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Depreciation, Investment, and Efficiency of Health Capital: An Empirical Analysis of Self-Rated Health Among Young-Old Adults

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ABSTRACT

Multiple factors associated with young-old adults' self-rated health (SRH) have been identified in previous studies, yet the quantitative ranking of their relative importance remains limited. Grounded in Grossman's Health Production Function theory, this research evaluates associations between chronic disease (health capital depreciation), income (investment capability), psychological flourishing (investment efficiency), and young-old adults' SRH. Drawing on 2022 China Family Panel Studies data, multiple linear regression, relative weight analysis (RWA), and restricted cubic spline (RCS) were employed to examine these relationships. Chronic disease stands out as the strongest predictor (48.79%), followed by depression (12.86%), relative income (11.00%), and subjective well-being (9.39%), with RCS revealing non-linear associations between psychological flourishing and SRH. Health interventions should prioritize chronic disease management and mental health services while addressing income-related health inequalities, and multi-source longitudinal data integration and machine learning methods could deepen the understanding of health production mechanisms in future research.

1.Introduction

1.1.Research background and significance

China is experiencing fast population aging[1]. According to the Seventh National Population Census, individuals aged 60 and above have reached 264 million, representing 18.70% of the total population[2]. Young-old adults (aged 60-69) constitute a critical demographic transitioning from active labor force participation to retirement; their health status bears implications not only for individual quality of life but also for social medical resource allocation and pension security system sustainability.

Self-rated health — an individual's subjective health evaluation — is an independent, important predictor of all-cause mortality, functional decline, and healthcare utilization[3]. Compared with objective health indicators, SRH integrates multi-dimensional information, including physiological, psychological, and social domains, thereby reflecting an individual's health state more comprehensively[4]. Given that young-old adults experience a critical period of health differentiation, analyzing the multiple determinants of their SRH has noteworthy public health implications.

Grossman's Health Production Function theory conceptualizes health as a form of capital stock subject to investment, jointly influenced by initial endowment, investment level, and depreciation rate[5]. This theoretical framework offers a systematic lens for understanding multidimensional determinants of health among young-old

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adults. Existing research, however, predominantly examines single-dimensional factors, lacking integration of physiological, economic, and psychological elements into unified frameworks or quantitative comparisons of relative importance.

Drawing on CFPS 2022 data, this research employs relative weight analysis to quantify physiological, economic, and psychological contributions to young-old adults' SRH. Restricted cubic spline (RCS) analysis explores the dose-response relationships among key variables. From a data science perspective, RWA addresses multicollinearity in quantifying proportional contributions to R^2, while RCS enables flexible exploration of nonlinear relationships without preset parameter constraints, providing empirical evidence for targeted health interventions.

1.2.Literature review

1.2.1.Physiological factors: chronic disease as health capital depreciation

Chronic disease represents the core physiological factor in older adults' SRH. Research indicates that the number of chronic diseases correlates negatively with SRH: each additional chronic disease reduces the SF-12v2 Physical Component Summary (PCS) score by 3.1-6.2 points[6]. Different chronic disease types exert varying impacts on SRH: cardiovascular disease and diabetes patients demonstrate remarkably lower SRH scores than the control groups, with comorbidity prevalence leading to cumulative disease burden[7]. On one hand, chronic disease is strongly associated with functional limitations and symptomatic burden; on the other hand, chronic disease indirectly relates to health evaluation through psychological pathways such as depressive symptoms. Studies have shown that depressive symptoms play an important mediating role between chronic disease and SRH[8], meaning that physical illness further reduces SRH scores by inducing psychological depression.

1.2.2.Economic factors: income as health investment capacity

Socioeconomic status (SES) is a major source of health inequality[9]. Among young-old adults (60-69 years), where occupational status transitions to retirement, income is a core SES indicator. It directly determines older adults ' health investment capacity (e.g., nutrition, healthcare service accessibility) and maintains a stable positive association with SRH[10][11]. Due to social comparison mechanisms, relative income is considered a better predictor of SRH than absolute income[12]. While education enhances health literacy and lifestyle choices, income relates more directly to healthcare access during health deterioration. Higher educational attainment can partially buffer the negative health impacts of low income according to research findings[13].

1.2.3.Psychological factors: subjective psychological flourishing, efficiency, and regulatory mechanisms

Within the Health Production Function framework, "Efficiency" refers to parameters regulating health investment productivity. While traditional theory often views education as the primary efficiency parameter, this study conceptually extends this to subjective psychological flourishing, treating it as a form of "psychological human capital." This distinction proves critical: chronic disease represents health capital depreciation (health stock loss), whereas psychological flourishing functions as the efficiency parameter determining investment-to-health conversion rates (e.g., through enhanced behavioral adherence or resource optimization).

