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Factors associated with physical fitness and disparities in population segments among older adults: A cross-sectional study

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ABSTRACT

Objectives: This study aimed to investigate the factors associated with physical fitness and disparities in population segments among older adults, using data from the National Physical Fitness Surveilling Survey of China.
Study design: A cross-sectional study.
Methods: A total of 13524 older adults aged 60–79 years were involved in the study. Participants completed physical fitness assessments encompassing body fat percentage, lung capacity, high leg raise in place, grip strength, seated forward bending, 30-s sit-to-stand test, single-leg standing with eyes closed, and choice reaction time. A profile analysis model was constructed by feature extraction, label design and clustering using principal component analysis and k-prototypes. Factors associated with physical fitness were analyzed using ordered probit regression, and within-group differences were evaluated through the bootstrap method.
Results: The older adults were categorized into four clusters based on the clustering results (Cluster I: n = 2728, Cluster II: n = 6067, Cluster III: n = 4189, Cluster IV: n = 540). Significant positive associations were identified between moderate-to-vigorous transport-related activities ($\alpha = 0.001$, $p < 0.05$), moderate-to-vigorous household chores ($\alpha = 0.003$, $p < 0.01$), work-related physical activity ($\alpha = 0.001$, $p < 0.01$), exercise ($\alpha = 0.002$, $p < 0.01$) and physical fitness levels. Conversely, the number of illnesses ($\alpha = -0.089$, $p < 0.01$) and sedentary behavior ($\alpha = -0.002$, $p < 0.05$) were negatively associated with physical fitness. Inflection points were observed, indicating shifts from lower level to higher physical fitness levels as the volume of diverse moderate-to-vigorous physical activities increased. Disparities in factors associated with physical fitness were identified across the different clusters. The associations of household chores, transport-related activities, and work-related physical activity with physical fitness lacked robustness during heterogeneity processing. In contrast, exercise consistently demonstrated a facilitating role across all clusters. Furthermore, greater marginal effects on achieving higher physical fitness test scores were observed among individuals classified as inactive when engaging in more moderate-to-vigorous activities and exercise.
Conclusion: The findings demonstrate that engagement in moderate-to-vigorous physical activities and exercise is associated with a significantly higher probability of achieving better physical fitness among older adults. Participating in physical activities and exercise should be encouraged based on population segments for precise and quantitative interventions to improve physical fitness.

1. Introduction

Physical fitness includes components such as muscle strength, flexibility, aerobic capacity, and coordination, which are essential for an autonomous and healthy life in older adults.[1,2] Aging is a natural stage of life characterized by a series of physical, psychological, and social

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changes. With the increasing aging population, physical fitness has become a critical health indicator for older adults, which was relevant with the possibility of independent living, the risk of chronic diseases and quality of life.[3,4] As individuals age, it is important to adopt measures to maintain or improve their quality of life to age actively and healthily. Among the most recommended non-pharmacological strategies for improving quality of life in old age is physical exercise.[5,6] Physical inactivity, however, remains a significant public health concern, imposing substantial disease and economic burdens, and is closely linked to co-occurring health problems, particularly in older adults.[7,8]Therefore, designing personalized exercise programs is essential to encourage participation and improve physical fitness.

A growing body of research has highlighted the critical role of engaging in various forms of physical activity, including household chores, transport-related, work-related activities and various exercise forms.[9–12] According to World Health Organization, older adults are advised to participate in moderate-to-vigorous physical activities to maintain health and functionality.[13] Additionally, evidence suggests that strength training serves as an effective intervention, which could enhance overall physical fitness and contribute to improving quality of life and autonomy in older adults.[14] Except for physical activities and training, it is recognized that physical fitness can be determined by various factors such as ascribed, achieved characteristics as well as health conditions.[15–17] Ascribed characteristics, such as gender and age, are determined at birth, while achieved characteristics, including education and occupation, represent social positions attained throughout an individual's life. Both of these characteristics have been shown to shape an individual's position within the social hierarchy.[18] Notably, socioeconomic inequalities widen disparities in older adults' quality of life,[19] underscoring the importance of addressing these inequities in efforts to improve physical fitness.

Findings from research on physical fitness among active, community-dwelling older adults suggest the importance of designing tailored health programs that consider individual physical fitness levels and specific reference points.[20] The results from theoretical and content analysis further indicate that customized exercise programs, aligned with individual needs and preferences, may enhance adherence and foster consistent participation. This highlights the critical role of improving physical fitness among older adults, a population where inactivity remains prevalent.[21] Despite its significance of adopting precise measures, there is a gap in studies exploring whether older adults could be divided into differentiated clusters based on socio-demographic characteristics along with behavioral preferences and how physical fitness would be associated in different population segments.

