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Unveiling the long-term impact: exploring the link between exposure to the great Chinese famine and health-related quality of life in middle-aged and elderly populations through propensity score matching

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Abstract

Objective This study aimed to explore the relationship between exposure to the Great Chinese Famine (1959–1961) and health-related quality of life (HRQoL) in middle-aged and elderly people after adjusting for selection bias using propensity score matching (PSM).

Methods This cross-sectional study was conducted in Ningxia, China, in 2022. A multi-stage stratified cluster-randomized design was used to obtain a representative sample in each county. We included participants aged 45 years and older, who had lived there for more than 1 year. This study included 5,793 middle-aged and elderly people in Ningxia, China as the research subjects. This study used propensity score matching (PSM) to empirically examine the association between exposure to the Great Famine and HRQoL in middle-aged and older adults. In the first step, we estimated a binary logistic regression model with Great Chinese Famine exposure as the dependent variable and 7 factors as confounding variables. In the second step, we performed propensity score analysis using the confounding variables identified in the first step to control for potential selection bias. To avoid bias due to age differences, we introduced the age variable into the regression model to explore the effect of the Great Famine impact. Different definitional criteria were used to define the exposed and control groups in order to robustly test the findings.

Results The results showed that middle-aged and elderly people who reported exposure to the Great Famine had lower HRQoL than middle-aged and elderly people who were not exposed to the Great Famine, after adjusting for gender, educational background, economic level, BMI, Chronic conditions, smoking and drinking. In order to avoid the influence of age differences on the results, this study used matched samples and included the age variable in the regression analysis to minimise the bias due to age. Also, exposure was defined in different ways to test the robustness of the results.

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Conclusions The health-related quality of life of middle-aged and older adults who experienced China's Great Famine (1959–1961) declined substantially in later life, but the inclusion of the age variable made the statistical results non-significant.

Keywords Survival, EQ-5D-3L, Causal inference, Propensity score matching, Health-related quality of life, Great Chinese famine

Introduction

With the steady development of China's economy and the improvement of health service levels, human life expectancy has also been greatly extended [1, 2]. China is facing an aging tsunami. At the same time, this population model also makes China's medical and health industry face huge challenges [3]. An aging population also increases the complexity and burden of care in terms of chronic disease, functional impairment, and health care utilization, and their excessive demands for care and social support are challenges that urgently need to be addressed. It is therefore crucial to improve the health-related quality of life (HRQoL) of these populations. Currently, "Healthy China" and "Actively Responding to Population Aging" are China's two important national strategies. Promoting demand-driven high-quality development of health services for middle-aged and elderly people is an important way to achieve these strategies [4].

The Great Famine in China that occurred from 1959 to 1961 had a serious impact on the health of the elderly in China. Research over the past few decades has shown that early exposure to famine is associated with an increased risk of chronic disease later in life [5]. In famine areas, exposed cohort had a.

significant increased risk of hypertension, dyslipidemia, non-alcoholic fatty liver and diabetes compared with non-exposed cohort [6–9]. Although the relationship between famine and specific diseases has been studied [5, 6], there is a lack of research on the impact of famine on the health-related quality of life of middle-aged and elderly people.

EQ-5D is a simple and globally used health assessment tool developed by EuroQol Group to measure, compare, preference-based and evaluate the health status of people aged 12 years or above [10]. Currently, 2 versions of the EQ-5D exist: the 3-level option (3 L) and the 5-level option (5 L). EQ-5D can be used as a measure of HRQoL, which describes health into multiple dimensions and provides a single utility value for summary [11].

This study only selected survivors who were exposed to the famine years as the subjects of observational research, because exposure to famine may lead to irrecoverable bias. Observational studies of survey data are unable to control for randomization and therefore face serious challenges of selection bias, making it difficult to obtain convincing evidence for causal inference. In order to overcome this problem, this study used propensity score matching (PSM) to empirically verify the impact of exposing the Great Famine on the HRQoL of middle-aged and elderly people. The propensity score matching method is based on the Neyman-Rubin counterfactual framework to automatically control confounding variables, which can effectively reduce the selection bias caused by confounding variables between two different groups [12]. such as the impact of different economic levels on the physical condition of middle-aged and elderly survivors who experienced famine and survivors who did not experience famine. Therefore, the selection of suitable confounding variables is the key to applying PSM. Previous research surveys have shown that HRQoL is not only related to age-related diseases, but also closely related to factors such as gender, education, economic level, chronic diseases, smoking, drinking, and a series of health-related behavioral habits and living environment. Better health-related quality of life was significantly associated with factors such as higher BMI, no drinking habits, and fewer chronic diseases [1, 13–15]. These confounding variables have led to selection bias in the observation data, and we cannot directly draw convincing conclusions about whether experiencing the Great Famine years will affect the HRQoL of middle-aged and elderly people. However, PSM methods may provide more favorable methodological improvements for making stronger causal inferences in observational data.

This study examined exposure to the Great Famine years as a treatment and middle-aged and older adults as the treatment group for representative cross-sectional data. The PSM method could match middle-aged and elderly people who did experience the Great Famine years in the same data as the treatment group, and select a control group that is balanced with the treatment group. This approach will prevent selection bias between treatment and control groups. Then, calculating the average treatment effect (ATT) between the treatment group and the control group can provide stronger evidence to verify the impact of early experience of the Great Famine years on the healthy quality of life of middle-aged and elderly people in later life.

