis "groups together individual indicators which are collinear to form a composite indicator that captures as much as possible of the information common to individual indicators" (pp.89)

[8] The SET encompasses a considerable number of base indicators within each category that are not conceptually uncorrelated. Therefore, we allow compensations among them, particularly since the statistical weighting method applied at this level addresses potential issues related to double counting.

[9] Given the limited number of variables aggregated at these levels and their conceptual independence, we restrict substantial compensations among them.

$$DC_i(t) = \frac{2}{m(m-1)} \cdot \left(\sum_{j \neq i}^{k(t)} 0.5 \cdot m_j(t) \cdot \left| \frac{x_j(t) - x_i(t)}{\overline{X(t)}} \right| \right) \tag{3}$$

where m shows the number of countries; $k(t)$ is the total number of unique values at year t (each value can correspond to one or several countries); $x_i(t)$ is the SET value or dimension studied for country i; j is another country index that goes through all the $x_j(t)$ values from the SET or dimension studied different from the value of country i; $m_j(t)$ is the number of times that values $x_j(t)$ appear in year t; $\overline{X(t)}$ is the mean value of the SET or dimension of all the countries in year t.

3.2.2. Clustering

To identify the most representative patterns in addressing the demographic challenge across countries over time, we apply a K-means as a non-supervised clustering technique. This technique is particularly useful to group countries with similar features, allowing for a better understanding of similarities between different countries in different years.

The process of training a K-means model begins with the selection of variables to be clustered. Our selection includes the four dimensions -demographic, institutional, macroeconomic, and individual- along with the SET. Therefore, each sample comprises 5 variables and embeds a single country in a given year.

Before clustering, values are yearly normalized using the z-score method to suppress the temporal bias. The z-score is calculated for each variable, country and year using the Eq. (4):

$$z_{x,i}(t) = \frac{x_i(t) - \overline{X(t)}}{\sigma_X(t)} \tag{4}$$

where $x_i(t)$ is the min-max normalized value of the dimension or SET x, in country i at year t. $\overline{X(t)}$ and $\sigma_X(t)$ are the mean and the standard deviation of the variable x, considering all the countries in year t.

The next step is identifying the optimum number of clusters using the Elbow method (Calvo-Bascones et al., 2021; Thorndike, 1953). To this end, we train 40 instances of K-means, each one with a range set from 1 to 20 clusters. Then, we determine the average dispersion associated with each number of clusters as the average (among the 40 instances) of the sum of the square distances of all the samples to their corresponding centroid. The optimum number of clusters -five- results from the point where the average dispersion becomes stable, as shown in Fig. 1.

Upon determining the optimal number of clusters, we executed an additional 40 instances of the K-means algorithm, each configured with five clusters, to identify the most representative centroid locations. The selection criterion was based on achieving the most balanced distribution of samples across the clusters.

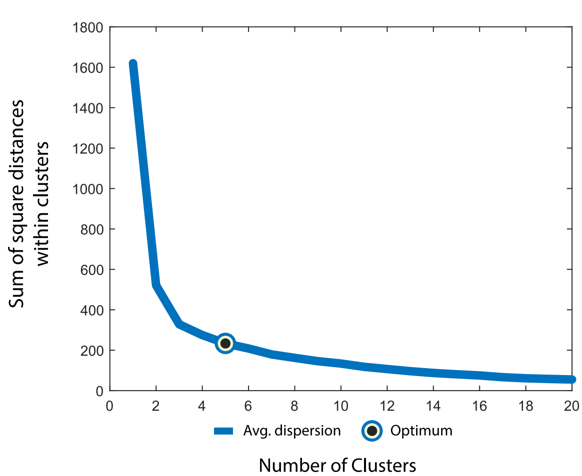

Fig. 1. Elbow method for the identification of the optimum number of K-means clusters.

4. Results

4.1. The SET in Europe

We implement our methodology over 27 European countries[10] for the 2010-2021 period. Fig. 2 maps the geographical distribution of the SET across the 27 European countries analyzed. Fig. 2 (*panel a*) shows the scores of the SET in 2021 whereas Fig. 2 (*panel b* and *c*) presents its performance over 2010-2021 and 2015-2021 respectively. We categorize countries into four quartile groups (Q), each denoted by a varying intensity of color. In this scheme, Q4, represented by the darkest color, includes countries with the highest values, while Q1, indicated by the lightest color, comprises countries with the lowest values. The map in *panel a* evidences a clear geographical pattern in which Nordic countries enjoy a greater level of advancement in 2021, followed by central Europe, while Eastern Europe obtains the worst results. In terms of improvement trends, *panel b* shows some of the countries in weaker quartiles for *panel a* moving into higher quartiles, which denotes leading efforts in adapting to the demographic challenge. This is the case of Bulgaria, Latvia, and Lithuania. Similarly, *panel c* displays the performance over the 2015-2021 period, with countries showing low scores in *panel a* experiencing significant positive performance, such as Romania.