This study aims to generate demographic profiles of older adults based on national physical fitness surveillance data, exploring how demographic and health factors associated with their fitness levels. Population segments, defined as demographic, physical, and health profiles generated from data clustering, were analyzed to identify common patterns and disparities in specific groups of older adults. Building on these segments, factors associated with physical fitness and disparities across groups were examined to assess functional status and inform tailored health interventions.[22,23] It is hypothesized that greater participation in physical activities (independent variable) is positively associated with higher physical fitness levels (dependent variable), while factors such as depression or loneliness may serve as negative moderators. Furthermore, these associations are expected to vary across population segments, underscoring the need for segment-specific analyses and interventions.

2. Methods

2.1. Data source and sample

The data used in this study were derived from the National Physical Fitness Surveilling Survey of Shanghai, China, conducted in 2020. A stratified, randomized cluster sampling design was employed to select a sample of older civilians. Older adults were categorized based on urban-rural distinctions across 16 districts in Shanghai, dividing participants into three groups: rural, suburb and urban. Stratification was further applied according to sex (male and female), and age groups (60–64, 65–69, 70–74, 75–79) within each district category. The nested structure of the data was considered in the subsequent statistical analysis. The sample was restricted to older adults aged 60–79, resulting in a total of 14,026 observations. Of these, 502 participants were excluded due to missing or incomplete data on physical activity, sedentary behavior, health conditions and covariates. Finally, 13524 older adults were included in the analysis.

2.2. Measurements

2.2.1. Physical fitness

Physical fitness in this study was assessed using a battery of tests based on the National Physical Fitness Measurement Standards for Chinese older adults (Revised in 2023). The sample was selected based on the criteria that participants did not have exercise contraindications, were capable of self-care, and had basic exercise abilities, making them suitable for standardized physical and physiological measurements. The components of the physical fitness test included: (1) Body shape: Body mass index (kg/m^2) and body fat percentage (%) are secondary indicators of body shape, accounting for 20 % of the physical fitness score. (2) Physical function: Lung capacity (mL) and high leg raise in place (count) serve as the evaluation indicators, contributing 20 % to the overall physical fitness score. (3) Physical quality: Grip strength (kg), sit-and-reach (cm), 30-s sit-to-stand (count), single-leg standing with eyes closed (sec), and choice reaction time (sec) constitute 60 % of the physical fitness score.

2.2.2. Physical activity

Physical activity including household, transport-related, work-related activities and exercise, was measured using the Metabolic Equivalent of Task (MET), which was multiplied by the total volume of activity (hours per week). The data on activity duration were obtained from participant questionnaires. In accordance with MET values from the IPAQ Reliability Study,[24] we assigned 2 METs for light-intensity exercise, 4 METs for moderate-intensity exercise, and 8 METs for vigorous-intensity exercise.[25] As regards physical activity and sedentary behavior, we assigned 1 MET for sedentary behaviors such as reading,[26] 2 METs for light-intensity physical activity, 3 METs for moderate-intensity household chores, 3.3 METs for walking, 5.5 METs for vigorous-intensity household chores, 6 METs for cycling, and 8 METs for vigorous intensity activities such as heavy lifting.[27,28] Moreover, the tasks associated with different physical activities varied. Transport-related activities included car and boat transportation, self-driving, motorbike riding, cycling, mobility scooter and walking. Work-related activities encompassed sedentary work, upper limb activities, walking while working and manual labor. Household chores and exercise volumes were categorized into light-intensity, moderate-intensity and vigorous-intensity activities. Additionally, sedentary behaviors were defined as TV-watching, chess-playing and reading.

2.2.3. Health-relevant outcomes

Health-relevant outcomes, including both physical and mental health, were obtained from interviewer-administered questionnaires. Morbidity conditions were self-reported and were stated to have been confirmed by hospital diagnoses, including hypertension, hyperlipidemia, diabetes mellitus, heart disease, digestive disease, joint disease, respiratory disease, occupational disease and osteoporosis. Psychological well-being was measured by PHQ-9 Depression Scale and the Emotional and Social Loneliness Scale.

2.3. Statistical analysis

2.3.1. Profile analysis model

A profile analysis model was employed, drawing on the user profile analysis methods widely used in the fields of artificial intelligence and engineering. This approach involves extracting features and embedding labels into the algorithm based on big data, enabling accurate population inferences.[29–31] In this study, we constructed a profile model to characterize the physical and health traits of older adults. Labels were created based on key attributes, including physical activity, sedentary behavior, physical and mental health. These labels were derived from specific indicators following the feature extraction, which grouped similar features and distinguished separate categories. Principal component analysis and K-prototypes clustering were used to generate the profiles. To visually represent and highlight key features in the different clusters, word cloud maps were utilized. The indicators for the three attributes generating the profiles are as follows: (1) Demographic: Age, gender and urban-rural distribution were used as demographic attributes, which were directly obtained from the survey. (2) Physical activity and sedentary behavior: cumulative hours per week of transport-related, household chores, work-related activities and sedentary behaviors were calculated separately for different groups of older adults. Additionally, exercise was measured through participation, frequency, average exercise hours per day and cumulative hours per week, calculated separately for different groups of older adults. (3) Physical and mental health: Physical fitness, mental health and the number of illnesses were assessed across three dimensions. Disease classification was directly obtained from the survey, while physical fitness, depression and loneliness levels were evaluated.