Healthy aging is an important aspect of the health and well-being of the elderly. Understanding the causal relationship between early life exposure to the Great Famine in China and the healthy quality of life of middle-aged and elderly people is also an important step in promoting the development of healthy aging. Examining health-related quality of life and related factors is critical for health policymakers, and this information may have a positive role in actively responding to population aging and promoting the healthy development of middle-aged and older adults. Therefore, this study uses the PSM method to eliminate the selection bias caused by survivors exposed to the Great Famine Era and explore the causal effect between exposure to the Famine Era and healthy quality of life.

Materials and methods

Sampling

The dataset originates from the 2022 Ningxia Rural Residents' Health Status and Medical Service Utilization Survey. This study used a multi-stage stratified sampling method, first randomly selecting four representative counties (Haiyuan, Yanchi, Xiji, and Pengyang counties) in the southern mountainous area of Ningxia. Subsequently, all administrative villages within these counties were classified based on socioeconomic indicators (high, medium, and low). Then randomly select 40% of natural villages from each stratum as sample villages. Using systematic sampling method, 20–33 households were selected from the roster of each sample village. This study selected rural middle-aged and elderly people aged 45 and above as the research subjects. The survey was conducted through standardized face-to-face interviews. This study followed the principles of the Helsinki Declaration and was approved by the Institutional Review Board of Ningxia Medical University(2023-G157). All participants gave informed written consent.

From an initial pool of 5,609 completed questionnaires demonstrating 97.25% validity rate, rigorous data quality control measures were implemented. This included logical consistency checks and exclusion of records with critical missing variables or ambiguous responses. The final analytical sample comprised 20,347 individuals from 5,455 households, of whom 9,294 were rural dwellers aged ≥ 45 years, accounting for 45.68% of the study subjects. Based on the sample size formula: $n = \frac{\left(Z_{\alpha/2}+Z_{\beta}\right)^2 \times 2\sigma^2}{d^2}$, $\alpha = 0.05$, $\beta = 0.8$, $\sigma = 0.2$, $d = 0.1$, calculations measured that a sample size of 63 persons was required for each group, for a total of at least 163 persons. Consistent with the research perspective, we eliminated variables with inconsistent age and missing key HRQoL variables and related health indicators, and the final sample size was 5793, accounting for 62.33% of the rural middle-aged and elderly residents aged 45 years or older. Meeting minimum sample size requirements. Participants were categorized into the following two predefined groups according to their date of birth(DOB): (1) Unexposed group, with DOB between January 1, 1962, and December 30, 1977, (2) Exposed group, with DOB before December 31, 1961. Among the 5793 individuals in the sample, 2512 (43.36%) middle-aged and elderly people were exposed to famine.

Measurement

Health-related quality of life using the EQ-5D-3 L instrument

The European five-dimensional quality of life scale (EQ-5D-3 L) was used to measure the health-related quality of life of middle-aged and elderly people. The EQ-5D-3 L instrument is widely used to evaluate an individual's overall health status using a description system and a visual analogue scale (VAS). The description system consists of five questions on five dimensions (5D): mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. The performance level of each dimension of EQ-5D is answered by 3 questions (3 L): no problems, some or moderate problems, extreme problems [16]. The established health utility value was calculated using the EQ-5d-3 L Chinese effect value for China's rural population [17]. The formula for calculating health utility value is as follows [17]: U = 1- 0.067–0.101 × MO2 -0.275 × MO3 -0.103 × SC2- 0.239 × SC3-0.086 × UA2- 0.217 × UA3 -0.110 × PD2- 0.232 × PD3- 0.074 × AD2- 0.172 × AD3- 0.016. MO, SC, UA, PD, and AD stand respectively for mobility, self-care, daily activities, pain/discomfort, and anxiety/depression. 2 and 3 correspond to some or moderate problems and extreme problems respectively. We calculated the health utility value based on the respondents' EQ-5D answers, with 1 representing complete health and 0 representing death. For instance, the value of "33311" was 1 – 0.067 – 0.275 – 0.239 – 0.214 – 0 – 0 – 0.016 = 0.186. The EQVAS is a quantitative measure that records an individual's self-rated health status on a 20-cm vertical visual analog scale, ranging from 0 to 100 (0 represents: the worst health you can imagine; 100 represents: the best health you can imagine) which reports a grade that best describes their self-rated health. The health utility value U is the evaluation utility value based on the perspective of the overall population, and the VAS score is based on the self-evaluation from the respondent's personal perspective. This study evaluates residents' HRQoL based on health utility value U and VAS score.

Confounding covariates

A perfect group of confounding covariates is the basis of exact matching. This study identified 7 confounding covariates from a literature review [1, 13–15], including demographic factors (gender, and education background), behavioral factors (smoking and drinking), physical health factors (BMI and chronic conditions) and socioeconomic factors (economic level).

