scientific reports

OPEN

A functional approach to model intrinsic capacity in ageing trajectories

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The ageing process is a multifaceted phenomenon that affects individuals' physical, cognitive, and psychological well-being over time. To promote healthy ageing, in the mid-2010s, the World Health Organisation introduced the concept of intrinsic capacity (IC) as the set of physical and mental capacities of an individual. These capacities, categorised into five domains, namely cognition, vitality, locomotion, psychological well-being, and sensory, are assessed by healthcare practitioners using the ICOPE guidelines, a laborious and time-consuming task. This study leverages existing data from longitudinal studies, such as the well-known Health and Retirement Study, to align their dimensions with the ICOPE framework and understand how existing ageing trajectories fit within the new IC paradigm. Moreover, a novel IC scoring system has been validated statistically using linear mixed models, and a simple yet comprehensive data visualisation strategy has been designed to illustrate IC trajectories. Results show the significant negative impact of time on all IC domains, except psychological well-being, showing a gradual IC decline over the years. Additionally, significant associations between lifestyle factors, such as physical activity, alcohol and tobacco consumption, and body mass index, with IC trajectories have been identified. This work suggests the feasibility of using existing longitudinal studies to quantitatively model IC ageing trajectories following the ICOPE framework.

Ageing is a natural process characterised by both structural and functional changes that occur throughout everyone's lifespan[1,2]. As society grows and ages faster[3], healthcare institutions will soon need help to provide efficient and sustainable healthcare services to the population[4]. Among the numerous challenges associated with ageing, it is essential to develop precise methods for assessing individuals' ageing processes and predicting who is at risk of suffering age-related health conditions. However, assessing ageing processes is far from simple due to their multifaceted implications in the physiological, cognitive, psychological, metabolic, and social dimensions of the individuals[5,6]. Ageing biomarkers, cognitive tests, functional assessments, and psycho-social evaluations are some of the most popular tools that healthcare practitioners employ to quantify overall health status and well-being[7–9]. Moreover, ageing is a gradual and slow process, making changes noticeable only after many years. Therefore, longitudinal studies are needed to track individuals over extended periods, allowing researchers to discover ageing trajectories and identify the most relevant factors to such ageing processes[10]. Understanding all these aspects will help implement adequate evidence-based intervention strategies and promote healthy and active ageing programs effectively.

The concept of healthy ageing involves a holistic approach emphasising not only longevity but also well-being and quality of life in older age. In this context, the World Health Organisation (WHO) recently proposed an innovative model to reshape clinical practices in elderly healthcare, shifting from disease-centred approaches to function-centred approaches[11]. Within this model, two key concepts are introduced: functional ability (FA) and intrinsic capacity (IC). While FA refers to the individuals' abilities (e.g., physical, cognitive, social,...) to perform their everyday tasks effectively and independently, IC refers to the underlying factors influencing such FA, categorised into five domains: cognition, vitality, locomotion, psychological well-being, and sensory[12,13]. To properly operationalise IC, the WHO also released the Integrated Care for Older Adults (ICOPE) framework[14], which provides guidelines for comprehensively assessing IC through standardised tests. These tests help detect cognitive decline, mobility limitations, malnutrition, visual impairment, hearing loss, and depressive symptoms—factors that negatively impact IC. Unfortunately, these tests do not prescribe quantitative assessment tools, and they are conducted intermittently by healthcare practitioners, limiting the continuity of care and

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ongoing assessment of IC. Evaluating the relationship between IC and ageing-related factors is a hot topic in current ageing research.

The current lack of quantitative prediction models limits the comprehensive assessment of IC. Previous studies have provided valuable insights into the definition, structure, and role of IC in older adults, but there is no general consensus on how to assess the different IC domains or how to determine an overall IC score[15–17]. Some studies have focused on validating IC within specific populations, such as those in China[18] and Brazil[19], using different measurement methods and, in some cases, aligning their data with the ICOPE recommendations. Even more challenging, it is uncertain which IC domains are affected first by ageing and to what extent they affect the overall ageing process. Although the IC/ICOPE paradigm is relatively new, ageing has been studied for decades through longitudinal studies. These studies contain rich, valuable data on ageing trajectories that could be aligned with this novel paradigm. To the best of our knowledge, this is the first article to leverage longitudinal study data to estimate IC following the ICOPE guidelines. Specifically, the goals of this article are threefold: (1) identify and map those variables from longitudinal studies related to the ICOPE framework, (2) develop a model able to quantify IC using a novel multidimensional scoring system and visualisation strategy, and (3) examine the role of lifestyle factors in the evolution of IC.

The rest of the article is organised as follows: section Methods describes the methodology employed to develop the proposed model, section Results outlines the main study's findings and validates the proposed model statistically, section Discussion provides a fruitful discussion on the implications of the results, and section Conclusions closes the article with some concluding remarks and future research endeavours.

Methods

Data

Data are obtained from the Health and Retirement Study (HRS), an ongoing well-known open-source longitudinal study of a nationally representative sample of men and women over age 50 in the United States[20]. HRS conducts surveys every two years, either by telephone or in-person, while supplemental surveys are conducted in off years via email or the Internet. Since 2004, face-to-face interviews have been the primary method, accounting for approximately 60–70% of all interviews[21]. More meaningfully, since 2006, HRS began collecting extensive physical measurements and biomarkers as part of the extended personal interview. This interview is conducted face-to-face with half of the sample in one wave and the other half in the next wave, ensuring that each respondent is interviewed, at least, every other wave (i.e., every 4 years)[22]. Notwithstanding, no physical measurements were collected in 2020 due to the COVID-19 pandemic.