During the profile model construction process, principal component analysis (PCA) was employed for dimensionality reduction.[32] Principal components were extracted from multiple continuous variables related to physical activity and sedentary behaviors attributes, effectively capturing the underlying structure while reducing the number of metrics. Given that the dataset included both numerical and categorical variables, a multi-view clustering algorithm based on k-prototypes was applied to classify older adults into distinct clusters. This method integrates the Euclidean distance principle from k-means and the Hamming distance principle from k-modes.[33] Clustering and profiles analysis were conducted using python Version 3.12. The model construction process is illustrated in Fig. 1.

2.3.2. Ordered probit regression

The ordered logit model was initially considered for pre-estimation due to the discrete nature of the dependent variables. However, the Brant test indicated that the parallel regression assumption was violated. Given that physical fitness levels are inherently ordinal, the ordered probit regression was deemed more appropriate for estimating the factors associated with these levels. The independent variables included the volume of physical activity and sedentary behavior, exercise participation and health-related variables. The regression model is as follows:

$$fitness_i^* = x_i\alpha + \beta CV_i + \varepsilon_i, \varepsilon_i \sim N(0, \sigma^2) \tag{1}$$

$$fitness_i = \begin{cases} 1 \text{ if } fitness_i^* \in (-\infty, \mu_1) \\ 2 \text{ if } fitness_i^* \in [\mu_1, \mu_2) \\ 3 \text{ if } fitness_i^* \in [\mu_2, \mu_3) \\ 4 \text{ if } fitness_i^* \in [\mu_3, +\infty) \end{cases} \tag{2}$$

Dependent variable. *fitness* represents physical fitness which was classified into four levels (1 = substandard, 2 = eligible, 3 = good, 4 = excellent) while *fitness** is a hidden variable of physical fitness.

Independent variable. x_i represents a vector of underlying factors associated with physical fitness levels for the older population, including a broad range of moderate-to-vigorous physical activities (household chores, transport-related activities, work-related activities and exercise), sedentary behavior, number of illnesses, depression and loneliness. α is the column matrix of the parameters to be estimated.

Control variable. CV_i, control for individual, external and geographic factors including gender, age, marital status, regions, education, occupation and loneliness. ε_i is a random error term obeying a standard normal distribution and μ_j (j = 1,2,3) is known as the threshold value.

Due to the limited interpretability of coefficient estimates in nonlinear regression models, significant variables were further analyzed through marginal effect analysis. This approach evaluated and compared the magnitude of marginal values of the dependent variables under different situations.[34] Furthermore, subgroup regressions were conducted on the basis of equation (1) to explore the heterogeneity of factors associated with the physical fitness levels of older adults in different clusters, and the average marginal coefficients of significant independent variables on subgroup regression models were tested for within-group differences using the Bootstrap method.[35,36] Ordered