Statistical analysis

In this study, we selected PSM, which is superior to traditional regression methods in controlling confounding factors, as the key method to eliminate selection bias. "The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates. Both large and small sample theory show that adjustment for the scalar propensity score is sufficient to remove bias due to all observed covariates." For non-randomized studies, observational studies with cross-sectional data take survivors of exposed factors as research subjects and need to reduce the impact of selection bias on causal inference conclusions. The PS is the probability for a subject to receive a treatment conditional on a set of baseline characteristics (confounders). PSM incorporates confounding variables into logistic regression to estimate propensity values, which can convert multidimensional covariates into unidimensional covariate propensity scores (one dimension), and then match patients with similar confounder distributions to balance the covariate distributions of the two groups, and are comparable. Therefore, the differences after matching can be determined as unbiased differences in treatment effects [18, 19].

PSM usually consists of four analysis steps. The first step is the selection of confounders, the second step is the calculation of propensity values, the third step is matching based on propensity values, and the last step is estimating the average treatment effect on the Treated (ATT), which is the effect for those in the treatment group [19]. In order to ensure the reliability and robustness of matching and estimating ATT results, this study adopts three common matching methods, kernel matching, radius matching, and nearest neighbor matching. For the treatment group, this study uses the bootstrap method to estimate ATT and empirical standard errors to avoid the erroneous standard errors present in traditional ATT estimates [12, 20].

We performed Psmatch2 in Stata 16.0 (Stata Corp., College Station, Texas, USA) to conduct the statistical analysis. We provide a preliminary description of baseline characteristics of study subjects' HRQoL. The continuous variables were delineated as means along with standard deviations, whereas the categorical variables were presented as case counts and percentages (%). Student's t-test was used for continuous variables; the chi-square test or analysis of variance was used for categorical variables. For paired data, linear regression analysis was used to explore the impact of experiencing the Great Famine years on HRQoL. All results are based on $P < 0.05$ as the criterion for statistical significance.

Results

Descriptive statistics

Descriptive analyses were carried out for two different types of samples in this study, as well as for the comparison of differences between the two groups of samples. There were 2,512 middle-aged and elderly people exposed to the famine and 3,281 not exposed. U value and VAS score are expressed as mean ± SE. The results showed that the U value and VAS score of the middle-aged and elderly people in the unexposed group were 0.87 ± 0.002 and 74.32 ± 0.248 respectively. The U value and VAS score of the exposed group were 0.79 ± 0.004 and 66.35 ± 0.316 respectively. The difference between the two groups was statistically significant (T test value = 20.11, $P < 0.001$; T test value = 18.83, $P < 0.001$). However, Table 1 shows that there are also statistically significant differences between the two groups of sample populations in the comparison of the other seven covariates. This finding suggests that the causal relationship between middle-aged and older adults' exposure to the Great Famine and their HRQoL cannot be simply inferred.

Propensity score

First, the Logistic regression model is performed by the Great Famine's exposure as the dependent variable, and the 7 association variables are used as independent variables. The regression results show that the overall explanation of the model is good, and other covariates except drinking are statistically significant. These findings indicate that this model has a strong impact on the exposure of middle-aged and elderly people, as shown in Table 2. Second, the regression results were used to establish a prediction model to calculate the tendency of all samples to expose to Great Famine. The higher the tendency, the greater the possibility of the sample people exposed to the famine.

Matching and balanced test

We used the calculated propensity to match the 2512 middle-aged and elderly people who were exposed to famine with the 3281 who do not exposed to famine. To ensure the robustness of the results, we adopt three common matching methods: kernel matching, radius matching, and nearest-neighbor matching. Using the U-value as the outcome variable, 16 people were off support by any of the three matching methods. Using the VAS score as the outcome variable, 16 people were off support by any of the three matching methods. In this study, the independent sample t-test of the 7 covariates between the control group and treatment group was not significant after matching in all three matching samples, as shown in Tables 3 and 4, which met the relevant PSM indicators. Results showed that the 7 covariates did not provide any

Table 1 Descriptive characteristics of the sample before matching

Variables	Total	Exposed group	Unexposed group	χ^2/t	*P*
Gender					
Male(=1)	3122(53.89)	1424(24.58)	1698(29.31)	13.947	< 0.001
Female(=0)	2671(46.11)	1088(18.78)	1583(27.33)		
Education background					
Illiterate(=0)	2391(41.27)	1335(23.05)	1056(18.23)	333.342	< 0.001
Primary school(=1)	2151(37.13)	864(14.91)	1287(22.22)		
Middle school(=2)	972(16.78)	234(4.04)	738(12.74)		
High school background or above(=3)	279(4.82)	79(1.36)	200(3.45)		
Smoking					
No(=0)	4419(76.28)	1989(34.33)	2430(41.95)	20.591	< 0.001
Yes(=1)	1374(23.72)	523(9.03)	851(14.69)		
Drinking					
No(=0)	5329(91.99)	2355(40.65)	2974(51.34)	18.639	< 0.001
Yes(=1)	464(8.01)	157(2.71)	307(5.30)		
Economic level					
Low income	1159(20.01)	611(10.55)	548(9.46)	105.044	< 0.001
Middle and low income	1159(20.01)	558(9.63)	601(10.37)		
Middle income	1158(19.99)	493(8.51)	665(11.48)		
Upper middle income	1159(20.01)	464(8.01)	695(12.00)		
High income	1158(19.99)	386(6.66)	772(13.33)		
BMI					
Normal weight(=0)	3231(55.77)	1417(24.46)	1814(31.31)	88.673	< 0.001
Underweight(=1)	451(7.79)	282(4.87)	169(2.92)		
Overweight(=2)	1615(27.88)	614(10.60)	1001(17.28)		
Obesity(=3)	496(8.56)	199(3.44)	297(5.13)		
Chronic conditions					
NO(=0)	2891(49.91)	881(15.21)	2010(34.70)	390.355	< 0.001
Yes(=1)	2902(50.09)	1631(28.15)	1271(21.94)		
Age(M ± *SD*)	60.35 ± 9.72	69.56 ± 6.40	53.30 ± 4.57	-1.1e + 02	< 0.001