Complementing the maps' visual data, Table 2 furnishes the quantitative figures for the SET, employing the same color coding to signify quartiles as used in the map. Columns labeled 'Score' display the SET scores for countries at three selected years: the beginning, middle, and end of the sample period, namely 2010, 2015, and 2021. The results reveal advancements in the adjustment to the demographic transition across most countries except for Greece, Ireland, Romania, and Slovenia in 2015. The SET descriptive statistics in Table 2 indicate a significant improvement across the three periods considered, shown by the mean score of the indicator. However, the interquartile range has changed very little, suggesting stable country distances within quartiles over the three periods. That is, the SET score advances overall, but the disparities within quartiles remain.

The 'Rank' columns reveal the position of each country within the 27 European nations, based on their scores for the selected years. Analyzing the three prominent positions in the SET score, we observe that Denmark maintains the leading position across the sample in the three selected periods (2010, 2015 and 2021). Norway follows with the second position in the ranking during 2010 and 2015, although it falls two places in 2021, with Sweden improving its score to attain the second position in 2021. Finally, the Netherlands achieves the third best score is 2010 and 2021, descending temporarily one position in 2015. Regarding the least favored countries, we observe stability with Bulgaria and Romania at the tail of the score distribution. Other countries exhibit more pronounced variations in their rankings. From 2010 to 2021, Croatia and Ireland each fell six places, and Slovakia dropped by five. In contrast, Estonia and Hungary climbed six and five positions, respectively. The 'Performance' columns in Table 2 illustrate each country's long-term (2010-2021) and mid-term (2015-2021) performance, computed as the percentage of variation in the score from the initial to the final year of each period. During the mid-term period (2015-2021) seven countries registered a performance exceeding 30 %, with Latvia notably achieving a 67 % improvement. For the long-term span (2010-2021), seven countries also surpassed a 30 % increase in performance, with Estonia and Bulgaria standing out with 91 % and 82 % performance, respectively.

The temporal evolution of the SET values for all the countries is shown in Fig. 3, which presents a gentle positive evolution since 2014.

[10] The selection criteria were the European countries with available data across all the base indicators. This left us with 27 European countries shown in Fig. 2.

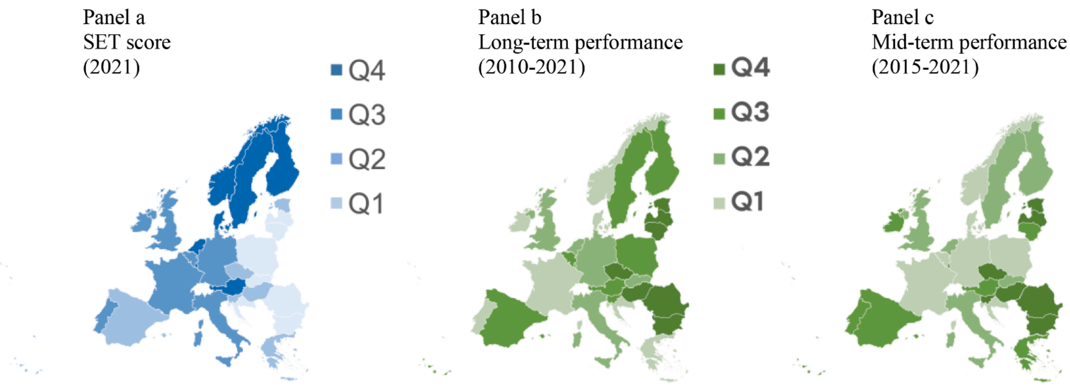

Fig. 2. Geographical distribution of the SET score (2021) (*panel a*), long-term performance (2010-2021) (*panel b*), and mid-term performance (2015-2021) (*panel c*)

Table 2
SET scores and performance for European countries 2010-2021.

	SET 2010		SET 2015		SET 2021			
Country	Score	Rank	Score	Rank	Score	Rank	Performance 2010-2021	Performance 2015-2021
Austria	30.87	10	33.38	8	39.71	7	29%	19%
Belgium	28.03	12	32.09	11	35.68	11	27%	11%
Bulgaria	10.03	27	12.35	26	18.24	26	82%	48%
Croatia	18.71	18	19.96	17	19.97	24	7%	0%
Czech Republic	18.35	19	18.88	18	25.56	17	39%	35%
Denmark	39.22	1	40.92	1	44.76	1	14%	9%
Estonia	13.03	25	18.11	20	24.95	19	91%	38%
Finland	33.13	7	36.49	5	41.36	5	25%	13%
France	31.15	9	32.83	9	36.24	10	16%	10%
Germany	32.54	8	34.86	6	38.03	8	17%	9%
Greece	21.34	17	18.65	19	23.46	20	10%	26%
Hungary	15.55	23	17.07	24	25.17	18	62%	47%
Ireland	33.38	6	30.59	12	35.02	12	5%	15%
Italy	24.79	13	25.84	13	29.46	13	19%	14%
Latvia	13.35	24	13.44	25	22.41	21	68%	67%
Lithuania	16.34	22	17.30	23	22.33	22	37%	29%
Luxembourg	33.60	5	34.82	7	40.71	6	21%	17%
Netherlands	35.70	3	37.52	4	42.42	3	19%	13%
Norway	37.78	2	40.29	2	42.01	4	11%	4%
Poland	16.36	21	18.07	21	20.28	23	24%	12%
Portugal	24.76	14	25.10	14	28.63	14	16%	14%
Romania	11.13	26	9.86	27	14.90	27	34%	51%
Slovakia	16.88	20	17.41	22	19.65	25	16%	13%
Slovenia	22.55	16	21.30	16	27.69	16	23%	30%
Spain	23.31	15	24.98	15	28.54	15	22%	14%
Sweden	35.47	4	38.90	3	44.30	2	25%	14%
United Kingdom	30.13	11	32.15	10	36.54	9	21%	14%
Interquartile Range	16.22		16.01		15.94			
Mean	24.72		26.04		30.67			
Standard deviation	8.92		9.43		9.11			