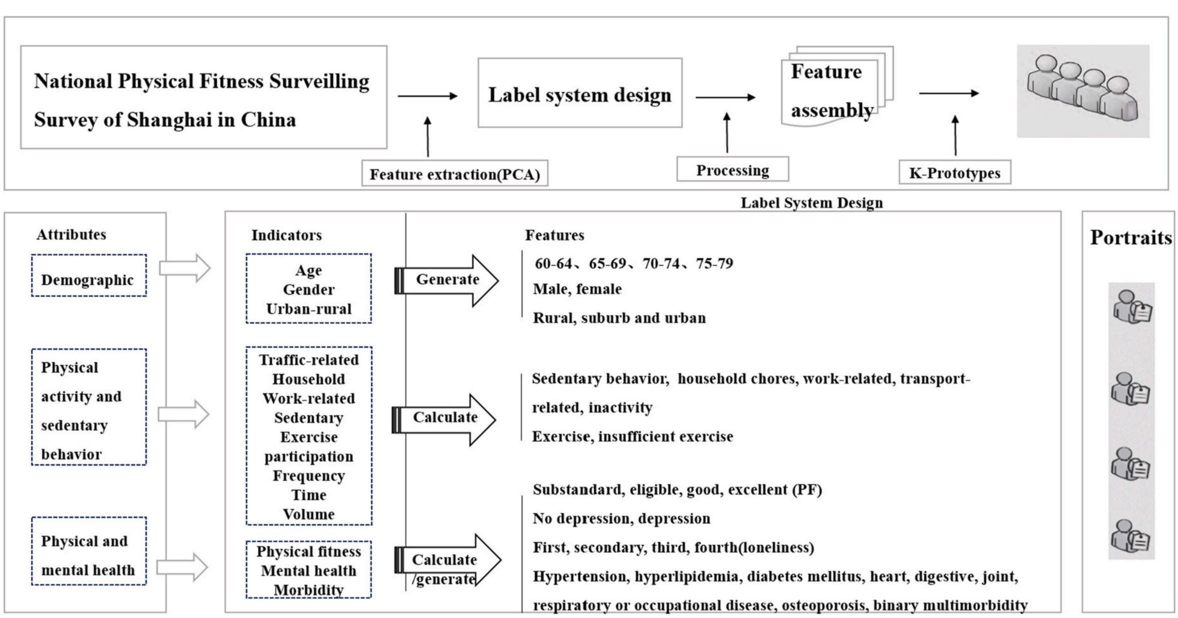

Fig. 1. Flowchart of demographic profiles model construction.

probit regression analyses were conducted using Stata Version 17.0.

3. Results

3.1. Cluster evaluation and profile analyses

The results of the cluster analysis showed that older adults can be classified into 4 categories. The label word maps are illustrated in Fig. 2. Through the gravel plot of K and Sum of Square Error (SSE), it was observed that when the value of K was larger than 4, the clustering degree returned to become smaller, and the decline of SSE slowed down tending to flatten out as the K value continued to increase. Combined with the contour coefficient measuring the clustering effects, when K = 3, the contour coefficient was 0.27; when K = 4, the contour coefficient was 0.29; when K = 5, the contour coefficient was 0.28. Thus, it is determined that the clustering result is relatively better when the value of K is 4.

Therefore, the older adults could be classified into four clusters based on their activity preferences and participation: (1) sedentary behavior-preferred but participate in exercise; (2) lack of activity and exercise; (3) household chores-preferred and participate in exercise; (4) work-related physical activity-preferred but lack of exercise. The results of features and label visualization of classification are shown in Table 1. Most of older adults were split into Cluster II labeling lack of activity and exercise especially for those aged 75–79. The work-related activity-preferred seniors are relatively younger with higher proportion of living in rural and suburbs. The Cluster III are preferring household chores with more females. The Cluster I are preferring sedentary behaviors with highest proportion of multimorbidity. Both Cluster I and II are lacking household chores, traffic-related and work-related physical activities, who suffered from more illnesses.

3.2. Factors associated with physical fitness

The model estimation results are presented in Table 2. The analysis indicates that the associations with moderate-to-vigorous household chores, work-related physical activity, transport-related physical activity and exercise on the physical fitness levels were positively significant, while sedentary behavior and number of illnesses had negative associations controlling for possible confounders such as districts, education, occupation, loneliness, marital status, gender and age. Notably, no significant associations were found between physical fitness levels and loneliness or depression.

The marginal probability of physical fitness levels as a function of physical activity volumes are illustrated in Fig. 3. The intersection points of the probability curves indicate critical thresholds for activity volumes associated with improved physical fitness outcomes. Specifically, the marginal probabilities of achieving “good” and “excellent” physical fitness converge when moderate-to-vigorous transport-related activities reach approximately 140 MET-h/Week. Similarly, transition points to “excellent” physical fitness were observed at approximately 65 MET-h/week for moderate-to-vigorous household chores and 221 MET-h/week for moderate-to-vigorous work-related activities. These results highlight the volume thresholds at which increased physical activity contributes to optimal fitness levels. The results further revealed that physical fitness excellence exhibited continuous growth with increasing volumes of moderate-to-vigorous exercise, reaching an inflection point between “good” and “excellent” fitness levels at approximately 102 MET-h/Week. On the contrary, sedentary behaviors demonstrated a negative impact, with a threshold of 42 MET-h/Week marking a shift where the marginal probability of “eligible” physical fitness surpassed that of “excellent”. Additionally, the number of illnesses played a significant role in diminishing fitness outcomes. A transition was observed when the number of illnesses increased from 0 to 2, with the marginal probability of “eligible” fitness surpassing “excellent,” indicating that multimorbidity undermines physical fitness. When the number of illnesses reached to 4, the marginal probability of “eligible” physical fitness likely exceeded “good,” underscoring the compounded adverse effects of multiple health conditions on fitness levels.