Table 2 Logistic regression analysis of famine exposure

Variables	REF	B	SE	Z	*P*
Gender					
Male	Female	0.92	0.07	12.53	< 0.01
Education background					
Primary school	Illiterate	-0.66	0.07	-9.46	< 0.01
Middle school		-1.33	0.10	-13.56	< 0.01
High school background or above		-1.01	0.16	-6.37	< 0.01
Smoking					
Yes	No	-0.27	0.09	-3.14	0.002
Drinking					
Yes	No	-0.16	0.12	-1.29	0.195
Economic level					
Middle and low income	Low income	-0.09	0.09	-0.93	0.352
Middle income		-0.23	0.10	-2.41	0.016
Upper middle income		-0.28	0.10	-2.91	0.004
High income		-0.40	0.10	-4.16	< 0.01
BMI					
Underweight	Normal weight	0.75	0.12	6.38	< 0.01
Overweight		-0.25	0.07	-3.59	< 0.01
Obesity		-0.31	0.11	-2.78	0.005
Chronic conditions					
Yes	No	0.99	0.06	16.11	< 0.01

valid predictive information about famine exposure after matching. Therefore, it passes the overall balance test.

Sensitivity analysis

Sensitivity analyzes were performed to explore the extent to which hidden selection bias could alter the results of the treatment effectiveness obtained. Generally speaking, if the sensitivity score is greater than or equal to 2, the study is less sensitive and the results are reliable [21, 22]. Therefore, this study conducted sensitivity analysis for U value and VAS score as outcome variables respectively, and the sensitivity scores were 1.3 and 1.8 respectively. Although it did not reach the standard score of ≥ 2, we think it was within the acceptable range.

Final results

After matching based on propensity scores, the bootstrap method was used in this study to estimate the ATT and empirical standard errors of the three matching outcomes. The estimation results show that the HRQoL of middle-aged and elderly people exposed to the Great Famine is significantly lower than that of the group not exposed to the Great Famine. Among the three matching methods, the U value was significantly reduced by 0.0651, 0.0651, and 0.0637, respectively, and the VAS

Table 3 T-test of covariates between treatment and control group after matching (U value)

Variables	Neighbor matching (1:1)		Kernel Matching		Radius matching	
	t value	*P*	t value	*P*	t value	*P*
Gender	0.26	0.798	0.45	0.653	0.51	0.613
Education background	-0.20	0.842	-0.89	0.371	-0.92	0.357
Smoking	1.52	0.129	-0.51	0.608	-0.49	0.621
Drinking	1.96	0.500	-0.33	0.739	-0.25	0.803
Economic level	-0.03	0.976	-0.28	0.779	-0.28	0.780
BMI	-0.17	0.862	-0.46	0.642	-0.25	0.804
Chronic conditions	0.06	0.953	0.20	0.845	0.31	0.760

Table 4 Vas T-test of covariates between treatment and control group after matching (VAS score)

Variables	Neighbor matching (1:1)		Kernel Matching		Radius matching	
	t value	*P*	t value	*P*	t value	*P*
Gender	-0.23	0.820	0.45	0.656	0.52	0.600
Education background	-0.24	0.813	-0.89	0.371	-0.93	0.352
Smoking	1.41	0.159	-0.51	0.608	-0.50	0.615
Drinking	1.90	0.006	-0.33	0.739	-0.25	0.806
Economic level	0.04	0.968	-0.28	0.779	-0.33	0.744
BMI	-0.25	0.799	-0.46	0.645	-0.23	0.820
Chronic conditions	0.03	0.976	0.19	0.846	0.30	0.763

Table 5 Average treatment effect on the treated in three matching methods (U value)

Matching Method	U		ATT	Bootstrap SE	z value	*P* value
	Exposed group	Unexposed group				
Kernel Matching	0.7901	0.8552	-0.0651	0.0050	-12.89	0.000
Radius Matching	0.7901	0.8552	-0.0651	0.0051	-12.87	0.000
Nearest-neighbor Matching	0.7901	0.8538	-0.0637	0.0056	-11.33	0.000

Table 6 Average treatment effect on the treated in three matching methods (VAS score)

Matching Method	EQVAS		ATT	Bootstrap SE	z value	*P* value
	Exposed group	Unexposed group				
Kernel Matching	66.3517	71.2489	-4.8972	0.4424	-11.07	0.000
Radius Matching	66.3517	71.2640	-4.9124	0.4427	-11.10	0.000
Nearest-neighbor Matching	66.3517	70.8590	-4.5074	0.5124	-8.80	0.000

score was significantly reduced by 4.8972, 4.9124, and 4.5074, respectively (see Tables 5 and 6).