Subjective psychological flourishing thus plays regulatory and efficiency-enhancing roles in the health production function, with different dimensions exhibiting distinct contribution patterns while all directly improving SRH scores[14]. Life satisfaction, as the cognitive evaluation dimension, increases the probability of SRH improvement by 23% four years later for every one standard deviation increase[15]. Meaning in life, as the purpose-oriented dimension, also demonstrates a noteworthy direct positive effect on SRH[16]. This effect operates independently of demographics, SES, and lifestyle, indicating its unique predictive value[17].

Depressive symptoms represent the most noteworthy negative predictor among psychological factors: higher levels of depressive symptoms correlate with more negative health evaluations[18]. Besides, as a critical psychological mechanism, depression links physiological status to health evaluation[19]. Previous studies have identified it as a pathway bridging chronic disease and health, intimately connecting meaning in life with health outcomes[20]. Given these complex interrelations, quantifying depression's net contribution and relative importance alongside physiological and economic inputs becomes important for understanding the hierarchy of health determinants.

1.2.4.Limitations of existing research

Existing research exhibits four key limitations: (1) Insufficient integration of multidimensional factors makes determining the relative importance of each factor difficult; (2) Lack of exploration regarding non-linear relationships; (3) Inadequate explanation of psychological mechanisms' role in the health production function; (4) Limited systematic research specifically targeting Chinese young-old adults.

2.Theoretical framework and research hypotheses

2.1.Theoretical foundation of the health production function

Grossman's Health Production Function theory treats health as a stock of human capital whose value manifests in two aspects: as a consumption good providing utility and as an investment good increasing healthy time. According to HPF theory, the evolution of an individual's health stock Ht at time t follows the equation:

$$H_{t+1}=H_t+I_t-\delta_t H_t \quad (1)$$

where I_t represents health investment and δ_t denotes the health capital depreciation rate. For the young-old adult population, this study operationalizes the theoretical elements into three dimensions:

(1)Health Capital Depreciation (δ): Primarily manifests as the superposition of natural depreciation (physiological function decline) and accelerated depreciation caused by

chronic disease burden, with chronic disease being the core mechanism for the accelerated depreciation of health capital in young-old adults.

(2)Health Investment Capacity (*I*): Economic resources, influenced by education, time costs, and social support networks, are core determinants. Income positively associates with healthcare accessibility, healthy lifestyle choices, and social participation, thereby determining health investment quantity and quality.

(3)Health Investment Efficiency Parameter: This study introduces psychological status (comprising subjective psychological flourishing and depression) as the efficiency parameter. Subjective psychological flourishing (subjective well-being, meaning in life, and life satisfaction) positively regulates the efficiency of converting material investments into health outcomes by enhancing adherence and coping abilities. Conversely, depression acts as a negative efficiency factor, potentially impeding the conversion of health resources into health stock.

2.2.Research hypotheses

Based on the above theory and literature, this study proposes the following hypotheses:

H1 (Main Effects): Chronic disease (H1a) and depression (H1d) are negatively associated with SRH; income (H1b) and each dimension of subjective psychological flourishing (H1c) are positively associated with SRH.

H2 (Relative Importance): As a direct factor of capital depreciation, chronic disease has the greatest relative weight in predicting SRH.

H3 (Nonlinearity): Non-linear relationships exist between subjective well-being and meaning in life with SRH, with specific threshold effects.

3.Research design

3.1.Data sources and sample selection

Data for this study derive from the 2022 China Family Panel Studies (CFPS), a nationally representative survey using multistage stratified sampling, implemented by Peking University's Institute of Social Science Survey.

Sample selection criteria include: (1) aged 60–69 years old; (2) no missing values in core variables; and (3) no logical inconsistencies. A total of 3,666 valid cases are included, with a mean age of 66.40 years.

The dependent variable is SRH, measured with a single item: "How would you rate your current physical health?" Response options range from "very unhealthy (0)" to "very healthy (4)," with higher scores indicating better SRH. Assessment criteria and descriptive results for the independent variable are presented in Table 1. Control variables include gender, educational attainment, place of residence, social connections, and social status.