Despite this upward trend, ranges between leading (maximum values) and lagging (minimum values) countries persist throughout the years. Notably, the impact of COVID-19 (years 2020 and 2021) did not mark an inflection point on the SET results.

4.2. Discriminant analysis and clustering

The analysis using the DC examines country differences in each dimension and in the final SET, revealing which country aspects are most distinctive to explain spatial disparities in adapting to the demographic challenge. Fig. 4 presents each country's contribution to the DC in the four dimensions and in the SET in 2021. To indicate whether a country is above or below the average, we reversed the sign of $DC_i(t)$ for countries below the mean. Therefore, countries with the highest absolute values in Fig. 4 are those that deviate most from the rest in the index/dimension studied. This differentiation primarily arises from the presence of extreme values.

Analyzing Fig. 4, in the demographic dimension we observe a significant concentration of similar countries with values above the mean, with Spain (ESP) and Italy (ITA) as outliers, thus indicating a more intense demographic transition. In contrast, Romania (ROU) and Latvia (LVA) show the largest negative DC, indicating a less advanced demographic transition. However, their deviation from other countries below the mean is less pronounced (they are not outliers). In the

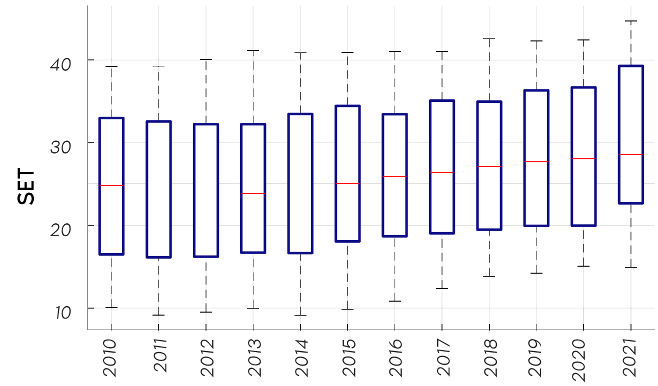

Fig. 3. Temporal evolution of SET values for all the countries.

institutional dimension, we observe a strong and positive discriminating power in Denmark (DNK), indicating further advancements in institutional structures that support the socioeconomic adjustment to aging (indeed, it is the most differentiated country among all the dimensions studied), followed by Sweden (SWE) and the UK (GBR). In contrast, Romania and Bulgaria demonstrate the largest negative discriminating power, denoting the need for institutional change in social and labour protection to accommodate the demographic challenge. Regarding the macroeconomic dimension Luxembourg (LUX) and the Netherlands (NLD) stand out, indicating significant development of the goods and services and labour markets for the senior population, with Romania, Slovakia (SVK) and Bulgaria portraying the opposite direction. In turn, the individual dimension presents strong discriminating power at Nordic countries such as Norway (NOR), Sweden and Finland, suggesting significant efforts in improving healthy aging, financial security and social participation of older cohorts, whereas Romania and Bulgaria maintain their negative discriminating power as in the prior dimensions. Finally, regarding the SET, the most differentiated countries are, in sequence, Romania (below the mean), Denmark, Norway (both above the mean) and Bulgaria (below the mean).

Fig. 5 displays the outcomes of the clustering based on the z-score values of the SET and its dimensions. The results show the countries in our sample grouped into five clusters according to their underlying structures in the readiness and progress in managing the impacts of aging: Emerging strugglers, Raising awareness, Mature in transition, Progressive pioneers, and, Role models.

Cluster 1 ("*Emerging strugglers*") presents weaker results across all dimensions and a considerable low demographic pressure (this is, by far the youngest cluster). Cluster 2 ("*Raising awareness*") exhibits very similar weaknesses than cluster 1, but with less intensity (all centroids have standard deviation smaller one, except for the macroeconomic dimension's centroid). Cluster 3 ("*Mature in transition*") groups countries that show substantial efforts in every dimension, with all the centroids near the mean, except for the corresponding with the demographic dimension. Indeed, the demographic pressure in cluster 3 is the most significant across clusters, which demands strengthening existing advancements. Cluster 4 ("*Progressive pioneers*") evolves above the average in every dimension, surpassing the impact of the pressing demographics. Finally, Cluster 5 ("*Role Models*") includes countries where aging is accentuated (only surpassed in this dimension by countries in cluster 3) and, at the same time, where the rest of dimensions and the SET stand out (with standard deviations above 1 in all of them), achieving the best results across clusters.