It has been noted that important age differences between famine births and study controls were not recognised in the China Famine Study, and that age-adjusted controls were needed to estimate the impact of the famine [23]. In this study it was age that was used in determining whether middle-aged and older people had experienced the Holodomor, allowing for the fact that putting age into the PSM analysis would lead to the presence of full covariance. Therefore, this study first selected middle-aged and older adults by matching them successfully in the PSM analysis. Then, the age variable was included in the linear regression equation to investigate whether age differences lead to misleading results on famine effects. The results of the study showed that famine exposure positively affected both U-values and EQVAS scores in middle-aged and older adults ($B=0.135$, $B=0.620$), but none of the results showed statistical significance. Age negatively affected both U-values and EQVAS scores in middle-aged and older adults (B=-0.04, B=-0.334), and the results were statistically significant (See Tables 7 and 8).

In order to reduce the bias of age differences in the results of the study, 'age-balanced' was used in this study to reduce the effect of age on famine exposure [24]. Some studies have shown that the average age of pre-famine and post-famine babies combined is close to the average age of famine-born babies [25]. Therefore, in this study, middle-aged and elderly people born in 1959–1961 were defined as the famine-exposed group, and middle-aged and elderly people born in 1956–1958 and 1962–1964 were defined as the non-exposed group. After regrouping, there were 416 and 1,227 elderly people

Table 7 Linear regression analysis of U value

Variables	REF	B	SE	T	P
The Great Famine					
Yes	No	0.135	0.007	1.83	0.067
Age		-0.004	0.000	-11.52	< 0.001
Gender					
Male	Female	0.013	0.005	2.53	0.0011
Education background					
Primary school	Illiterate	0.015	0.005	3.18	0.001
Middle school		0.013	0.006	1.98	0.048
High school background or above		0.029	0.010	2.84	0.005
Smoking					
Yes	No				
Drinking					
Yes	No	0.004	0.008	0.53	0.593
Economic level					
Middle and low income	Low income	0.014	0.006	2.20	0.028
Middle income		0.015	0.007	2.33	0.02
Upper middle income		0.001	0.007	0.15	0.885
High income		0.009	0.007	1.38	0.169
BMI					
Underweight	Normal weight	-0.039	0.008	-4.92	< 0.001
Overweight		0.009	0.005	1.89	0.059
Obesity		0.005	0.008	0.63	0.528
Chronic conditions					
Yes	No	-0.057	0.004	-13.18	< 0.001

Table 8 Linear regression analysis of EQVAS

Variables	REF	B	SE	T	P
The Great Famine					
Yes	No	0.620	0.661	0.94	0.348
Age		-0.334	0.035	-9.62	< 0.001
Gender					
Male	Female	1.838	0.443	4.15	< 0.001
Education background					
Primary school	Illiterate	1.912	0.430	4.44	< 0.001
Middle school		2.126	0.578	3.68	< 0.001
High school background or above		4.220	0.919	4.59	< 0.001
Smoking					
Yes	No	-0.677	0.526	-1.29	0.198
Drinking					
Yes	No	2.370	0.740	3.20	0.001
Economic level					
Middle and low income	Low income	1.469	0.580	2.53	0.011
Middle income		1.784	0.582	3.07	0.002
Upper middle income		2.086	0.583	3.58	< 0.001
High income		1.678	0.590	2.84	0.004
BMI					
Underweight	Normal weight	-4.603	0.704	-6.53	< 0.001
Overweight		0.914	0.428	2.14	0.033
Obesity		-0.347	0.676	-0.51	0.608
Chronic conditions					
Yes	No	-8.543	0.388	-21.99	< 0.001

in the exposed and non-exposed groups, with ages of 61.34 ± 3.30 and 61.85 ± 1.28, respectively, which balanced the ages of the two groups. We used kernel matching to explore the effects of Great Famine prenatal exposure and HRQoL in middle-aged and older adults.Using the U-value as the dependent variable, the matching results show that 7 people off support were not matched successfully. Before and after matching, the ATT was 0.017 and 0.012 respectively, but none of them showed statistical significance. Using EQVAS scores as the dependent variable, the matching results showed that before and after matching, the ATT was 0.619 and 0.219, respectively, but both also showed statistical significance. (see Table 9).

Table 9 Average treatment effect of great famine prenatal exposure on HRQoL

Matching Method	Exposed group	Unexposed group	ATT	SE	T
U-value	0.855	0.843	0.012	0.008	1.55
EQVAS	70.005	69.786	0.219	0.816	0.27

Discussion

This study aimed to explore whether the exposure of middle-aged and elderly people to the Great Famine has an impact on HQRoL by adopting control and treatment groups using the PSM approach. This study was based on data from a sample population of middle-aged and elderly people in Ningxia, China in 2022, to better understand the impact of exposure to the Great Famine on their HRQoL. Specifically, the HRQoL of middle-aged and elderly people exposed to the Great Famine was relatively poor compared with the unexposed group. After controlling for confounders through PSM methods, the independent effect of famine exposure did not show statistical significance after correcting for covariates such as age, although preliminary analyses showed that the famine-exposed group had lower HRQoL scores than the non-exposed group. Further sensitivity analyses using different definitions of exposure (the 1959–1961 birth cohort as the exposed group and the 1956–1958 and

1962–1964 birth cohorts as the control group) showed that the results remained robust.