Table 1. Assessment criteria and collection results for independent variables

Independent Variables	Chronic Disease	Income Relative to Local Standards	Subjective Well-Being	Meaning in Life	Life Satisfaction	Depression
Assessment criteria	Ask whether the doctor informed you that you have a chronic illness Code as "No" (0), "Yes" (1)	Ask: "Where do you think your household's economic status ranks locally?"Use a 5-point scale from "Far below average" (1) to "Far above average" (5)	Ask: "Overall, how happy are you with your life?" Use a 0-10 scale, where 0 indicates "very unhappy" and 10 indicates "very happy".	Ask: "How meaningful do you find your life?" using a 0-10 scale, where 0 indicates "completely meaningless" and 10 indicates "extremely meaningful"	Ask "How satisfied are you with your current life" using a 5-point scale ranging from "Very dissatisfied" (1) to "Very satisfied" (5)	Based on the Center for Epidemiological Studies Depression Scale - 8 scale, participants were asked about the frequency of depressive symptoms in the past week. Responses were categorized as "No (< 7 points)" (0) or "Yes (≥7 points)" (1) according to the standard threshold (7 points)[22].
Mean/Percentage	30.69%	3.12	7.62	7.51	4.21	25.18%
Standard Deviation	-	1.148	2.174	2.188	0.882	-

Methodological note on chronic disease measurement

In this study, chronic disease is operationalized as binary (presence/absence) due to CFPS 2022 data constraints. This dichotomous coding implies disease homogeneity, potentially underestimating disease burden complexity. Previous research has demonstrated that comorbidity patterns often exhibit dose-response relationships with health outcomes and may involve synergistic detrimental effects[21]. The ideal approach would employ weighted comorbidity indices (e.g., age-adjusted Charlson Comorbidity Index) to capture disease severity and interaction effects. However, such detailed clinical diagnostic data are not available in the current dataset. Despite this

limitation, binary measurement remains justified for capturing "health capital depreciation" in Grossman's framework—distinguishing presence versus absence of accelerated depreciation. Future studies with access to detailed clinical diagnoses should introduce weighted comorbidity indices to more accurately quantify disease impact[22].

3.2.Analytical methods

SPSS 26.0 was used for descriptive statistics and multiple linear regression analysis. In the regression analysis, the Enter Method was employed to screen variables, addressing multicollinearity issues and identifying the optimal model. The RWA-Web online tool (Relative Importance and RWA Web — Scott Tonidandel, Ph.D.) was used for Relative Weight Analysis, quantifying each variable's proportional contribution to R^2 through orthogonal decomposition. Restricted Cubic Spline (RCS) analysis was conducted using the rcssci package in R 4.5.1 to examine non-linear relationships between key continuous variables (subjective well-being and meaning in life) and SRH, with 3 knots placed at the 10th, 50th, and 90th percentiles of the predictor distribution — consistent with Harrell's recommendation for optimizing the flexibility-parsimony trade-off[23]. RCS provides a data-driven approach to explore non-linear patterns without presetting parameter forms, which is more flexible than traditional polynomial regression. Binary multiple logistic regression analysis was used for robustness testing of the linear regression model.

While H3 specifically predicts nonlinear relationships, the primary multiple linear regression model (Table 3) employs linear specifications for the psychological flourishing variables. This methodological choice reflects the analytical priorities: (1) the primary research question (H1-H2) focuses on relative importance comparison, which the linear model adequately addresses; (2) nonlinear effects are explored through RCS analysis as the dedicated analytical framework for this purpose, avoiding multicollinearity issues that would arise from including both linear and polynomial terms in the same model; (3) the linear coefficients still provide valid unbiased estimates of average treatment effects across the distribution. Thus, RCS analysis and linear regression serve complementary purposes — the former reveals the dose-response curve pattern, while the latter quantifies the average effect and enables relative weight comparison. This separation is theoretically justified and methodologically sound for the two-pronged analytical objectives.

4.Empirical results analysis

4.1.Descriptive statistics

The average age of the sample was 66.40 years, with males accounting for 52.24%. Educational attainment was predominantly at the primary education level or below (54.01%). 30.69% reported chronic disease, and 25.18% exhibited depressive symptoms. The average SRH score was 1.70 (falling between "unhealthy" and "fair").

4.2.Univariate linear regression results

Table 2 shows univariate linear regression results for SRH. Except for place of residence, all variables were remarkably correlated with SRH.

Table 2. Univariate linear regression results (N = 3666)

Predictor Variable	B	SE	β	t	*P*	R^2
Chronic disease (Yes = 1)	-0.935	0.042	-0.342	-22.037	< 0.001	0.117
Depression (Yes = 1)	-0.678	0.047	-0.234	-14.542	< 0.001	0.055
Income Relative to Local Standards	0.225	0.018	0.205	12.704	< 0.001	0.042
Subjective well-being	0.134	0.009	0.231	14.404	< 0.001	0.054
Meaning in Life	0.128	0.009	0.222	13.753	< 0.001	0.049
Life Satisfaction	0.277	0.023	0.194	11.945	< 0.001	0.037
Gender (Male = 1)	0.231	0.041	0.091	5.561	< 0.001	0.008
Education (secondary education and above = 1)	0.176	0.042	0.070	4.229	< 0.001	0.005
Age	-0.012	0.005	-0.039	-2.362	0.018	0.002
Social Connections	0.080	0.010	0.128	7.789	< 0.001	0.016
Social Status	0.165	0.018	0.146	8.938	< 0.001	0.021
Place of Residence (urban = 1)	0.062	0.042	0.024	1.482	0.138	0.001