To ensure a solid analysis, we need at least three consistent waves of data for each participant group: Group 1 in 2008, 2012, and 2016, and Group 2 in 2010, 2014, and 2018. Therefore, to ensure the availability of all survey variables and physical measurements, we have extracted all individuals' data who had records in the HRS Core from 2008 to 2018. As a result, our study comprises a total of 8,023 individuals with continuous observation over a ten-year period.

Measurements

Intrinsic capacity

Following the ICOPE guidelines, we carefully reviewed all variables collected by HRS (e.g., self-reported measures, physical measurements, cognitive assessments,...) that could be used to quantitatively estimate all five IC domains. For the sake of transparency, we refer the reader to the Supplementary Material section to check the set of variables included in each domain. The variables considered to evaluate these domains are listed below:

- **Cognition domain:** HRS contains numerous tests to assess people's cognitive state. Among the many tests suggested by ICOPE, HRS data can be mapped to operationalise the Mini-Mental State Examination (MMSE)[23]. This test measures memory using 10-word recall tests and orientation using basic tests, such as knowing today's date or the name of the current president. The total score of all items provides a measure of cognitive performance ranging from 0 to 12 points, where lower values indicate higher cognitive impairment.
- **Vitality domain:** Energy balance and metabolism are key contributors to people's vitality[24,25]. ICOPE highlights malnutrition as one of the main causes of reduced vitality. Related information is stored in HRS that could operationalise the Mini Nutritional Assessment (MNA), a 6-item scale that considers anthropometric assessment (weight, height, and weight loss), food intake, neuropsychological status, and mobility[26]. Particularly, mobility is assessed based on functioning items or the Nagi scale[27] for activities such as walking, sitting for two hours, getting up from a chair, climbing stairs, and extending the arms above the head. The scale for this domain uses a range of 0 to 12 points, where lower values indicate higher risk of malnutrition.
- **Locomotion domain:** Locomotion capacity was partially measured by the Short Physical Performance Battery (SPPB)[28], as suggested by ICOPE, which includes a hierarchical test of standing balance and a 4-meter walk test. Hence, a 12-point scale can be derived, with lower values indicating higher mobility disabilities.
- **Psychological well-being domain:** HRS stores related symptoms to those considered in the Patient Health Questionnaire (PHQ-9)[29], an ICOPE suggested tool. Particularly, it considers the lack of interest or pleasure in daily activities, sleep problems, fatigue or lack of energy, altered appetite, low self-esteem or feelings of failure, concentration problems, agitation, and suicidal or self-harm thoughts, among others. The impairment of each item is scored as 0 points. By considering 12 dimensions, the score in this domain ranges from 0 to 12 points, where lower scores indicate lower psychological well-being.
- **Sensory domain:** ICOPE recommends assessing hearing and visual impairments with audiometries and Snellen charts, respectively. Unfortunately, this information is not reported in HRS, which only contains self-reported data on a 6-point Likert scale (ranging from excellent to poor) for each. Therefore, the score of

the sensory domain ranges from 0 to 12 points, with lower values indicating total or severe loss in sensory abilities.

All things considered, each IC domain is scored from 0 to 12 points, with lower values negatively impacting IC. Conversely, a higher IC value in each domain indicates greater IC for the individual.

Lifestyle factors

Lifestyle factors play a central role in the ageing process. Well-accepted risks factors affecting health in middle-aged and older adults include smoking, poor diet, obesity, insufficient physical activity, and excessive alcohol consumption[30]. In this research, we have quantified these factors numerically from standardised questions and measures provided by the HRS:

- **Smoking:** Smoking status is assessed based on the number of cigarettes smoked daily. Non-smoking individuals are assigned a score of 0.
- **Alcohol consumption:** Drinking behaviour is assessed based on the quantity of alcohol consumed and the frequency of consumption. Alcohol consumption is scored by multiplying the frequency of drinking (measured as the number of drinking days per week) by the quantity consumed per day (measured as the number of drinks). Individuals who do not drink alcohol receive a score of 0.
- **Physical activity:** Physical activity is evaluated based on its intensity and frequency. On the one hand, intensity is reported as vigorous, moderate, and light activity and, on the other hand, frequency options include every day, more than once a week, once a week, one to three times a month, and never. Using a cut-off of twice a week or less, a composite variable is created to quantify physical activity levels. Scores are assigned as follows: 4 for vigorous activity, 3 for moderate activity, 2 for light activity, and 1 for sedentary behaviour or no activity.
- **Weight control:** Obesity, as an indicator of weight control, is assessed using the well-known body mass index (BMI). While alternative measures, such as waist circumference, are available in HRS, they are inconsistently recorded across longitudinal waves, making them unsuitable for this study. Hence, BMI was selected for its standardisation and consistent collection.

Socio-demographic and contextual variables

For comprehensive analysis, socio-demographic and contextual variables are also incorporated in this study to provide a well-rounded understanding of ageing processes[31]. This includes basic information such as age and gender (male and female), as well as whether individuals reside in a nursing home (or other healthcare facility) where they receive 24-hour nursing care, professional supervision, and medication management, among other services.

A novel scoring system model to estimate intrinsic capacity

We propose a novel scoring system to quantitatively estimate individuals' IC. In our scoring system, each of the five dimensions is equally weighted, resulting in a 12-point scale each. Thus, our model represents IC as a comprehensive set of five scores rather than a single composite score[32]. The higher the score, the more IC the individual has. This approach enables multidimensional assessment by identifying potential interrelationships among IC dimensions, facilitates the evaluation of temporal changes in IC for each dimension, and minimises information loss. Figure 1 depicts the proposed scoring system.