Finally, to examine temporal patterns across clusters and the country transitions from one cluster to another over the period analyzed, Fig. 6 shows the number of years that a country has been classified within a specific cluster. We observe that the cluster pertinence is stable with some exceptions (6 countries, 22.22 % of sample) that denote upward or downwards transitions across clusters. Finland can be an example of countries that scale to an upwards cluster, transitioning from cluster 4 to cluster 5 in 2015. In turn, Croatia shifts downwards, moving from cluster 2 to cluster 1 in 2020 and 2021.

5. Discussion and conclusion

The intensification of aging, described as a reversal of the population pyramid (Phillipson, 2015), presents a significant demographic challenge. However, the potential gains in life expectancy could offset the associated costs (Scott, 2021b). Given the notion that "demography is destiny" (Poston & Uhlenberg, 2009; Scammon & Wattenberg, 1970), it is imperative to leverage the opportunities and address the challenges presented by an extended lifespan (Scott, 2021b). To monitor this process, we introduce a reference framework that incorporates the socio-economic factors underpinning the demographic transition.

Our proposed composite indicator, the Socio-Economic Transition

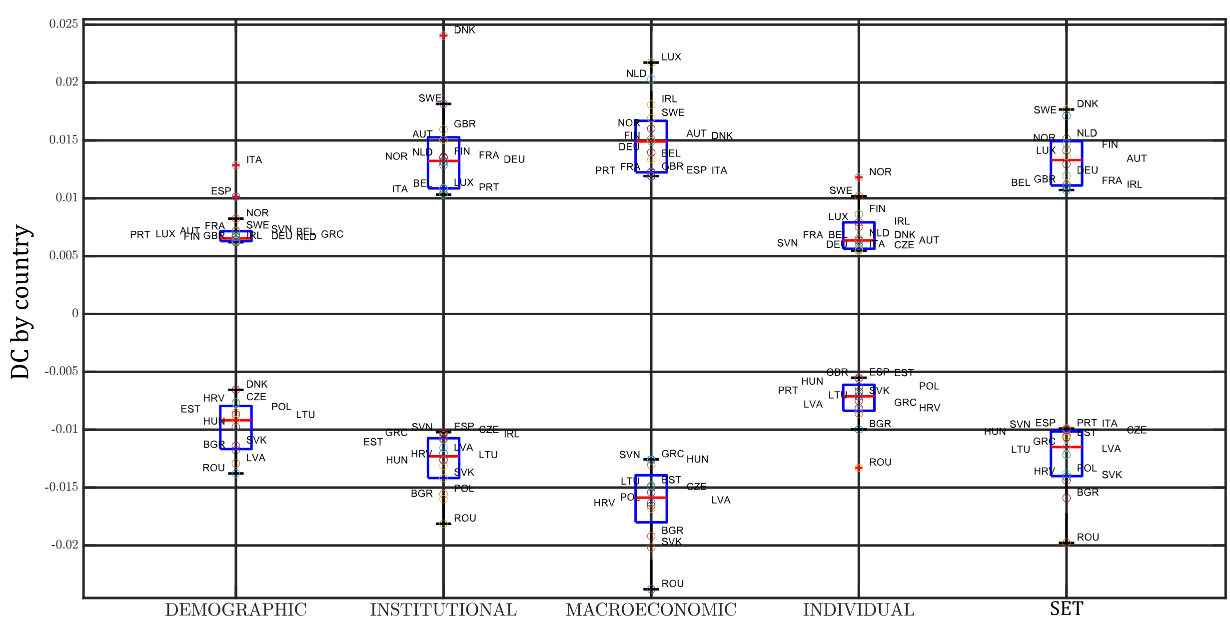

Fig. 4. Country contribution to the SET Discriminant Coefficients and its dimensions in 2021.