Core predictor variables showed the following patterns: Chronic disease demonstrated the strongest negative association, with those having chronic disease scoring an average of 0.935 points lower in SRH than those without (β = -0.342, $P < 0.001$). Depression also showed a substantial negative association (β = -0.234, $P < 0.001$), with affected individuals scoring 0.678 points lower on average. Income relative to local standards showed a positive association (β = 0.205, $P < 0.001$), with each level increase corresponding to a 0.225-point increase in SRH. The three psychological flourishing dimensions all demonstrated positive associations: subjective well-being (β = 0.231), meaning in life (β = 0.222), and life satisfaction (β = 0.194).

Among demographic and social control variables: Males reported an average 0.231-point higher SRH than females ($P < 0.001$). Educational attainment showed a modest positive

association, with those having secondary education or above scoring 0.176 points higher than those with primary education or below ($P < 0.001$). Each additional year of age was associated with a 0.012-point decrease in SRH ($P = 0.018$). Social connections ($\beta = 0.128$) and social status ($\beta = 0.146$) also showed noteworthy positive associations with SRH.

4.3.Multiple linear regression results

Relative Weight Analysis assessed each predictor's unique contribution to explained variance in the Table 3 model. Raw relative weights represent each predictor's proportion of total R^2, summing to the model's unadjusted R^2 (0.2046). To facilitate interpretation, each raw weight was rescaled by dividing it by the total R^2 and converting it to a percentage (Rescaled Relative Weight (%)), representing the predictor's share of the model's explainable variance.

Table 3. Multiple linear regression results (N = 3666)

Variable	B	SE	β	t	*P*	VIF
Chronic disease (Yes = 1)	-0.821	0.041	-0.300	-20.021	< 0.001	1.035
Depression (Yes = 1)	-0.329	0.046	-0.113	-7.096	< 0.001	1.174
Income Relative to Local Standards	0.131	0.018	0.120	7.452	< 0.001	1.184
Subjective well-being	0.053	0.012	0.091	4.316	< 0.001	2.057
Life Satisfaction	0.076	0.025	0.053	3.014	0.003	1.426
Meaning in Life	0.030	0.012	0.052	2.472	0.013	2.030
Gender (Male = 1)	0.119	0.038	0.047	3.119	0.002	1.057
Education (secondary education and above = 1)	0.082	0.040	0.033	2.068	0.039	1.141
Age	-0.010	0.005	-0.033	-2.191	0.028	1.073

Note: Raw Relative Weight values sum to the model's unadjusted R^2 (0.2046). Rescaled Relative Weight (%) = (Raw Weight / 0.2046) × 100.

The results show that chronic disease is the most important predictor of SRH ($\beta = -0.300$). Young-old adults with chronic disease scored an average of 0.821 points lower in SRH than those without, providing evidence for Hypothesis H1a and reflecting the strong association between disease burden and health capital depreciation. Depressive symptoms also showed a noteworthy negative association ($\beta = -0.113$): individuals with depressive tendencies scored 0.329 points lower than those without, validating Hypothesis H1d.

Regarding economic income, for each increase in income level, the SRH score increased by 0.131 points ($\beta = 0.120$), confirming Hypothesis H1b and reflecting the strong association of economic conditions with people's health investment capability and health status.

At the psychological level, subjective well-being ($\beta = 0.091$), life satisfaction ($\beta = 0.053$), and meaning in life ($\beta = 0.052$) all demonstrated noteworthy positive associations with SRH, validating Hypothesis H1c. Each 1-point increase in subjective well-being, life satisfaction, and meaning in life increased SRH by 0.05, 0.076, and 0.03 points, respectively. These three psychological indicators collectively reflect the important predictive role of subjective psychological flourishing in health perception.

4.4.Results of relative weight analysis

The results of the relative weight analysis are shown in Table 4. The nine predictor variables collectively explain 20.46% of the variance in SRH.