Results

Statistical validation of the scoring system

Linear mixed models are a well-known method for analysing data that are non-independent, longitudinal, and hierarchical[33]. This method helps understanding variability trends and assessing the influence of time on the five IC domains using the proposed scoring system. Additionally, these models examine the relationships between these domains and various lifestyle, socio-demographic, and contextual factors. An initial exploratory analysis revealed a maximum proportion of missing values of 3.04% and helped detect outliers. Time series analyses are also conducted to explore the longitudinal evolution of the dependent variables. This analysis confirmed that IC domains experienced a progressive decline, following both linear and quadratic trends. Such observations were crucial for determining the inclusion of time-related variables in the linear mixed models. Consequently, both linear and quadratic components of time were included, as the decline in IC domains was less pronounced in the early years of the study, indicating a non-constant rate of change over time. To avoid multicollinearity, an orthogonal transformation of these terms is performed.

The analysis using linear mixed models is conducted in several steps. First, the model is tested without predictors for each variable of interest. Next, the significance of the linear and quadratic terms of time is assessed as fixed effects, followed by an examination of these components as random effects. Model fit is then compared using difference variance-covariance structures for both the repeated observations and the residuals. This comparison uses indices such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Based on the exploratory phase results, an unstructured random effects matrix is employed, while a first-order autoregressive structure is applied for repeated measures. The maximum likelihood method is used for estimation, while residual plots are used to verify assumptions. While slight to moderate inconsistencies have been found, they do not pose significant issues, especially given the considerable sample size of the study. The significance of the results was determined to be at a level of less than 0.05. Table 1 presents the results of the linear mixed models, illustrating the influence of the variables and factors of study in the five IC domains. For

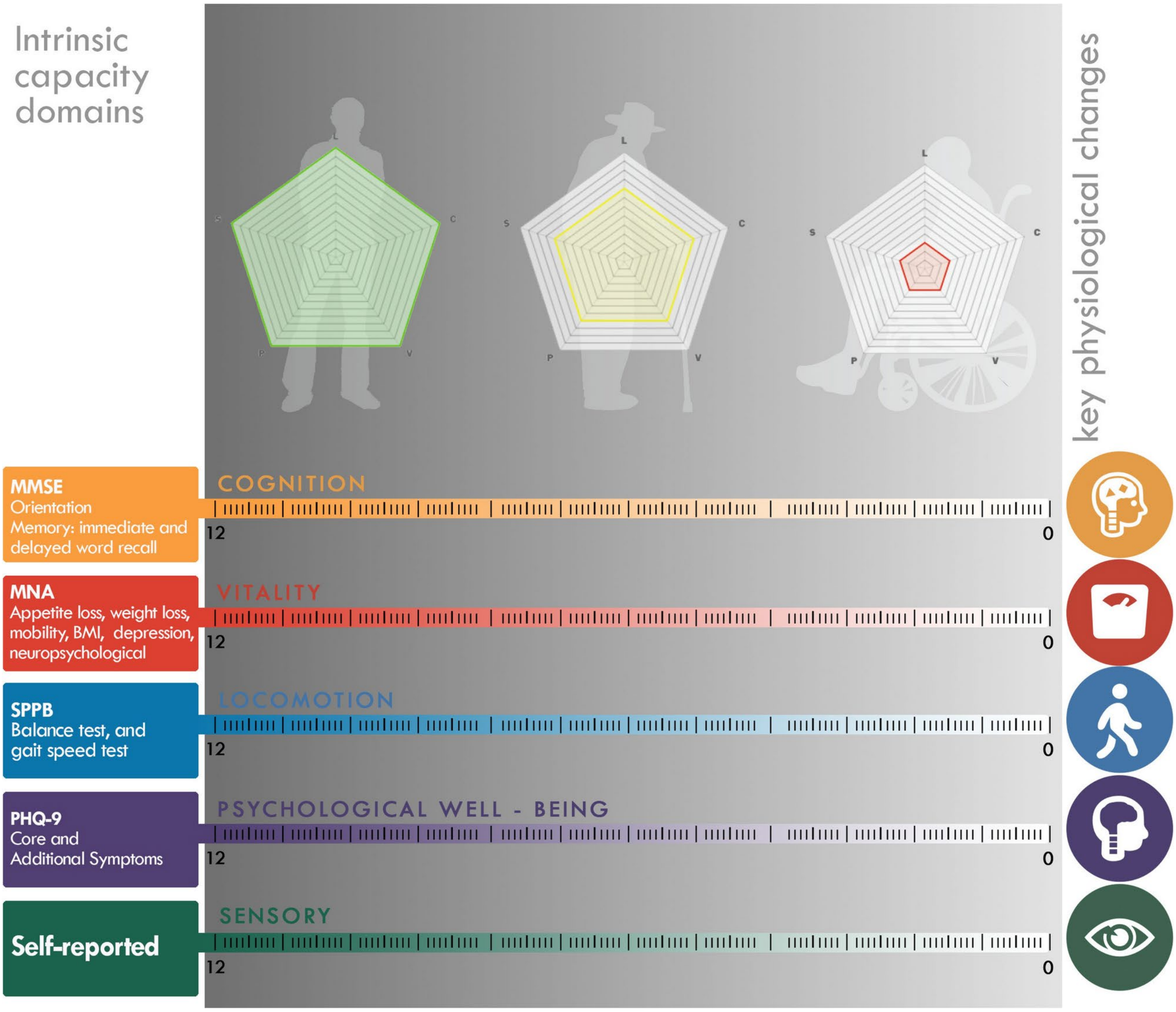

Fig. 1. General overview of the scoring system model to estimate IC. *SPPB* Short Physical Performance Battery, *MMSE* Mini-Mental State Examination, *MNA* Mini Nutritional Assessment, *PHQ-9* Patient Health Questionnaire-9.

the sake of reproducibility, the code used to process and analyse the data using SPSS version 27 is provided in a GitHub repository[34].