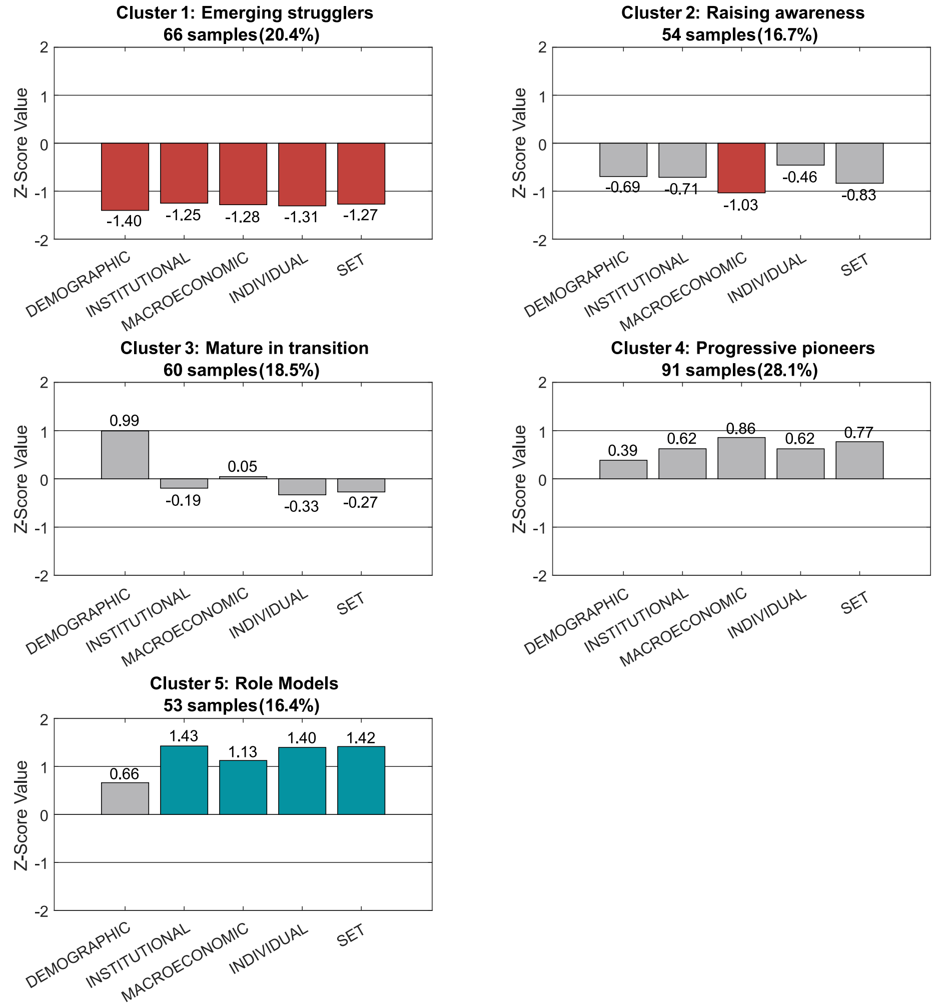

Fig. 5. Centroid values of the five clusters identified.
Note: values smaller than one standard deviation in grey, values exceeding one standard deviation in blue (for positive values) or red (for negative values).

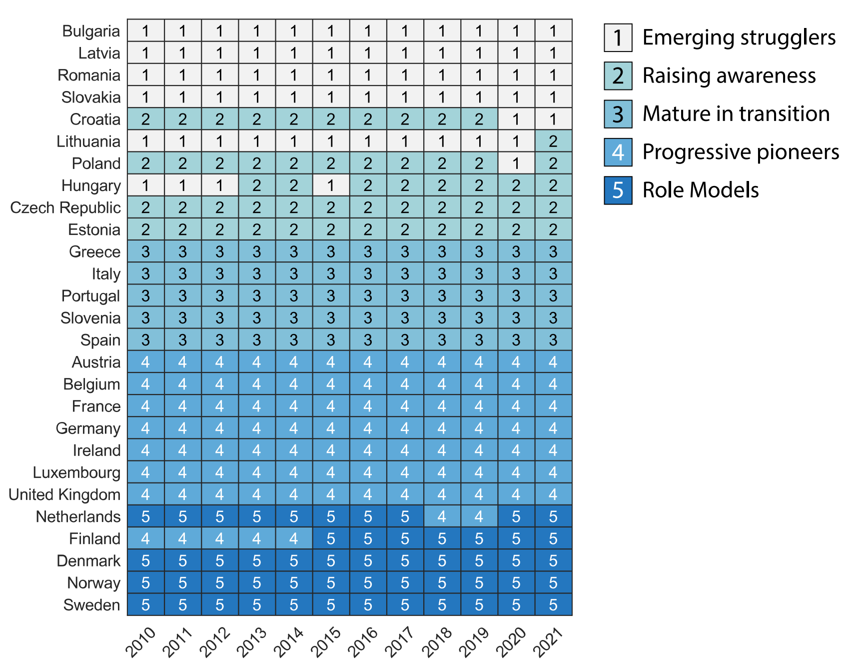

Fig. 6. Dynamic analysis: cross-country comparison of cluster transition (2010-2021).

(SET), assesses national readiness and progress in addressing the socioeconomic challenges and opportunities associated with an aging population. The SET evaluates four dimensions—demographic, institutional, macroeconomic, and individual—across nine categories and 67 base indicators. These dimensions reflect the structural changes economies face due to demographic transitions, highlighting the roles of key actors such as governments, corporations, and individuals in adapting to longer life spans.

We applied the SET to 27 European countries from 2010 to 2021, examining national readiness and progress from both cross-sectional and longitudinal perspectives. Our findings reveal that Nordic countries are the most advanced in addressing demographic challenges, followed by Central, Southern, and Eastern European countries. Using the discriminant coefficient (Ivanovic, 1974), we identified positive disparities in specific dimensions: Spain and Italy excel in the demographic dimension, Denmark in the institutional dimension, Luxembourg and the Netherlands in the macroeconomic dimension, and Norway and Sweden in the individual dimension. Conversely, Romania showed the most negative results across all dimensions and the SET. Through clustering techniques, we categorized countries into five clusters based on their progress, revealing consistent patterns in the socioeconomic management of aging societies over time

These findings lead to several key conclusions. First, the leadership of Nordic countries is driven by significant positive factors in institutional and individual dimensions, serving as role models for positive change. Second, advancements in macroeconomic dimensions for seniors do not translate into overall SET progress without integrated efforts from governments and civil society. Finally, countries further along in the demographic transition need to concentrate on institutional, macroeconomic, and individual dimensions to address the socioeconomic challenges effectively.