3.3. Heterogeneity test

Ordered probit regression models were performed for different clusters of older adults, with the results are shown in Table 3. There was no significance of household chores, traffic-related and work-related physical activities on physical fitness in all subgroup regression models. The heterogeneity existed in four clusters in view of household chores, work-related activities and sedentary behaviors. However, it still revealed exercise and number of illnesses were associated with the outcome robustly.

The marginal effects of significant variables in the regressions were estimated, and within-group differences tests were conducted as shown in Table 4. The results indicated that moderate-to-vigorous exercise had a significant promotion effect on the probability of physical fitness excellence for four clusters. The within-group differences in average marginal effects were significant, with Cluster IV and Cluster II showing

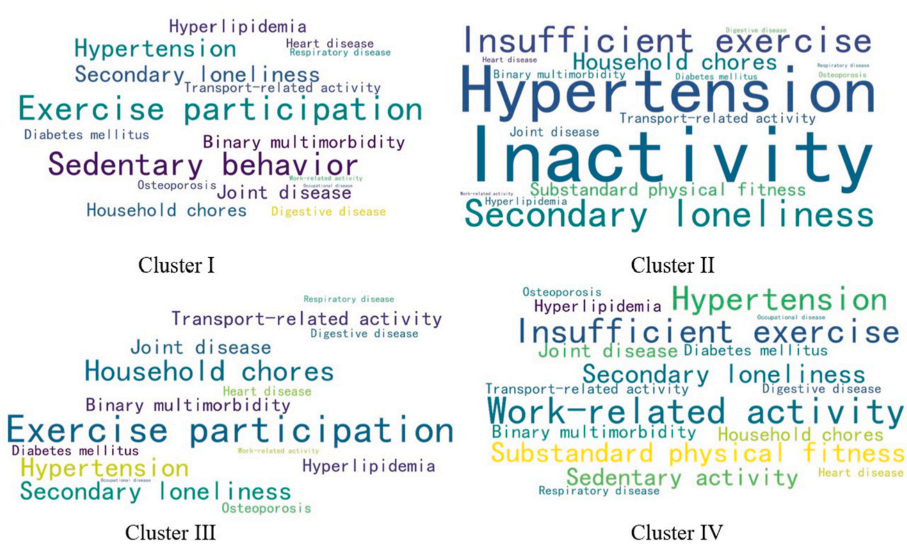

Fig. 2. Label word maps of four clusters based on population segments.

Table 1
Results of cluster classification and feature description on demographic profiles.

Cluster		Cluster 1	Cluster II	Cluster III	Cluster IV
Percentage(Sample size)		20.21 % (2728)	44.77 % (6067)	31.01 % (4189)	4.01 % (540)
Demographic	Gender percentage (male)	54.15 %	53.03 %	38.22 %	62.65 %
	Age group at maximum percentage	70–74	75–79	65–69	60–64
	Rural percentage	22.87 %	28.69 %	18.11 %	41.54 %
	Suburb percentage	27.35 %	28.49 %	31.36 %	39.67 %
	Urban percentage	49.78 %	42.82 %	50.52 %	18.79 %
Physical activity and sedentary behavior	Proportion of Sedentary behaviors	66.52 %	46.21 %	40.25 %	25.41 %
	Proportion of household chores	19.71 %	29.54 %	41.03 %	15.61 %
	Proportion of transport-related activities	12.15 %	21.24 %	16.86 %	8.67 %
	Proportion of work-related activities	1.63 %	3.01 %	1.87 %	50.31 %
	Average accumulative minutes of overall activities per week	1159	769	1694	2923
	Exercise participation percentage	74.55 %	64.36 %	76.65 %	56.93 %
	Average accumulative minutes of exercise per week	392	272	422	234
Physical and mental health	Average number of illnesses	1.23	1.07	0.96	1.04
	Multimorbidity percentage	33.97 %	28.83 %	25.19 %	24.91 %
	Average physical fitness scores	79.03	77.65	79.17	79.07
	Depression percentage	7.51 %	6.20 %	5.61 %	5.68 %
	Secondary loneliness percentage	30.37 %	36.69 %	30.64 %	30.55 %

Notes: Proportion of sedentary behaviors, household chores, transport-related activities and work-related activities were measured by average percentages of accumulative overall activity hours per week.

a stronger promotion effect on the marginal probability of physical fitness excellence. However, the number of illnesses had a significant inhibitory effect on the probability of physical fitness excellence for four clusters. The within-group differences between the average marginal effects were significant, indicating a higher inhibiting effect on the physical fitness excellence for Cluster IV and I. Additionally, moderate-to-vigorous household chores positively associated with the probability of physical fitness excellence in Cluster II and IV, with a more pronounced effect in Cluster IV. Moderate-to-vigorous work-related physical activities significantly promoted physical fitness excellence in Cluster II. Sedentary behaviors had an inhibiting effect on physical fitness excellence in Cluster III, while depression significantly inhibited physical fitness excellence in Cluster I.