The influence of time is found to be statistically significant in all IC domains, except for psychological well-being. Notably, the linear component indicates a decline in the rest of the domains as follows: sensory abilities decrease by an average of 0.05 points (Est. = −0.05, SE = 0.00, t = 24.04, $p \leq 0.001$, LCI 95% = −0.06, UCI 95% = −0.05), vitality by an average of 0.07 points (Est. = −0.07, SE = 0.00, t = 22.82, $p \leq 0.001$, LCI 95% = −0.07 , UCI 95% = −0.06), and cognitive functions (Est. = −0.10, SE = 0.00, t = 40.13, $p \leq 0.001$, LCI 95% = −0.11, UCI 95% = −0.10), and locomotion (Est. = −0.10, SE = 0.01, t = 16.07, $p \leq 0.001$, LCI 95% = −0.12, UCI 95% = −0.09) by an average of 0.10 points each, assuming that the other factors remain constant. It is noteworthy that this coefficient is included orthogonally, indicating an average over the years rather than a rate of change from one period to another. Considering the accounted random effect of time, it is assumed that individuals experience different trajectories regarding their IC domains. Furthermore, it is observed that the quadratic coefficient of time is also negative and significant, indicating a slight decrease in the rate of change over the years.

Regarding gender, men statistically exhibit higher vitality scores (Est. = 0.40, SE = 0.03, t = 12.10, $p \leq 0.001$, LCI 95% = 0.34, UCI 95% = 0.47), psychological well-being scores (Est. = 0.44, SE = 0.03, t = 12.78, $p \leq 0.001$, LCI 95% = 0.37, UCI 95% = 0.51), and locomotion scores (Est. = 0.20, SE = 0.05, t = 3.73, $p \leq 0.001$, LCI 95% = 0.10, UCI 95% = 0.31) compared to women. Conversely, women tend to have higher scores in sensory abilities (Est. = −0.30, SE = 0.03, t = 9.03, $p \leq 0.001$, LCI 95% = −0.37, UCI 95% = −0.24) and cognitive function (Est. = −0.37, SE = 0.03, t = 12.60, $p \leq 0.001$, LCI 95% = −0.43, UCI 95% = −0.32) compared to men.