Our study contributes to the literature in several ways. We develop the conceptual understanding of the demographic transition and its associated challenges and opportunities, thus extending the fragmented literature on aging from a social sciences perspective (Scott, 2021); We also strengthen the link between a theoretical understanding of this social grand challenge with its empirical operationalization, thereby setting a methodology that evaluates national readiness and progress in adapting to demographic shifts. This extends methodologically the growing discipline of social indicators research, particularly in composite indicators used to gauge complex socioeconomic realities (Biggeri et al., 2019; Lafortune et al., 2018; Sachs et al., 2018).

Measurement in social sciences can influence the system being measured. By tracking progress in addressing the demographic transition, societies can accumulate evidence for comparisons over time or geography, facilitating accountability, transparency, and further progress. Aggregated measures, like the SET, can raise public awareness and embed longevity in economic, political, and social debates (OECD, 2008). Social awareness is crucial since an aging society must address the factors preceding healthy aging, starting from childhood to adulthood. Therefore, progress in the socioeconomic responses to aging becomes improvements in society's living conditions and well-being, beyond those of the elderly.

Enhanced knowledge of readiness and progress in tackling demographic challenges can lead to higher social innovations and large-scale behavioral changes. The SET provides a score valuable to develop innovations from different actors, since a successful transition requires collective action, or 'aging in unity' (Nature Aging, 2021). As seen in prior studies measuring socioeconomic realities (Cossío-Silva et al., 2019) standardized frameworks and methodological approaches to their measurement enable innovations to address the nascent opportunities. The SET can facilitate companies to identify market trends, and to adapt their working environments towards a more diverse labor force, enabling older workers job switch (Aitken & Singh, 2023); the SET may prompt individual action and behavioral shifts to achieve an active and healthy aging; finally, the SET can serve to policymakers to shape institutional changes such as the length of working careers or heightened investments in preventive health expenditures (Scott, 2023). It may also prove beneficial as a benchmark to assess the national progress in preparing for longer life spans, and as a target to define the success.

Despite its contributions, our study has limitations. Adhering to the criteria for indicator selection presented in section 2 (comparability, historical availability, reliability and specificity) led to the exclusion of many valuable indicators, particularly in category C1; Not all European countries were included due to data limitations, reducing international comparability; Our results are specific to European countries, and further research is needed in other regions which could require adapting the base indicators and using other databases; Methodologically, future changes in historical maximum and minimum may impact the normalization process, requiring careful analysis and treatment.

The SET methodology is applicable to sub-national areas, offering a novel approach to structure and understanding the demographic transition. Future studies could use the SET to examine the relationship between a successful demographic transition and other socioeconomic conditions, such as social welfare or competitiveness, and evaluate the potential wealth derived from aging, beyond its challenges.

CRediT authorship contribution statement

David Roch-Dupré: Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization, Data curation, Formal analysis. **Elisa Aracil:** Writing – review & editing, Writing – original draft, Conceptualization, Project administration. **Pablo Calvo-Bascones:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing.

Conflict of interest statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Data availability

The data utilized in this study were sourced from public databases, with specific references to these sources detailed within the paper.

Acknowledgments and funding

We express our gratitude to the **Ageingnomics Research Center in MAPFRE Foundation** for their financial support of this project. Special thanks to Juan Fernández Palacios and Iñaki Ortega Cachón for their invaluable help and engagement in this research.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve language and readability, not to replace key researcher tasks such as interpreting data or drawing scientific conclusions. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Annex A. Correlation within categories

The correlation between base indicators within each category is computed using their log difference to suppress possible spurious correlations. Fig. A1.