Table 4. Relative weight analysis results

Variable	Original Relative Weight	Rescaled Relative Weight(%)	Rank
Chronic Disease	0.0998	48.79	1
Depression	0.0263	12.86	2
Income Relative to Local Standards	0.0225	11.00	3
Subjective Well-Being	0.0192	9.39	4
Meaning in Life	0.0155	7.58	5
Life Satisfaction	0.0127	6.22	6
Gender	0.0045	2.20	7
Education	0.0025	1.23	8
Age	0.0015	0.73	9
Total	0.2046	100.00	-

Chronic disease was identified as the most influential predictor, accounting for 48.79% of the total explained variance (original RWA weight 0.0998 out of model $R^2 = 0.2046$)—far exceeding all other variables—thereby strongly validating H2. This indicates that among the explained variance in SRH (20.46%), chronic disease alone accounts for nearly half. This finding shows the fundamental role of disease as a driver of health capital depreciation. Depression ranks second (12.86%), with a relative weight slightly higher than that of income (11.00%). The three dimensions of subjective psychological flourishing jointly contribute 23.19%, surpassing the individual contribution of income and showing the overall importance of psychological factors as parameters of investment efficiency.

Figure 1 visually illustrates the relative contributions of each variable. Chronic disease alone accounts for nearly half of the explanatory power (48.79%). Mental health – related variables (depression plus the three dimensions of subjective psychological flourishing) together account for 36.05%. Economic variables (income) account for 11.00%, and demographic variables account for 4.16%. This pattern suggests that health interventions should prioritize disease management while simultaneously strengthening mental health services.

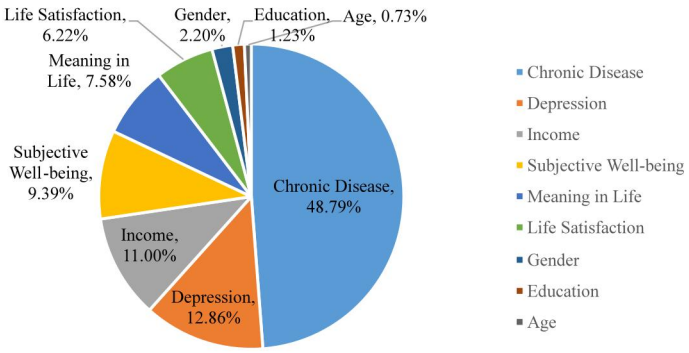

Fig 1. Pie chart of relative weights of variables

4.5.Results of restricted cubic spline analysis

4.5.1.Dose-response relationship of subjective well-being

Figure 2 presents the RCS analyses of subjective well-being and SRH. The univariate RCS (A) reveals a noteworthy dose–response relationship (nonlinearity test, $P < 0.001$) with an overall increasing trend. After adjusting for covariates (B), the dose–response relationship remains noteworthy ($P = 0.003$), although the overall slope of the curve becomes attenuated. Notably, the confidence intervals (CIs) in both Figure 2A and 2B widen remarkably at the extremes of subjective well-being (scores 0–2 and 8–10). This widening reflects the sparsity of data points at these tails, which consequently increases the uncertainty in the estimation of the marginal effect. Therefore, the positive association of subjective well-being with self-rated health is most reliably estimated within the central score range (approximately 3–8). Inferences regarding the groups at the extreme tails, particularly those with very high well-being (scores 8–10), should be drawn cautiously to avoid over-generalization due to increased uncertainty in the marginal effect estimation.