Notably, there was a significant age stratification problem between the exposed and non-exposed groups, which may have introduced residual confounding through the complex age-health non-linear relationship. Although this study attempted to control for age effects through PSM and regression adjustments, it may be difficult for traditional methods to fully capture the confounding of results by cohort heterogeneity. This finding suggests that future studies need to employ more refined causal inference frameworks to isolate the independent effects of famine exposure.

Other scholars have also found that experiencing the Great Famine in early life not only reduces self-health status in adulthood but also greatly reduces physical function in later life [5, 26]. The Great Chinese Famine not only affects the occurrence of cardiovascular disease, hypertension and other diseases and the physical health of the exposed population, but also has an intergenerational effect, affecting the physical health and cognitive function of the offspring of the exposed population [27–31]. Laura's research found that exposure to the Dutch Famine affected the physical health of exposed people and accelerated cognitive aging [32]. Although, the PSM-corrected effect did not reach statistical significance in this study. However, we still agree with the view reported by Xu et al. [33]. Because foetuses, infants, children and adults in poorer health are more likely to die in famine, the surviving famine group may consist of the healthiest individuals who have adapted to the unfavourable environment, not to mention that our study population is middle-aged and elderly. Analysing the reasons for such differential results may be due to the presence of survivor bias.

Exposure to famine at an early age may be associated with the growth and development of life and affect HRQoL in adulthood. Previous research indicates that malnutrition early in life can permanently alter gene expression in the hypothalamus, a core element in the development of metabolic disease [34]. Hypotheses about early origins of disease suggest that adaptations induced by severe malnutrition during fetal, infancy, and early childhood may contribute to early survival but may also increase the risk of certain common metabolic diseases later in life [31]. Therefore, early malnutrition may bring long-term health risks. However, historical famines provide us with a unique setting to study the effects of early severe famine exposure on healthy quality of life [35]. With the acceleration of aging, our government has stepped up efforts to promote institutional care and long-term care insurance to improve the popularity and economic burden of elderly care. However, the long-term care system is still in its infancy, and the elderly face many physical and mental problems [36]. Therefore, it is crucial to pay close attention to the life and health of middle-aged and elderly people and improve the quality of life of the elderly. The government should increase investment in medical and elderly care services, improve service quality, and explore a long-term care insurance system to reduce financial barriers for the elderly to improve their health and quality of life.

The EQ-5D has been widely used in public health systems as a tool for health policy program evaluation [37]. However, this study used the three-level EuroQol-5D scale (EQ-5D-3 L) [17], which is weighted according to the health status preferences of the Chinese rural population, combined with the visual analogue scale (VAS) to measure the health-related quality of life of the study population. Wei Li and other researchers used Multivariable logistic regression to explore the impact of exposure to famine in early life on the self-rated health status of Chinese adults [5].

This study used PSM to construct a quasi-experimental study with a control group and an experimental group of 2512 people each. Balancing 7 covariates that may have an impact on HRQoL, the results of no significant differences between all three matched control and treatment groups further indicate that the control and treatment groups were well balanced. Compared with other research methods, PSM selects experiments and control groups with the same propensity scores for comparison, which reduces the interference of confounding factors as much as possible, increases the comparability of research subjects, and makes the causal relationship of experimental conclusions more convincing.

In this study, PSM was used to construct a balanced cohort, which controls confounders more tightly than traditional regression models, and although the covariates were balanced after matching, the difference in age span between the exposed and non-exposed groups may still famine influence the results of the study to produce bias. The present study recognises the important issue of age differences between famine births and study controls, making the results misleading. It has been shown that in future famine studies, there should be a focus on age-balanced controls, that exposed and non-exposed groups should be correctly defined according to sample characteristics, and that sensitivity analyses can be conducted using different methods of definition to ensure robustness of results [23]. At the data analysis stage, age-balanced controls, difference-in-difference analysis, or age-period-cohort analysis, and other appropriate methods to minimise the bias of age differences on the results [33, 38].

Famine exposure provides a natural experiment, especially studies on the comparison of famine exposure in the Netherlands and China. Most studies have shown consistent associations between prenatal famine and adult body size, diabetes and schizophrenia [39, 40]. Although the direct effect of famine exposure on HRQoL did not reach statistical significance in the present study, its potential health inequality warnings need to be kept in mind, and a growing body of literature also highlights the link between foetal malnutrition and poor health in later life, but the findings with health status still need to be considered with caution [39–41].

Strengths and limitations

There were limited literature reports on health-related quality of life and its influencing factors in middle-aged and elderly people in China. This study explores the impact of famine exposure on health-related quality of life, providing a new perspective for related research. However, some limitations of our study should be mentioned. First, this study failed to examine the effects of famine exposure on health-related quality of life in male and female separately. Previous research has found that during famines, male survivors were stronger and healthier [6, 7, 42]. This bias may underestimate the impact of hunger exposure on men's HRQoL. Second, our study cannot explore the different impact effects across different provinces. The severity of famine varied across Chinese provinces due to differences in regional climate, population density, and local food policies. Due to the selection of the southern mountainous areas of Ningxia for this study, prefecture-level cohort size shrinkage (CSSI) [33]indices were not available, and there are some limitations on the dose effect between famine exposure and HRQoL. Finally, this study cannot yet confirm the potential influencing mechanism between exposure to the Great Famine and HRQoL. Also, based on the availability of data, this study has not yet been able to explore the bias of some early factors (e.g., early physical health status, early family economic factors) on the outcomes. Despite these limitations, this study assesses the impact of famine on HRQoL in China. These important findings expand our understanding of the impact of HRQoL in middle-aged and older adults in China, provide evidence for HRQoL research, and can be used to identify potential high-risk groups. This information may provide some inspiration for some countries and regions that still have food security and food shortage problems to formulate effective public health strategies to maintain high-quality and healthy life for the elderly.