Coefficient	M (SE)	t (p)	CI 95%	Main categ.	Ref. categ.
Sensory domain					
Intercept	8.57 (0.02)	414.97 (<0.001)	[8.53, 8.61]	n. a.	n. a.
Linear time (orthogonal)	-0.05 (0.00)	-24.04(<0.001)	[-0.06, -0.05]	n. a.	n. a.
Gender (reference = women)	-0.30 (0.03)	-9.03(<0.001)	[-0.37, -0.24]	8.20a (0.05)	8.50b (0.05)
Location (reference = do not live with nursing care)	**-0.13 (0.10)**	**-1.38 (0.168)**	**[-0.32, 0.06]**	**8.28a (0.10)**	**8.42a (0.02)**
Body mass index (standardised)	-0.04 (0.01)	-3.22 (0.001)	[-0.06, -0.01]	n. a.	n. a.
Physical activity level (standardised)	0.11 (0.01)	15.05 (<0.001)	[0.09, 0.12]	n. a.	n. a.
Number of drinks per day (standardised)	0.03 (0.01)	3.25 (0.001)	[0.01, 0.05]	n. a.	n. a.
Number of cigarettes per day (standardised)	**-0.01 (0.01)**	**-1.86 (0.063)**	**[-0.02, 0.00]**	**n. a.**	**n. a.**
Vitality domain					
Intercept	9.85 (0.02)	480.68 (<0.001)	[9.81, 9.89]	n. a.	n. a.
Linear time (orthogonal)	-0.07 (0.00)	-22.82(<0.001)	[-0.07, -0.06]	n. a.	n. a.
Quadratic time (orthogonal)	-0.02 (0.00)	-13.98(<0.001)	[-0.03, -0.02]	n. a.	n. a.
Gender (reference = women)	0.40 (0.03)	12.10 (<0.001)	[0.34, 0.47]	9.65a (0.06)	9.25b (0.06)
Location (reference = do not live with nursing care)	-1.21 (0.11)	-10.73(<0.001)	[-1.43, -0.99]	8.84a (0.11)	10.06b (0.02)
Body mass index (standardised)	0.75 (0.01)	59.73 (<0.001)	[0.72, 0.77]	n. a.	n. a.
Physical activity level (standardised)	0.23 (0.01)	27.09 (<0.001)	[0.21, 0.24]	n. a.	n. a.
Number of drinks per day (standardised)	0.10 (0.01)	9.90 (<0.001)	[0.08, 0.12]	n. a.	n. a.
Number of cigarettes per day (standardised)	**0.00 (0.01)**	**-0.48(0.633)**	**[-0.02, 0.01]**	**n. a.**	**n. a.**
Psychological well-being domain					
Intercept	10.75 (0.02)	510.51 (<0.001)	[10.71, 10.79]	n. a.	n. a.
Linear time (orthogonal)	**0.00 (0.00)**	**1.48 (0.139)**	**[0.00, 0.01]**	**n. a.**	**n. a.**
Quadratic time (orthogonal)	-0.01 (0.02)	-2.24(0.025)	[-0.01, -0.00]	n. a.	n. a.
Gender (reference = women)	0.44 (0.03)	12.78 (<0.001)	[0.37, 0.51]	11.32a (0.09)	10.88b (0.09)
Location (reference = do not live with nursing care)	**0.24 (0.17)**	**1.46 (0.145)**	**[-0.08, 0.57]**	**11.22a (0.17)**	**10.98a (0.02)**
Body mass index (standardised)	-0.08 (0.01)	-5.54(<0.001)	[-0.10, -0.05]	n. a.	n. a.
Physical activity level (standardised)	0.15 (0.01)	15.13 (<0.001)	[0.13, 0.17]	n. a.	n. a.
Number of drinks per day (standardised)	**0.01 (0.01)**	**1.21 (0.228)**	[-0.01, 0.04]	**n. a.**	**n. a.**
Number of cigarettes per day (standardised)	**0.00 (0.01)**	**-0.46 (0.645)**	**[-0.02, 0.01]**	**n. a.**	**n. a.**
Cognition domain					
Intercept	8.94 (0.02)	489.52 (<0.001)	[8.90, 8.98]	n. a.	n. a.
Linear time (orthogonal)	-0.10 (0.00)	-40.13(<0.001)	[-0.11, -0.10]	n. a.	n. a.
Quadratic time (orthogonal)	-0.02 (0.00)	-9.89(<0.001)	[-0.02, -0.01]	n. a.	n. a.
Gender (reference = women)	-0.37 (0.03)	-12.60(<0.001)	[-0.43, -0.32]	8.19a (0.06)	8.56b (0.06)
Location (reference = do not live with nursing care)	-0.76 (0.12)	-6.47(<0.001)	[-0.99, -0.53]	7.99a (0.12)	8.76b (0.02)
Body mass index (standardised)	0.05 (0.01)	4.49 (<0.001)	[0.03, 0.07]	n. a.	n. a.
Physical activity level (standardised)	0.13 (0.01)	16.33 (<0.001)	[0.11, 0.14]	n. a.	n. a.
Number of drinks per day (standardised)	0.06 (0.01)	6.55 (<0.001)	[0.04, 0.08]	n. a.	n. a.
Number of cigarettes per day (standardised)	**0.00 (0.01)**	**-0.37 (0.715)**	**[-0.01, 0.01]**	**n. a.**	**n. a.**
Locomotion domain					
Intercept	5.72 (0.04)	161.74 (<0.001)	[5.65, 5.79]	n. a.	n. a.
Linear time (orthogonal)	-0.10 (0.01)	-16.07(<0.001)	[-0.12, -0.09]	n. a.	n. a.
Gender (reference = women)	0.20 (0.05)	3.73 (<0.001)	[0.10, 0.31]	3.67a (0.07)	3.48b (0.07)
Location (reference = do not live with nursing care)	-4.27 (0.12)	-34.27(<0.001)	[-4.51, -4.02]	1.39a (0.13)	5.76b (0.03)
Body mass index (standardised)	0.35 (0.03)	13.67 (<0.001)	[0.30, 0.40]	n. a.	n. a.
Physical activity level (standardised)	0.81 (0.02)	41.30 (<0.001)	[0.78, 0.85]	n. a.	n. a.
Number of drinks per day (standardised)	0.30 (0.03)	11.72 (<0.001)	[0.25, 0.35]	n. a.	n. a.
Number of cigarettes per day (standardised)	0.08 (0.02)	3.87 (<0.001)	[0.04, 0.12]	n. a.	n. a.

Table 1. Assessment of IC domains. M: mean, SE: standard error, t: test statistic, p: p-value or significance level, CI 95%: 95% two-sided confidence interval, Main categ.: Main category (men in the case of gender and people living with nursing care in the case of place of residence). Ref. Categ.: Reference category (women in the case of sex and people living without nursing care in the case of location of residence), n. a.: not applicable. Note 1: Variables without significant statistical relationship at the 0.05 level are shaded in bold. Note 2: Averages in the "Main categ." and "Ref. categ." columns with differing subscripts indicate statistical differences at the 0.05 level. Note 3: Quadratic time was omitted from the sensory and locomotion domains due to their linear and constant decrease rate.

The residential location also plays a major role in the evolution of IC. Results indicate that people residing in non-healthcare facilities exhibit higher scores in vitality (Est. = −1.21, SE = 0.11, t = 10.73, $p \leq 0.001$, LCI 95% = −1.43, UCI 95% = −0.99), cognitive function (Est. = −0.76, SE = 0.12, t = 6.47, $p \leq 0.001$, LCI 95% = −0.99, UCI 95% = −0.53), and locomotion (Est. = −4.27, SE = 0.12, t = 34.27, $p \leq 0.001$, LCI 95% = −4.51, UCI 95% = −4.02). However, no significant differences are observed in the sensory and psychological well-being domains.

Regarding BMI factor, the analysis reveals that a one-unit increase in BMI leads to an average increase of 0.75 points in vitality, 0.05 points in cognition function, and 0.35 points in locomotion over time. Conversely, sensory abilities and psychological well-being decrease by 0.04 and 0.08 points, respectively, over time, assuming the other terms of the model remain constant. Interestingly enough, the level of physical activity is significantly associated with all IC domains. Specifically, a one-unit increase in physical activity yields an average increase of 0.11 points in sensory abilities (Est. = 0.11, SE = 0.01, t = 15.05, $p \leq 0.001$, LCI 95% = 0.09, UCI 95% = 0.12), 0.23 points in vitality (Est. = 0.23, SE = 0.01, t = 27.09, $p \leq 0.001$, LCI 95% = 0.21, UCI 95% = 0.24), 0.15 points in psychological well-being (Est. = 0.15, SE = 0.01, t = 15.13, $p \leq 0.001$, LCI 95% = 0.13, UCI 95% = 0.17), 0.13 points in cognitive function (Est. = 0.13, SE = 0.01, t = 16.33, $p \leq 0.001$, LCI 95% = 0.11, UCI 95% = 0.14), and 0.81 points in locomotion (Est. = 0.81, SE = 0.02, t = 41.30, $p \leq 0.001$, LCI 95% = 0.78, UCI 95% = 0.85).