4. Discussion

The present study introduces a demographic profiles model to split

Table 2
Results of ordered probit model estimation.

Variables		Coefficient (95%CI)	t	P
Age (60–64)	65–69	0.003(-0.082, 0.088)	0.060	0.952
	70–74	−0.165(-0.251, −0.079) ***	−3.782	0.000
	75–79	−0.419(-0.557, −0.281) ***	−6.014	0.000
Gender (female)	male	−0.066(-0.149, 0.018)	−1.549	0.124
Marital status (unmarried)	married	0.116(-0.184, 0.417)	0.765	0.446
	divorce	0.143 (-0.188,0.474)	0.855	0.394
	widow	0.150(-0.155, 0.455)	0.972	0.333
District (Huangpu)	Xuhui	−0.416(-0.668, −0.164) ***	−3.270	0.001
	Changning	−0.355(-0.717, 0.008) *	−1.937	0.055
	Jingan	0.175(-0.199, 0.548)	0.925	0.357
	Putuo	−0.014(-0.212, 0.184)	−0.140	0.889
	Hongkou	0.523(0.328, 0.717) ***	5.320	0.000
	Yangpu	0.036(-0.139, 0.211)	0.410	0.683
	Minhang	−0.150(-0.364, 0.064)	−1.385	0.168
	Baoshan	−0.285(-0.460, −0.111) ***	−3.238	0.002
	Jiading	0.788(0.602, 0.973) ***	8.401	0.000
	Pudong	−0.049(-0.238, 0.140)	−0.512	0.609
	Jinshan	0.215(-0.041, 0.472) *	1.660	0.099
	Songjiang	−0.314(-0.501, −0.127) ***	−3.316	0.001
	Qingpu	0.068(-0.143, 0.279)	0.639	0.524
	Fengxian	−0.323(-0.530, −0.116) ***	−3.082	0.003
	Chongming	−0.515(-0.718, −0.313) ***	−5.029	0.000
Education (illiteracy)	Literacy	0.124(-0.088, 0.335)	1.159	0.249
	primary	0.081(-0.043, 0.205)	1.291	0.199
	junior	0.220(0.090, 0.350) ***	3.339	0.001
	high school	0.316(0.172, 0.460) ***	4.337	0.000
	three-year college	0.422(0.273, 0.571) ***	5.601	0.000
	undergraduate	0.432(0.252, 0.612) ***	4.760	0.000
	postgraduate	0.362(-0.115, 0.840)	1.501	0.136
Occupation (heads of State organs, party organizations, enterprises and institutions)	professionals and technicians	−0.072(-0.152, 0.008) *	−1.774	0.078
	clerk	−0.039(-0.121, 0.044)	−0.929	0.355
	businessman	−0.086(-0.186, 0.013) *	−1.720	0.088
	agricultural practitioners	−0.155(-0.259, −0.052) ***	−2.965	0.004
	production and transport-related personnel	−0.039(-0.126, 0.047)	−0.903	0.368
	military	0.360(0.014, 0.706) **	2.059	0.042
	other employees	−0.136(-0.226, −0.046) ***	−2.989	0.003

(continued on next page)

Table 2 (*continued*)

Variables	Coefficient (95%CI)	t	P
occupation-free	−0.270(-0.465, −0.076) ***	−2.747	0.007
solitary	0.034(-0.057, 0.125)	0.737	0.462
Sports facilities near the neighborhood or not	0.012(-0.084, 0.108)	0.249	0.803
Moderate-to-vigorous transport-related activity	0.001(0.000, 0.003) **	2.154	0.033
Moderate-to-vigorous household chores	0.003(0.001, 0.005) ***	3.743	0.000
Moderate-to-vigorous work-related physical activity	0.001(0.000, 0.001) ***	3.060	0.003
Sedentary behavior	−0.002(-0.004, −0.000) **	−2.023	0.045
Moderate-to-vigorous exercise	0.002(0.002, 0.003) ***	8.078	0.000
Number of illnesses	−0.089(-0.112, −0.066) ***	−7.565	0.000
Loneliness	−0.002(-0.007, 0.004)	−0.591	0.556
Depression	−0.014(-0.113, 0.085)	−0.283	0.778
/:			
cut1	−2.239***	−9.965	
cut2	−0.544**	−2.308	
cut3	0.540**	2.387	
N	13524		

Abbreviations: CI, confidential intervals.
*Statistical significance($p < 0.1$); **($p < 0.05$); ***($p < 0.01$).

ageing population into differentiated subgroups, providing a comprehensive portrait of older adults in the sampling sites, with a focus on their physical activity and sedentary behavior characteristics, as well as physical and mental health conditions. Compared with demographic, socioeconomic and health profile described in the previous research,[37] our profiles described mainly drawn from national physical fitness surveilling data, aggregating detailed features such as overall physical activities, exercise, sedentary behavior, physical fitness, morbidity and relevant health status.