Conclusions

In conclusion, this study examined the long-term effects of prenatal exposure to the Chinese Famine on HRQoL among middle-aged and elderly people in Ningxia, China. Although preliminary analyses suggested a potential association between famine exposure and lower HRQoL, there was no statistically significant independent effect after balancing for age variables. The non-overlapping age spans between the exposed and non-exposed cohorts, coupled with potential survivor bias, may have introduced residual confounders that could not be fully addressed by traditional methods. These findings highlight the need for sound causal inference methods to clarify the complex interactions between historical adversity and ageing health. Although the results were not significant, this study highlights the importance of preventive health investments for famine survivors. Future policies should consider combining historical exposure data with contemporary health surveillance to address potential health risks.

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Author contributions
All authors contributed to the study conception and design. Data collection was conducted by H.Q. W.W. J.H. X.M. Z.H. B.G. and J.D. Quantitative data analysis was performed by Z.H, J.H. and B.G. Qualitative data analysis was performed by X.M, and J.D. The frst draft of the manuscript was written by W.W. and J.H. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
We hereby affirm that informed consent was obtained from all participants or their legal guardians, including those with "No education." The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethics Committee of Ningxia Medical University(2023-G157). The patients/participants provided their written informed consent to participate in this study. Participants were fully informed, and their voluntary participation was a primary consideration throughout the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References