Surprisingly, alcohol consumption shows a positive and significant association with vitality, sensory abilities, cognitive function, and locomotion scores. Specifically, a unit increase in the amount of alcoholic beverages consumed results in an increase of 0.10 points in vitality (Est. = 0.10, SE = 0.01, t = 9.90, $p \leq 0.001$, LCI 95% = 0.08, UCI 95% = 0.12), 0.03 points in sensory abilities (Est. = 0.03, SE = 0.01, t = 3.25, p = 0.001, LCI 95% = 0.01, UCI 95% = 0.05), 0.06 points in cognitive function (Est. = 0.06, SE = 0.01, t = 6.55, $p \leq 0.001$, LCI 95% = 0.04, UCI 95% = 0.08), and 0.30 points in locomotion (Est. = 0.30, SE = 0.03, t = 11.72, $p \leq 0.001$, LCI 95% = 0.25, UCI 95% = 0.35). Conversely, cigarette consumption is statistically significant solely for the locomotion domain. Precisely, an increase in this indicator by one unit results in an average increase of 0.08 points in locomotion over time (Est. = 0.08, SE = 0.02, t = 3.87, $p \leq 0.001$, LCI 95% = 0.04, UCI 95% = 0.12), while holding the other terms of the model constant.

Visualisation of intrinsic capacity trajectories

The effectiveness of the proposed scoring system is enhanced when its results can be strategically communicated. For this purpose, its graphical representation using a radar chart is crucial. This type of visualisation provides a comprehensive, simultaneous overview of multiple IC dimensions, facilitates clear comparisons between them, and tracks their evolution over time. Additionally, it aids in identifying individual strengths and weaknesses through chart superposition. Thus, radar charts promote self-awareness and informed decision-making, enabling the development of personalised interventions to improve an individual's health and well-being. Furthermore, they are useful for comparing IC between different individuals or groups, allowing for the identification of patterns.

For the sake of completeness, Fig. 2 depicts the temporal IC evolution of six individuals. Each axis of the radar chart corresponds to an IC domain. The distance from the centre of the chart to a point on a particular axis represents the score in that IC domain. In addition, overlaying yearly graphs with different colours indicates the changes in the IC domains over time, thereby altering their area. Each chart provides a unique fingerprint of an individual's IC across different domains over time. For instance, a 73 year old man with moderate physical activity who has overweight and smokes will exhibit a different IC profile compared to a 100 year old woman with light physical activity who is a non-smoker and has a normal BMI. This approach offers a dynamic and colourful visual representation of how an individual's IC changes and develops over time.

Discussion

The results of this study highlight the multidimensional nature of IC and emphasise the necessity for developing models that facilitate its assessment and monitoring. While ICOPE provides a framework for evaluating IC domains and guiding specific interventions, quantifying IC remains complex[35]. Although ICOPE is not specifically designed as an IC assessment measure, it might be suitable for identifying possible impairments in specific domains and examining their relationship with lifestyle, socio-demographic, and contextual factors. The proposed scoring system aims to pave the way towards a multidimensional, standardised tool that might be practical, especially in resource-limited settings. Likewise, our strategy of using radar charts for graphical representation enhances the interpretability of complex data and helps identify early signs of deterioration, which is crucial for timely interventions. By viewing these charts as unique fingerprints of individuals' IC, healthcare practitioners can monitor changes over time and investigate underlying factors using artificial intelligence techniques.

The statistical analysis conducted as a validation strategy for the scoring system, using linear mixed models, demonstrates the influence of time and lifestyle factors on each IC domain. Time exhibits a significant negative impact across all domains except psychological well-being, indicating a gradual decline in IC over the years. This decline follows both linear and quadratic trends, suggesting a diminishing rate of change over time. These findings align with previous research and emphasise the need for proactive interventions to maintain or improve IC in older adults[17]. Gender differences are also observed, consistent with other studies: men tend to have greater vitality and psychological well-being, while women typically have better sensory abilities and cognitive functioning[19]. However, our study extends these findings by revealing that men also possess a greater locomotion capacity. Additionally, residential location is another significant factor: individuals not residing in nursing homes generally exhibit higher scores in vitality, cognitive function, and locomotion.

Lifestyle factors significantly influence IC trajectories, with physical activity, BMI, alcohol consumption, and smoking showing notable associations with different IC domains. These findings are consistent with prior research[9,36], which also observed associations between these lifestyle factors and IC. Higher BMI is associated