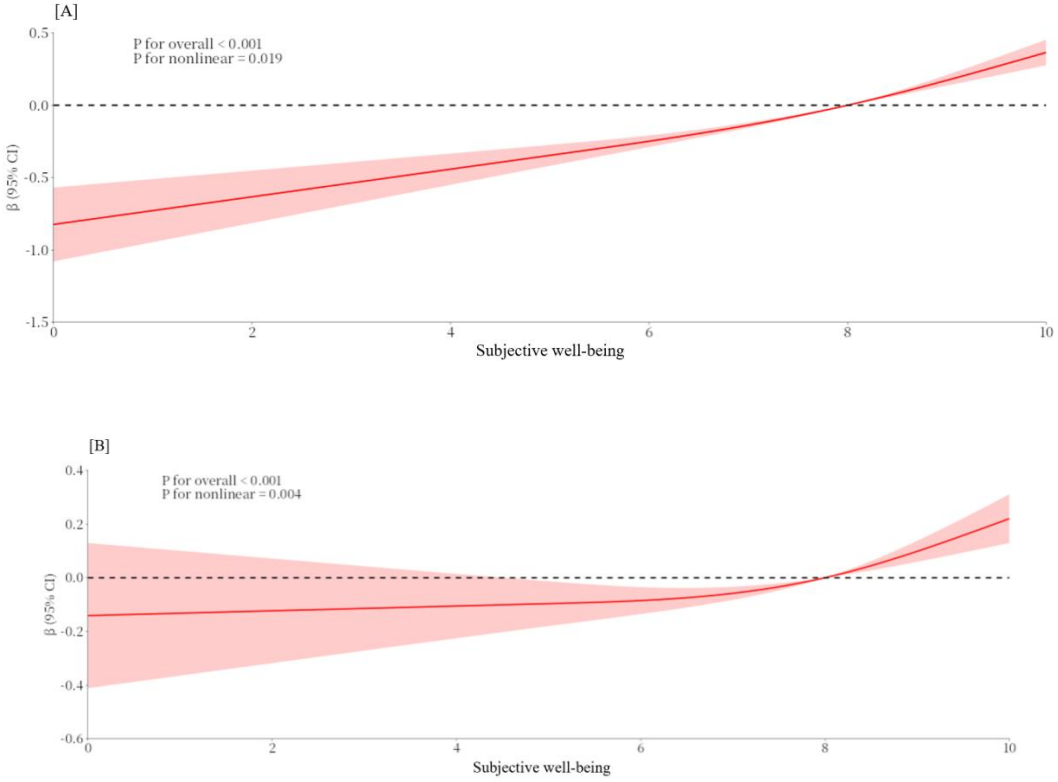

Fig 2. Restricted cubic spline analysis of subjective well-being and self-rated health (A: Univariate RCS; B: RCS adjusted for covariates)

4.5.2.Dose-response relationship for meaning in life

Figure 3 presents RCS analyses of meaning in life and SRH. The univariate RCS (A) reveals a dose – response pattern similar to that observed for subjective well-being (nonlinearity test, $P = 0.002$). After adjusting for covariates (B), the relationship remains noteworthy ($P = 0.021$), although the overall effect becomes attenuated. The RCS curve in Figure 3 displays a widening of the confidence intervals, specifically in the high-score range of meaning in life (scores 8-10). This statistical characteristic suggests that the sample size in this segment is limited, increasing the estimation risk of the marginal effect. Consequently, the beneficial health-promoting association of meaning in life is most reliably observed in the mid-to-high range (scores 4-8). The noteworthy widening of the confidence intervals in the highest score range (scores 8-10) indicates increased estimation risk, suggesting that the substantial marginal gains observed at these extremes require further validation through a larger, more representative sample.

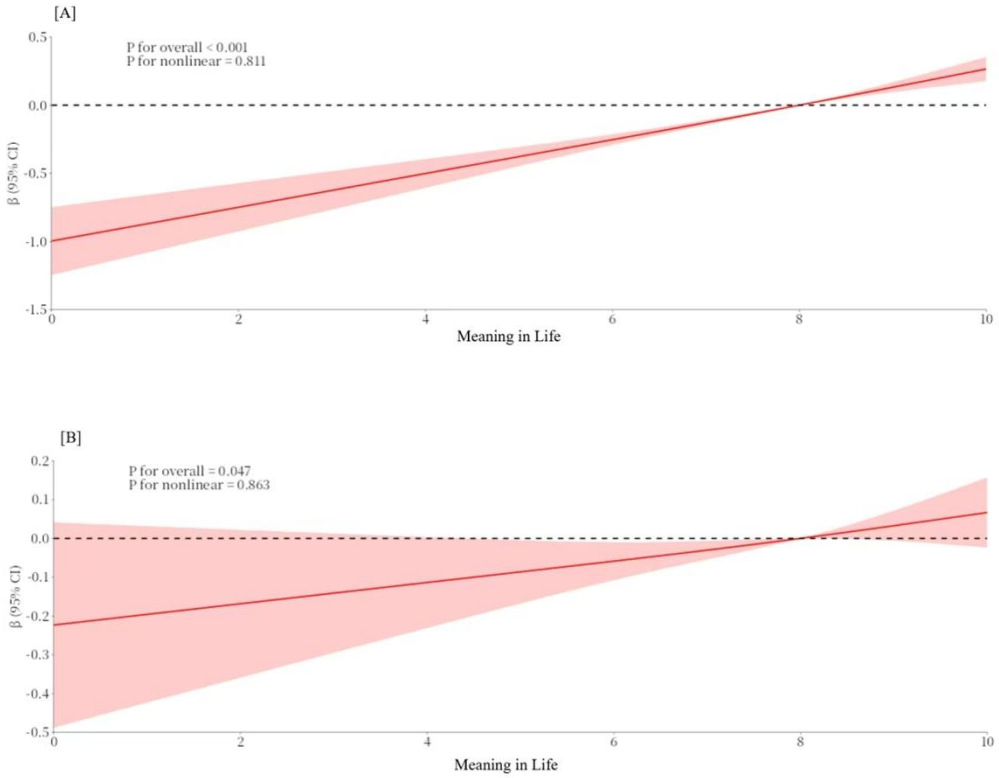

Fig 3. Restricted cubic spline analysis of meaning in life and self-rated health

4.6.Robustness test

To test the robustness of the results, this study uses a binary logistic regression model to reanalyze SRH status. The original SRH scale (0-4 points) is recoded into a binary variable: scores 0-1 are defined as poor health status (coded as 0), scores 2-4 are defined as good health status (coded as 1). Results are shown in Table 5.