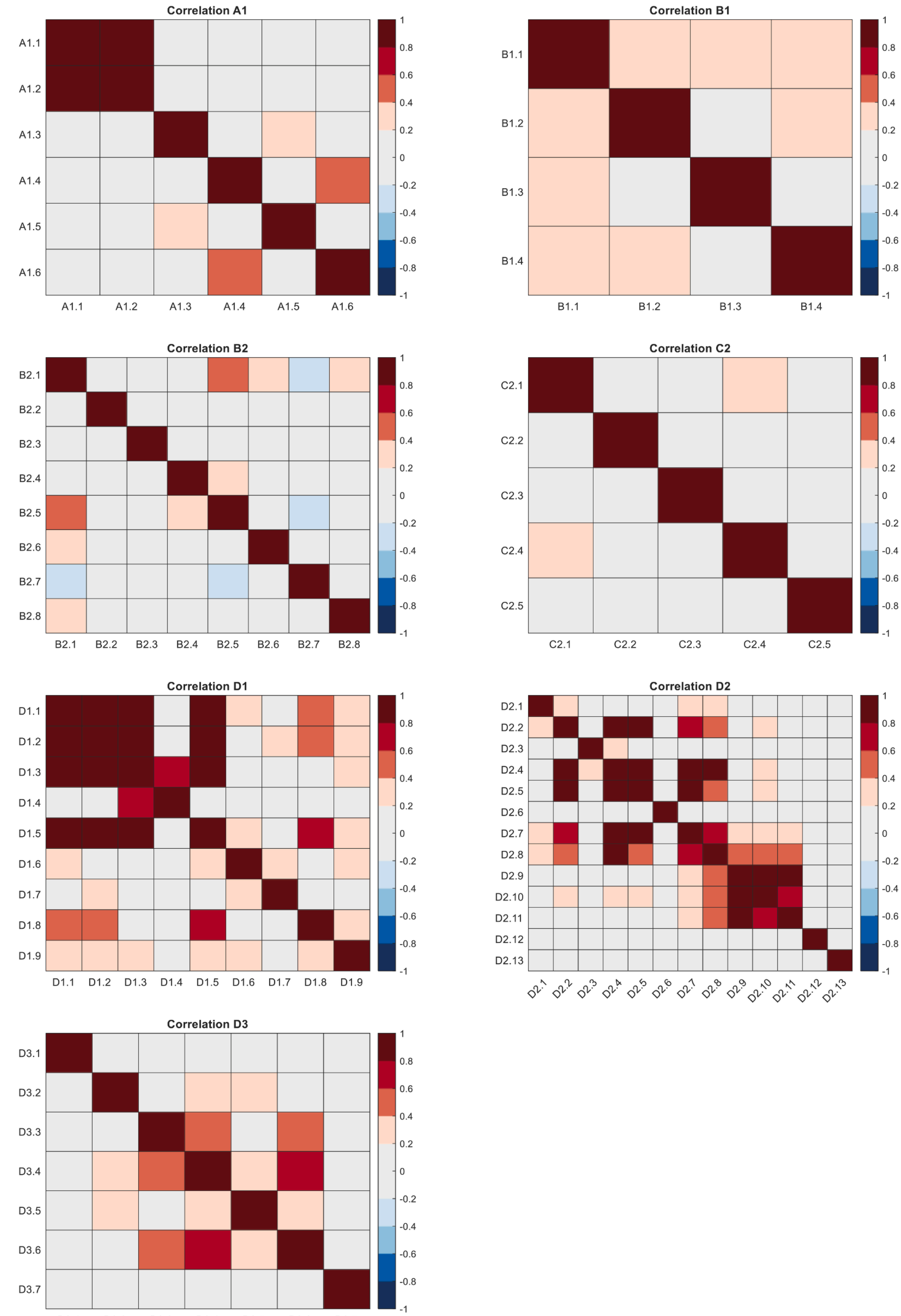

Fig. A1. Pearson correlations within the SET categories

Annex B. Computation method of base indicators and category weights

The methodology for the computation of statistical weights based on Principal Component Analysis (PCA) and Factor Analysis (FA) is as follows. We first present the terminology:

I: Total number of countries
T: Total number of samples (years) per country
J: Number of variables/base indicators that compose the category analyzed
K: Total number of factors
C: Number of total categories included in the study
$x_{j,i,t}$: Observation of the variable j, in country i, in year t
η_k: Factor k
$f_{j,k}$: Factor loading of variable $j$in factor k
λ_k: Eigen value corresponding to factor k
λ_k': Percentage of the variance explained by factor k

To compute the statistical weight of each variable within a category, we follow these steps:

1) Prepare individual input datasets for each category.
   The input dataset presents the following dimensions:
   - Rows$[I \cdot T]$
   - Columns $[J]$
2) Compute the correlation matrix of the input dataset after removing the trend through the first difference of the time series (if needed).
   The size of the correlation matrix is $[J \cdot J]$.
3) Compute the Eigen Vectors and their corresponding Eigen Values from the correlation matrix. The total number of Eigen Vectors η_j, and Eigen Values λ_j, obtained is the same as the number of variables, J.
   Where, $|\eta_j| = 1$, and therefore λ_j is proportional to the value of the total variance explained by each η_j.
   The percentage of the total variance explained by $\eta_j$is computed as shown in Eq. (5):

$$\lambda'_j = \frac{\lambda_j}{\sum_{x=1}^{J} \lambda_x} \cdot 100 \tag{5}$$

4) Select the minimum number of factors required to explain a certain percentage of the total variance, usually 90 %. For this purpose, the cumulative sum of λ'_j (sorted in descending order), allows identifying the minimum number (K) of factors that fulfil the condition shown in Eq. (6):

$$\sum_{j=1}^{K} \lambda'_j \geq 90 \text{ where } K \leq J \tag{6}$$

   The most representative Keigen vectors, are scaled (so that $|\eta_j| = \lambda'_j$) before applying a varimax rotation. Scaling the set of eigen vectors allows obtaining the explained variance from the new rotated eigen vectors, hereinafter, called factors. Varimax rotation allows a better explanation of the relationships between the variables that make up the factors and minimizes the correlation between them. These factors represent "groups" of variables with a high correlation between them.
   The rotated factors are η_k^{rot}, the module of which corresponds to their real explained variance, $|\eta_k^{rot}| = \lambda_k'^{\,rot}$, and the sum of the total variances explained is the same as the one before the rotation $\sum_{j=1}^{K} \lambda_j'^{\,rot} = \sum_{j=1}^{K} \lambda_j$, but the variance explained by each factor might be different before and after the rotation.
5) There are two types of weights: global and local. The local weight corresponds to the largest inner factor loading ($\varphi_j = \max\left(f_{j,1}, f_{j,2}, \ldots, f_{j,K}\right)$ that a variable (j) has across all the rotated factors.
   The highest factor loading determines the "group" to which each variable belongs. The global weight ($\lambda_j'^{\,rot}$) corresponds to the percentage of the variance explained by the factor that each variable belongs to.
6) The final weight assigned to each variable is computed as a combination of local and global weights according to Eq. (7).