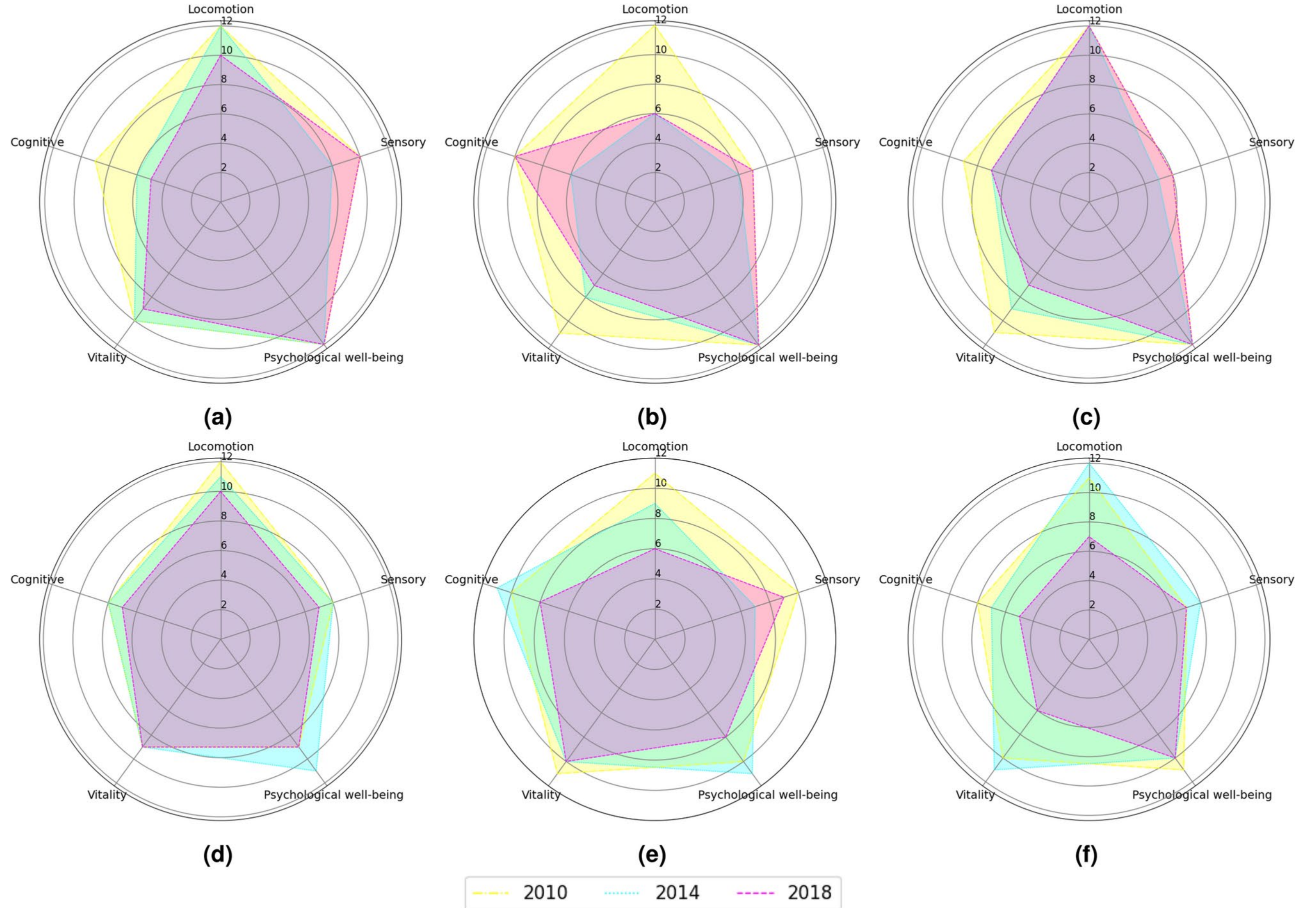

Fig. 2. Evolution of the IC domains in six individuals. (**a**) 73 year old man, moderate physical activity, smoker, low consumption of alcoholic beverages, overweight. (**b**) 82 year old man, sedentary physical activity, non-smoker, no consumption of alcoholic beverages, overweight. (**c**) 100 year old man, moderate physical activity, non-smoker, moderate consumption of alcoholic beverages, normal BMI. (**d**) 71 year old woman, sedentary physical activity, non-smoker, low consumption of alcoholic beverages, obese. (**e**) 81 year old woman, mild physical activity, non-smoker, no consumption of alcoholic beverages, overweight. (**f**) 100 year old woman, mild physical activity, non-smoker, no consumption of alcoholic beverages, normal BMI.

with increased vitality and locomotion but decreased sensory ability and psychological well-being over time. Increased physical activity correlates positively with all IC domains, with moderate or vigorous activity serving as a stimulus for higher IC, as suggested in previous studies[18,36]. Moreover, alcohol consumption shows slight positive associations with vitality, sensory abilities, cognition, and locomotion. Although controversial, similar patterns have already been reported in the literature[37–41]. However, these findings should be interpreted cautiously due to the contradictory evidence regarding the beneficial effects of alcohol consumption. For instance, selective survival may partially explain these results. Individuals with high alcohol consumption and substance abuse may experience higher mortality earlier in life, leading to a study sample biased toward individuals who consume alcohol in moderation and exhibit better overall health. Conversely, cigarette consumption is only significantly associated with locomotion.

Early detection of IC deterioration is crucial for implementing measures to preserve individuals' physical and mental abilities and to mitigate or reverse this decline. This makes us reflect on the utility of our IC-based scoring system for periodic assessment across different life stages, facilitating the implementation of preventive strategies during middle age. Assessing IC across the life course can elucidate connections between underlying biological ageing processes and the early adoption and adherence to a healthy lifestyle. Healthy lifestyle habits mitigate numerous long-term conditions, and initiating them at early ages yields greater benefits and makes it easier to keep them over time. This empowers adults with low IC to boost their health, prevent diseases, or re-calibrate their trajectory to avert deterioration.