The Hosmer-Lemeshow goodness-of-fit test yielded χ^2 = 9.339 (df = 8, P = 0.315), the P-value greater than 0.05 indicates an overall satisfactory fit for the logistic regression model. The omnibus test showed that the model coefficients were jointly noteworthy (χ^2 = 594.854, df = 12, P < 0.001). The -2 log-likelihood value was 4285.571, with Cox & Snell R^2 of 0.150 and Nagelkerke R^2 of 0.204, suggesting that the model possesses reasonable explanatory power.

Regarding the regression coefficients, the results of the binary logistic regression are highly consistent with those of the multiple linear regression. The direction and significance of the core predictor variables remain stable, further supporting the reliability of the study's conclusions.

Table 5. Binary logistic regression results (N = 3666)

Variable	B	Standard Error	Wald	*P*	Exp(B)	95% confidence interval for Exp(B)
Age	-0.015	0.009	2.670	0.102	0.985	[0.967, 1.003]
Coded Gender	0.156	0.076	4.162	0.041	1.168	[1.006, 1.357]
Income Relative to Local Standards	0.143	0.039	3.481	< 0.001	1.154	[1.069, 1.246]
Binary Education Level	0.475	0.082	3.830	< 0.001	1.609	[1.371, 1.888]
Chronic Disease	-1.226	0.079	242.497	< 0.001	0.294	[0.252, 0.342]
Depression	-0.631	0.088	50.925	< 0.001	0.532	[0.448, 0.633]
Subjective well-being	0.076	0.025	8.982	0.003	1.079	[1.027, 1.133]
Meaning in Life	0.048	0.024	4.051	0.044	1.049	[1.001, 1.100]
Life Satisfaction	0.105	0.049	4.567	0.033	1.111	[1.009, 1.224]
Place of Residence Code	-0.049	0.077	0.405	0.524	0.952	[0.818, 1.108]
Social Connections	-0.006	0.022	0.072	0.788	0.994	[0.952, 1.038]
Local Social Status	0.008	0.041	0.042	0.838	1.008	[0.931, 1.092]

5.Discussion

5.1.Main research findings

Based on the Health Production Function theory, this study systematically evaluates the multidimensional determinants of SRH among young-old adults using relative weight analysis and restricted cubic spline analysis. Key findings are summarized as follows:

The Decisive Association of Chronic Disease: Chronic disease is the dominant predictor of SRH (relative weight: 48.79%). Its negative association (β = -0.300) is the strongest among all variables. This finding strongly supports the empirical validity of chronic disease's central role as a "health capital depreciation" mechanism within the Health Production Function. Chronic disease is associated directly with functional limitations and symptom burdens, indirectly through psychological pathways such as depression, revealing a physiological-psychological interconnection.

The Critical Predictive Role of Mental Health Factors: The relative importance of depression (12.86%) exceeds that of income (11.00%), the combined contribution of the three dimensions of subjective psychological flourishing reaches 23.19%, showing the core predictive role of mental health in health evaluations. Depression not only shows direct associations with health assessments as an independent predictor (β = -0.113) but may also function as a potential linking mechanism among physiological factors, economic conditions, and SRH. This suggests that disease treatment and financial assistance alone cannot comprehensively safeguard older adults' health; mental health services must be integrated into intervention systems for health promotion. Besides, all three subjective psychological flourishing indicators exhibit clear dose-response relationships, with their positive association with health being relatively more pronounced among groups with high levels of happiness and meaning in life.

5.2.Theoretical contributions

5.2.1.Core proposition: psychological capital as the "conversion catalyst" of health production

This study translates the empirical findings to a core theoretical proposition: Subjective psychological flourishing functions as the "conversion catalyst" in health production, exerting a "leverage effect" on health investments.

Unlike traditional views treating psychological factors as mere additive predictors, psychological capital acts as a decisive efficiency parameter determining material input-to-health conversion rates. This "Leverage Effect of Psychological Capital" is distinct from Grossman's original "efficiency" concept (which primarily focuses on education's role in improving health production technology) and "investment" concept (which emphasizes material and time inputs). While Grossman's efficiency parameter is rooted in cognitive human capital (education) that optimizes production technology, the leverage effect of psychological capital operates through three distinct logical pathways centered on subjective psychological states:

• Optimizing Health Behavioral Efficiency: Psychological flourishing enhances the adherence to health-promoting behaviors (e.g., medication compliance, dietary discipline), so that health investments yield tangible physiological benefits.