The results of this study demonstrated that moderate-to-vigorous physical activities and exercise were positively associated with physical fitness, while sedentary behaviors and morbidities contributed to lower physical fitness levels. Furthermore, the marginal probability of achieving higher physical fitness levels shifted positively when the volumes of moderate-to-vigorous household chores, exercise, traffic-related and work-related physical activities reached approximately 65 MET-h/Week, 102 MET-h/Week, 140 MET-h/Week and 221 MET-h/Week, respectively. In the heterogeneity tests, marginal effects were estimated on physical fitness excellence, which showed higher marginal effects of exercise on those lacking of exercise. Meanwhile, the number of diseases had higher marginal inhibiting effects on older adults labeled sedentary behavior-preferred and insufficient exercise. Household chores posed higher marginal effects among those labeled work-related physical activity-preferred while work-related physical activities had a significant effect only on older adults who preferred household chores.

This study aligns with the previous research that participation in various physical activities is associated with better physical fitness.[38–40] However, not all physical activities were proved to make significant contributions to physical fitness, leading to heterogeneity across differentiated clusters. Only moderate-to-vigorous exercise was found to

Table 3
Subgroup regression results of ordered probit model.

Variables	(1)	(2)	(3)	(4)
	Cluster I	Cluster II	Cluster III	Cluster IV
Moderate-to-vigorous transport -related activity	0.001 (0.860)	0.002 (1.054)	0.002 (1.506)	0.003 (0.783)
Moderate-to-vigorous household chores	0.002 (0.664)	0.005** (2.293)	0.001 (1.054)	0.008* (1.984)
Moderate-to-vigorous work-related physical activity	0.002 (1.255)	0.002** (2.055)	0.000 (0.251)	0.000 (0.876)
Sedentary behavior	−0.002 (-0.654)	0.002 (0.455)	−0.012*** (-3.117)	−0.002 (-0.316)
Moderate-to-vigorous exercise	0.002*** (2.867)	0.003*** (5.747)	0.002*** (5.286)	0.006*** (3.555)
Number of illnesses	−0.100*** (-5.082)	−0.090*** (-6.221)	−0.085*** (-4.077)	−0.160*** (-3.626)
Loneliness Scores	−0.006 (-1.347)	0.002 (0.627)	−0.006 (-1.064)	−0.001 (-0.134)
Depression	−0.248** (-2.118)	0.064 (0.904)	0.049 (0.699)	−0.138 (-0.610)

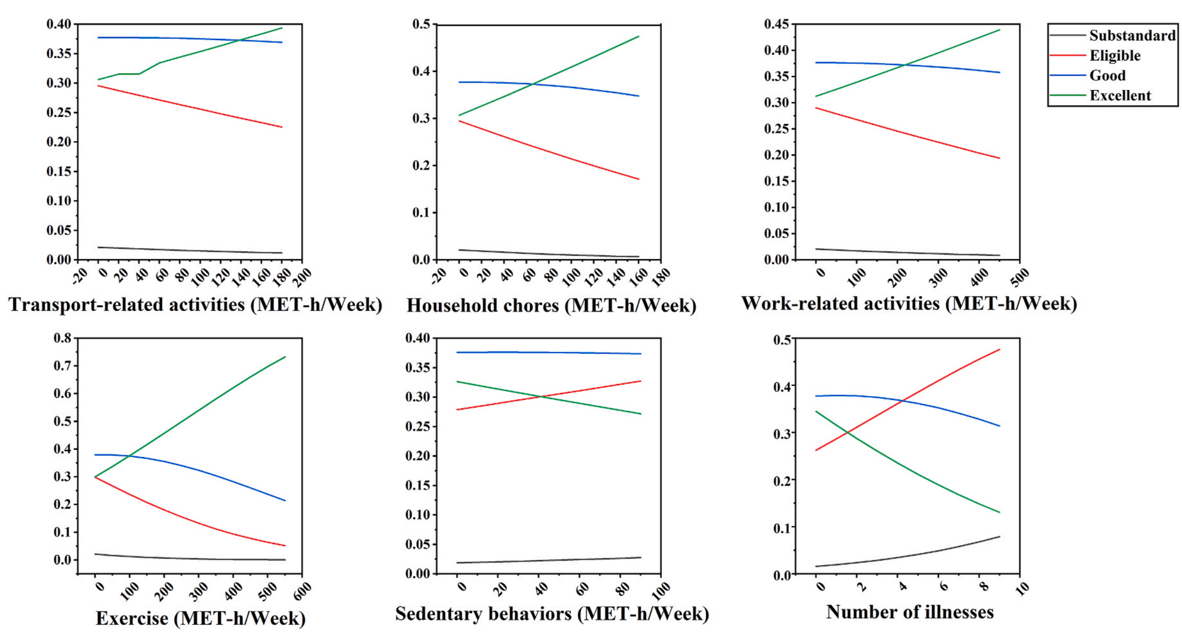

Fig. 3. Marginal probability of physical fitness in the ordered probit model.