1. Chen C, Liu GG, Shi QL, Sun Y, Zhang H, Wang MJ, et al. Health-Related quality of life and associated factors among Oldest-Old in China. J Nutr Health Aging. 2020;24:330–8.
2. Li H-W, Lee W-J, Lin M-H, Peng L-N, Loh C-H, Chen L-K, et al. Quality of life among Community-Dwelling Middle-Aged and older adults: function matters more than Multimorbidity. Arch Gerontol Geriatr. 2021;95:104423.
3. Tu W-J, Slevin M, Xianwei Zeng. Strategies for managing the aging tsunami in China: Weifang model. J Am Geriatr Soc. 2019;67:403–4.
4. Yi H, Wang Z. Multidimensional health heterogeneity of Chinese older adults and its determinants. SSM - Popul Health. 2023;24:101547.
5. Li W, Sun N, Kondracki AJ, Kiplagat S, Osibogun O, Kalan ME, et al. Exposure to famine in early life and self-rated health status among Chinese adults: a cross-sectional study from the Chinese health and retirement longitudinal study (CHARLS). BMJ Open. 2021;11:e048214.
6. Ningjian Wang Y, Chen Z, Ning Q, Li B, Han C, Zhu, et al. Exposure to famine in early life and nonalcoholic fatty liver disease in adulthood. J Clin Endocrinol Metabolism. 2016;101:2218–25.
7. Wang Z, Li C, Yang Z, Ma J, Zou Z. Fetal and infant exposure to severe Chinese famine increases the risk of adult dyslipidemia: results from the China health and retirement longitudinal study. BMC Public Health. 2017;17:488.
8. Wang Z, Li C, Yang Z, Zou Z, Ma J. Infant exposure to Chinese famine increased the risk of hypertension in adulthood: results from the China health and retirement longitudinal study. BMC Public Health. 2016;16:435.
9. Zhenghe Wang Z, Zou Z, Yang Y, Dong J, Song B, Dong, et al. The association between fetal-stage exposure to the China famine and risk of diabetes mellitus in adulthood: results from the China health and retirement longitudinal study. BMC Public Health. 2018;18:1205.
10. Xu RH, Shamay SM, Ng N, Luo D, Dong S, Zhang. Measurement of Health-Related quality of life in individuals with rare diseases in China: Nation-Wide online survey. JMIR Public Health Surveill. 2023;9:e50147.
11. Nancy J, Devlin R, Brooks. EQ-5D and the EuroQol group: past, present and future. Appl Health Econ Health Policy. 2017;15:127–37.
12. Wang Y, Zhang H, Feng T, Wang H. Does internet use affect levels of depression among older adults in China? A propensity score matching approach. BMC Public Health. 2019;19:1474.
13. Billingsley Kaambwa L, Gill N, McCaffrey E, Lancsar ID, Cameron M, Crotty, et al. An empirical comparison of the OPQoL-Brief, EQ-5D-3 L and ASCOT in a community dwelling population of older people. Health Qual Life Outcomes. 2015;13:164.
14. Elena Savoia MP, Fantini PP, Pandolfi L, Dallolio, Natalina Collina. Assessing the construct validity of the Italian version of the EQ-5D: preliminary results from a cross-sectional study in North Italy. Health Qual Life Outcomes. 2006;4:47.
15. Bodur S, Dayanir Cingil D, USING, WHOQOL-BREF TO EVALUATE QUALITY, OF LIFE AMONG TURKISH ELDERS IN DIFFERENT RESIDENTIAL ENVIRONMENTS. J Nutr. 2009;13.
16. Agota Szende B Janssen, Juan Cabases, editor. Self-Reported population health: an international perspective based on EQ-5D. Dordrecht: Springer Netherlands; 2014.
17. Gordon G, Liu H, Guan X, Jin H, Zhang SA, Vortherms. Hongyan Wu. Rural population's preferences matter: a value set for the EQ-5D-3L health States for China's rural population. Health Qual Life Outcomes. 2022;20:14.
18. Paul R, Rosenbaum, Donald B, Rubin. The central role of the propensity score in observational studies for causal effects [J]. Biometrika. 1983;70(1):41–55. https://doi.org/10.1093/biomet/70.1.41
19. Umberto Benedetto, Stuart J, Head GD, Angelini, Eugene H, Blackstone. Statistical primer: propensity score matching and its alternatives†. Eur J Cardiothorac Surg. 2018;53:1112–7.
20. Jiaqi Liang Z, Wang HCZQ. Using propensity score matching to balance the baseline characteristics. J Thorac Oncol. 2021;16:e45–6.
21. Dillie KS, Fleming MF, Mundt MP, French MT. Quality of life associated with daily opioid therapy in a primary care chronic pain sample. J Am Board Family Med. 2008;21:108–17.
22. PR Rosenbaum. Overt bias in observational studies. Observational Stud. 2002. https://doi.org/10.1007/978-1-4757-3692-2_3.
23. Li C, Lumey LH. Early-Life exposure to the Chinese famine of 1959–1961 and type 2 diabetes in adulthood: A systematic review and Meta-Analysis. Nutrients. 2022;14:2855.
24. Liu C, Li C. The need for appropriate 'age-balanced' controls and transparent reporting in Chinese famine studies: a re-analysis of the China Patient-centred evaluative assessment of cardiac events million persons project. Eur J Prev Cardiol. 2023;30:e16–7.
25. Li C, Lumey L. Exposure to the Chinese famine of 1959–61 in early life and long-term health conditions: a systematic review and meta-analysis. Int J Epidemiol. 2017;46:1157–70.
26. Tao T, Dai L, Ma J, Li Y, Guo Z. Association between early-life exposure to the great Chinese famine and poor physical function later in life: a cross-sectional study. BMJ Open. 2019;9:e027450.
27. Tan CM, Tan Z, Zhang X. The intergenerational legacy of the 1959–1961 great Chinese famine on children's cognitive development. Econ Hum Biology. 2023;51:101300.
28. Li Y, Li Y, Edip Gurol M, Liu Y, Yang P, Shi J et al. In utero exposure to the great Chinese famine and risk of intracerebral hemorrhage in midlife. Neurology. 2020;94.
29. Korbua Srichaikul RA, Hegele, David JA, Jenkins. Great Chinese famine and the effects on cardiometabolic health for future generations. Hypertension. 2022;79:532–5.
30. Guo J, Di Teng X, Shi Y, Li J, Ba B, Chen, et al. Exposure to the Chinese great famine in early life and thyroid function and disorders in adulthood: A Cross-Sectional study. Thyroid. 2021;31:563–71.
31. Zhenghe Wang Y, Dong R, Xu X, Wang Y, Li ZZ. Early-Life exposure to the Chinese great famine and later cardiovascular diseases. Int J Public Health. 2021;66:603859.
32. Laura C. Schulz. The Dutch hunger winter and the developmental origins of health and disease. Proc Natl Acad Sci USA. 2010;107:16757–8.
33. Xu H, Li L, Zhang Z, Liu J. Is natural experiment a cure? Re-examining the long-term health effects of China's 1959–1961 famine. Soc Sci Med. 2016;148:110–22.
34. Ricardo Orozco-Solís RJB, Matos et al. Omar Guzmán-Quevedo, Sandra Lopes De Souza, Audrey Bihouée, Rémi Houlgatte,. Nutritional Programming in the Rat Is Linked to Long-Lasting Changes in Nutrient Sensing and Energy Homeostasis in the Hypothalamus. PLoS ONE. 2010;5:e13537.
35. Susanne R, De Rooij, Tessa J, Roseboom. The developmental origins of ageing: study protocol for the Dutch famine birth cohort study on ageing. BMJ Open. 2013;3:e003167.
36. Li F, Otani J. Financing elderly People's long-term care needs: evidence from C Hina. Health Plann Manage. 2018;33:479–88.
37. Peter J, Neumann, Joshua T. Cohen. QALYs in 2018—Advantages and concerns. JAMA. 2018;319:2473.
38. Li C, Tobi EW, Heijmans BT, Lumey LH. The effect of the Chinese famine on type 2 diabetes mellitus epidemics. Nat Rev Endocrinol. 2019;15:313–4.
39. Ó, Gráda C, Li C, Lumey LH. How much schizophrenia do famines cause? Schizophr. 2023;9:90.
40. Lumey LH, Stein AD, Susser E. Prenatal famine and adult health. Annu Rev Public Health. 2011;32:237–62.
41. Li C, Lumey LH. Interaction or mediation by adult obesity of the relation between fetal famine exposure and type 2 diabetes? Int J Epidemiol. 2019;48:654–6.
42. Li Y, Zhao L, Yu D, Ding G. Exposure to the Chinese famine in early life and depression in adulthood. Psychol Health Med. 2018;23:952–7.