In this sense, longitudinal studies are invaluable resources for understanding all these factors across individuals' lifespan, offering insights through the combination of data from diverse studies and facilitating international comparisons. However, challenges such as missing values, discrepancies in participant characteristics, variations in data collection methods, and disparities in eligibility criteria for physical tests can introduce biases that impact study outcomes. Also, the reliability and validity of data obtained from population surveys and self-reported data may be questioned due to inconsistencies in participant responses, which could arise from comprehension difficulties or memory lapses. Moreover, strict reliance on standardised questionnaires, although beneficial for clinical practice, may limit the depth and precision of IC measurement, as they may not cover all relevant aspects of each domain adequately. This limitation is indeed evident in the assessment of the vitality domain. While the MNA evaluates various aspects related to nutrition and mobility, it may overlook the impact of weight gain on frailty risk—a significant factor in vitality decline[42]—even though malnutrition is more prevalent than obesity among older adults[43,44]. Other methods for assessing vitality also lack specificity, completeness, and standardisation for interpretation, highlighting the necessity for consensus in measurement and monitoring approaches[45]. Likewise, the lack of objective measurements, as in the sensory domain that only considers self-reported data, hinders the reliability of their results. Furthermore, assessing the psychological aspects of IC over time is challenging due to the temporal fluctuations in emotional and cognitive states, which complicates the interpretation of observed changes. Our study finds inconclusive evidence of a decline in the psychological domain over time, indicating the complexity of measuring psychological aspects of IC. Addressing these practical challenges is crucial for enhancing the accuracy and reliability of IC assessment tools and promoting effective interventions to support healthy ageing.

Biomarkers have the potential to revolutionise the assessment of IC by offering deeper insights into its dynamics and supporting healthy ageing practices. However, research on their application remains limited[46]. Furthermore, traditional biomarkers diverge from the functional focus of ICOPE, which prioritises the use of tools that healthcare and social workers can easily use in primary care settings without requiring invasive or resource-intensive interventions. To comply with this, digital biomarkers can capture real-time, unbiased data on various aspects of physical and mental health, including physical activity, sleep patterns, heart rate, and stress levels, among others[47]. Moreover, digital biomarkers enable the establishment of personalised behaviour and health patterns, enabling individuals to make informed decisions about their lifestyle choices and their impact on IC, specifically on the cognition, vitality, and psychological well-being domains. For instance, by analysing data on physical activity and sleep patterns, digital biomarkers can provide tailored recommendations on exercise regimens or dietary habits to optimise cognitive and physical health. However, several limitations associated with digital biomarkers, such as data reliability, complexity in result interpretation, limited technological accessibility, and privacy concerns, must be addressed to harness their full potential. Adopting an integrated approach that combines human expertise with technological advancements can effectively enhance health literacy and promote proactive health management practices[48].

Conclusions

Healthy ageing is emerging as a prominent research spotlight in response to demographic shifts leading to a significant increase in the global older population. Initiatives such as the United Nations Decade of Healthy Ageing highlight a global effort to improve the quality of life and well-being of older adults. Understanding ageing trajectories and maintaining IC are crucial elements in achieving these goals. In this study, overcoming existing literature limitations in measuring IC, we have proposed a novel, multidimensional scoring system model. This model, validated using the ICOPE framework, demonstrates consistency and discriminative capacity. Notably, IC trajectories are visualised using radar charts, which offer a unique, individualised fingerprint of IC domains over time. This tool helps both healthcare professionals and individuals in understanding and managing age-related functional decline and well-being impairment. Using data from the HRS longitudinal study, we have evaluated the proposed model by assessing the interplay between specific lifestyle factors and IC trajectories. Our findings have revealed significant associations between them, validating the proposed estimation approach with similar results from the literature. For instance, higher levels of physical activities have been associated with better outcomes across all IC domains, indicating the importance of regular exercise in maintaining overall well-being as individuals age.

Further research should focus on refining such complex, multidimensional models to accurately represent the multifaceted nature of IC. Investigating the role of additional lifestyle factors, such as diet, sleep patterns, and stress levels, in IC decline is also crucial. Moreover, future efforts should aim to develop integrated systems that combine diverse data collection methods, such as questionnaires, ICT-based tests, and non-invasive sensors, to provide continuous assessment and tailored health advice. Additionally, these models should be validated across diverse populations using other longitudinal datasets like SHARE and NHATS, which present their own challenges, such as remapping their variables to the ICOPE framework and dealing with inconsistent data collection waves. Besides, applying this model over extended periods as the HRS is updated with additional data would be highly valuable to validate the strength of the proposed model.

Data availibility

The datasets from the Health and Retirement Study (HRS) used and analysed in this study are publicly available in the repository of the University of Michigan (https://hrs.isr.umich.edu).

Received: 3 July 2024; Accepted: 26 February 2025
Published online: 06 March 2025

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Acknowledgements
This research has been supported by Ministerio de Ciencia, Innovación y Universidades, Gobierno de España (Agencia Estatal de Investigación, Fondo Europeo de Desarrollo Regional -FEDER-, European Union) under the research grant PID2021-127409OB-C33 CONDOR. Also, it has also been partially founded by AGAUR research group 2021SGR-00111: "ASCLEPIUS: Smart Technology for Smart Healthcare". M. C. Bernal is supported by the International Experts Program promoted by the Ministerio de Ciencia, Tecnología e Innovación through Instituto Colombiano de Crédito Educativo y Estudios Técnicos en el Exterior - ICETEX, and by internal funds for research strengthening from Universidad Simón Bolívar, Vicerrectoría de Investigación, Extensión e Innovación of Colombia.

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M.C.B.: Conceptualisation, Methodology, Validation, Formal analysis, Visualisation, Data curation, Writing - Original Draft. E.B.: Methodology, Writing - Original Draft, Writing - Review & Editing. A. M.-B.: Methodology, Writing - Review & Editing, Supervision, Funding acquisition. A. S.: Conceptualisation, Methodology, Formal analysis, Writing - Review & Editing, Supervision, Funding acquisition.

Declarations

Competing interest
The authors declare no competing interests.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-92271-7.

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