Table 4
Marginal effects of significant factors on physical fitness excellence in four clusters.

Variables	(1) Cluster I	(2) Cluster II	(3) Cluster III	(4) Cluster IV
Moderate-to-vigorous exercise	0.0006*** (2.892)	0.0008*** (5.751)	0.0007*** (5.398)	0.0018*** (3.705)
Number of illnesses	−0.0316*** (-5.081)	−0.0274*** (-6.111)	−0.0282*** (-4.043)	−0.0488*** (-3.715)
Depression	−0.0789*** (-2.129)			
Moderate-to-vigorous household chores		0.0015** (2.284)		0.0023** (1.986)
Moderate-to-vigorous work-related physical activity		0.0006** (2.058)		
Sedentary behavior			−0.0039*** (-3.153)	
Within-group difference tests for moderate-to-vigorous exercise	(1) 0.0008***(2) 0.0007***(3)0.0019***(4) 0.0007***(5) 0.0019***(6) 0.0019***			
Within-group difference tests for moderate-to-vigorous household chores	0.0023**			
Within-group difference tests for number of illnesses	(1) −0.0274*** (2) −0.0282*** (3) −0.0488*** (4) −0.0282*** (5) −0.0488*** (6) −0.0488***			
N	2728	6067	4189	540

be positively and significantly associated with physical fitness in the subgroup regression models. It could be interpreted that exercise has a more substantial impact than household chores, transport-related and work-related physical activities,[41] which benefits more. Interestingly, no significant associations were found between loneliness, depression, and physical fitness levels in this study. It is conceivable that most of older adults in our sample were not suffering from depression or deep loneliness, and their psychological conditions were relatively similar. Moreover, the study provides valuable insights by examining the marginal effects of physical fitness levels at different volumes of physical activities and exercise. This can serve as a significant reference for developing quantitative interventions aimed at improving the physical fitness for older adults.

These results extend beyond previous studies by suggesting that health interventions of improving physical fitness in older adults could be more effective if tailored to specific demographic profiles and supported by quantitative criteria. Planned, structured, repetitively and purposefully physical activity called exercise should be encouraged to put into overall health interventions for older adults. Policymakers should attach importance to provide tailored, accuracy and personalized physical activities and exercise recommendations or guidelines for older adults optimizing the big data of demographic profiles in order to maintaining and promoting physical fitness. Also, priority surveilling populations should be identified for those who are physical inactivity, sedentary and suffering with multiple morbidities.

The major strengths and innovations of the present study include the use of physical fitness surveillance data from a large sample of Chinese older adults, allowing for a detailed conceptualization of physical activity, sedentary behaviors and health conditions. To the best of our knowledge, our study is among the first to provide comprehensive profiles of older adults and to examine the disparities in factors associated with physical fitness, which offered differentiated findings in four representative subgroups. In terms of methodology, principal component analysis and k-prototypes were utilized to deal with the mixed data, to construct more comprehensive profiles model. The present study contributes to providing insights for accuracy health intervention, which helps improve physical fitness in older adults.

There are several limitations in this study. First, all the participants were recruited from Shanghai, a well-developed and aging society city in China, which may differ from other cities where older adults may have different demographic features and PA habits.[42] Second, there is no exact calculating parameters to measure different types of physical activity and exercise graded by the intensity. We assumed metabolic equivalent tasks assignments with reference to previous literature.[43] However, there are somewhat different in validity and accuracy from multiple metrics.[44,45] Third, physical activity, exercise behaviors and morbidities were from self-reported data, which may lead to reported bias. Last, it was hard to infer causality between multiple factors and physical fitness restricted to the cross-sectional data.

5. Conclusions

In summary, this study highlights the importance of both population-wide and personalized strategies to enhance physical fitness in older adults, taking into account demographic, health, and behavioral factors. The study also identifies specific volumes of different physical activities and exercise that are recommended to help transition older adults from relatively lower to higher levels of physical fitness. These findings suggest that targeted interventions, tailored to distinct population segments, could provide a more accurate and effective approach to improving physical fitness among older adults.

Ethical approval

The study protocol was approved by the ethical review committee of the Shanghai Research Institute of Sports Science (LLSC20230017) and written informed consent was obtained from each participant at enrolment.

Author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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