$$\rho_j = \frac{\varphi_j \cdot \lambda_j'^{\,\mathrm{rot}}}{\sum_{x=1}^{J} \varphi_x \cdot \lambda_x'^{\,\mathrm{rot}}} \tag{7}$$

where J is the total number of variables, while φ_j and $\lambda_j'^{\,\mathrm{rot}}$ correspond to the local and global weights of variable j, respectively.

Annex C

Table C1
Factor analysis to assign weights to the SET base indicators

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Weight within dimension	Cat. / Dim. Weight
Demographic (A)									
Factor Loadings	33.8%	32.2%	17.0%	17.0%					
A1.1	48.9%	~	~	~				16.8%	
A1.2	49.0%	~	~	~				16.8%	
A1.3	~	49.9%	~	~				16.3%	
A1.4	~	~	99.7%	~				17.2%	
A1.5	~	49.7%	~	~				16.2%	
A1.6	~	~	~	96.5%				16.7%	

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Weight within dimension	Cat. / Dim. Weight
Institutional (B)									33.3%
Health and social protection (B1)									50%
Factor Loadings	41.8%	29.6%	28.6%						
B1.1	49.7%	~	~					21%	
B1.2	50.2%	~	~					21%	
B1.3	~	93.3%	~					28%	
B1.4	~	~	99.6%					29%	
Pensions and labour protection (B2)									50%
Factor Loadings	17.3%	13.5%	14.8%	13.6%	13.5%	13.7%			
B2.1	~	~	~	~	~	96%		14%	
B2.2	~	~	~	~	99%	~		14%	
B2.3	57%	~	~	~	~	~		10%	
B2.4	~	~	~	96%	~	~		14%	
B2.5	~	~	80%	~	~	~		13%	
B2.6	~	97%	~	~	~	~		14%	
B2.7	~	~	~	~	~	~		14%	
B2.8	42%	~	~	~	~	~		8%	

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Weight within dimension	Cat. / Dim. Weight
Macro-economic(C)									33.3%
Goods and services market-seniors (C1)									50%
Factor Loadings	100%								
C1	100%							100.00%	
Labor market - seniors (C2)									50%
Factor Loadings	32.3%	22.5%	22.5%	22.6%					
C2.1	53%	~	~	~				17.38%	
C2.2	~	98%	~	~				22.54%	
C2.3	~	~	100%	~				22.78%	
C2.4	46%	~	~	~				15.02%	
C2.5	~	~	~	97%				22.27%	

(*continued on next page*)

Table C1 (*continued*)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Weight within dimension	Cat. / Dim. Weight
Individual (D)									33.3%
Participation in society (D1)									33.3%
Factor Loadings	45.4%	16.0%	12.7%	13.1%	12.8%				
D1.1	25%	~	~	~	~			12.18%	
D1.2	23%	~	~	~	~			10.94%	
D1.3	24%	~	~	~	~			11.80%	
D1.4	~	~	~	~	80%			10.90%	
D1.5	25%	~	~	~	~			12.03%	
D1.6	~	45%	~	~	~			7.60%	
D1.7	~	55%	~	~	~			9.25%	
D1.8	~	~	~	88%	~			12.16%	
D1.9	~	~	98%	~	~			13.15%	
Financial security (D2)									33.3%
Factor Loadings	31.0%	23.1%	9.0%	10.0%	8.9%	9.0%	9.0%		
D2.1	~	~	~	80%	~	~	~	8.61%	
D2.2	21%	~	~	~	~	~	~	7.06%	
D2.3	~	~	~	~	92%	~	~	8.91%	
D2.4	26%	~	~	~	~	~	~	8.71%	
D2.5	26%	~	~	~	~	~	~	8.89%	
D2.6	~	~	~	~	~	97%	~	9.40%	
D2.7	20%	~	~	~	~	~	~	6.57%	
D2.8	~	~	~	~	~	~	14%	1.41%	
D2.9	~	32%	~	~	~	~	~	8.00%	
D2.10	~	33%	~	~	~	~	~	8.30%	
D2.11	~	34%	~	~	~	~	~	8.50%	
D2.12	~	~	~	~	~	~	79%	7.70%	
D2.13	~	~	81%	~	~	~	~	7.94%	
Healthy and active aging (D3)									33.3%
Factor Loadings	33.5%	16.5%	16.3%	16.4%	17.4%				
D3.1	~	~	~	~	84%			15.93%	
D3.2	~	~	~	98%	~			17.48%	
D3.3	~	44%	~	~	~			7.81%	
D3.4	43%	~	~	~	~			15.70%	
D3.5	~	55%	~	~	~			9.86%	
D3.6	43%	~	~	~	~			15.58%	
D3.7	~	~	100%	~	~			17.66%	

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