• Amplifying Social Support Utilization: It acts as a multiplier for social resources, strengthening the efficiency of the social support network by promoting active help-seeking and reciprocal exchanges, thereby reducing the "transaction costs" of health maintenance.

• Buffering Capital Depreciation: By modulating stress responses, positive psychological states reduce the "accelerated depreciation" of health capital caused by life stressors.

The relative weight analysis empirically validates this proposition: while the direct input of income contributes 11.00%, the efficiency parameter of psychological flourishing contributes 23.19%. This suggests that psychological capital provides the necessary leverage to maximize the marginal productivity of economic investments, expanding the connotation of "efficiency" in Grossman's Health Production Function beyond education.

5.2.2.Precise quantification of relative importance of influencing factors

By employing the relative weight analysis method, this study overcomes the limitations of traditional regression coefficients affected by multicollinearity and provides the first precise quantification of the relative importance of various factors associated with SRH among young-old adults. The study categorizes influencing factors into five major domains, with chronic disease and mental health factors constituting the primary drivers, their combined contribution remarkably exceeding 80%. In contrast, economic and demographic factors exhibit lower marginal contributions. This hierarchical structure provides evidence for optimizing health resource allocation priorities and correcting misjudgments from assessing importance solely via regression coefficients.

5.2.3.Identification of nonlinear effects and threshold characteristics

Restricted cubic spline analysis has revealed several noteworthy nonlinear effect patterns: subjective psychological flourishing indicators demonstrate a dose-response relationship with varying marginal effects across the range. These nonlinear characteristics are often overlooked in traditional linear models but are important for developing precise intervention strategies. For instance, the dose-response relationship suggests that while the marginal health improvement effect is evident across the range, the most reliably estimated positive effect occurs within the central score range. Given the high uncertainty at the extreme high end (scores 8-10) due to sparse data, intervention strategies should prioritize resources toward lifting individuals from low flourishing levels (e.g., depression management) up into the mid-to-high range. Achieving this mid-range flourishing yields a statistically reliable and substantial health return, providing a clear, actionable goal for public health programs. Maintaining the well-being of high-flourishing individuals

remains important but should not be the sole focus of priority resource allocation based on the current data's findings.

The adjusted R^2 of 0.203 in this model indicates that approximately 79.7% of the variance in self-rated health remains unexplained. Rather than representing a model deficiency, this substantial residual variance points toward dimensions of the health production function not covered by the current analytical framework. Genetic endowment, as a core component of the initial health capital stock conceptualized by Grossman, lacks corresponding measurement in CFPS data, yet extensive empirical research has confirmed its foundational influence on health in later life. Beyond individual-level factors, community culture and macro-environmental contexts-such as regional healthcare accessibility and urban-rural disparities in eldercare norms—introduce considerable heterogeneity in health determinants[24]. The pronounced developmental imbalances across China's eastern, central, and western regions also suggest that the relative importance of various health production factors may vary substantially by geographic context. Besides, life-course cumulative effects, including early-life poverty and occupational exposure history, exert lagged influences on both health capital depreciation and investment efficiency that cross-sectional designs inherently cannot capture[25]. These path-dependent mechanisms operate through complex trajectories that unfold over decades, creating variance attributable to historical rather than contemporaneous factors. Future research integrating longitudinal data with multilevel modeling frameworks could nest individual, community, and macro-level factors within a unified analytical structure, thereby expanding the theoretical boundaries of the health production function and more fully accounting for the multilayered determinants of health in aging populations.

5.3.Limitations and future directions

This study has the following limitations: (1) Causal inference constraints in the research design. As a cross-sectional study, establishing causal relationships between variables is challenging, and a potential risk of reverse causality exists. Future research should use longitudinal data and methods (e.g., fixed-effects models, instrumental variables) to clarify sspecific relationships. (2) Insufficient precision of measurement tools. SRH was assessed using a single-item measure, while chronic disease was categorized only by presence or absence without considering disease type or severity, potentially underestimating the complexity of disease burden. Employing a dichotomous variable (0/1) for chronic disease measurement statistically implies an assumption of "disease homogeneity". Future studies with access to detailed clinical diagnoses should introduce weighted comorbidity indices to more accurately quantify disease impact. (3) Absence of regional heterogeneity analysis. Noteworthy disparities exist across China's regions in economic development, healthcare resources, and cultural norms[26]. The absence of regional stratification analysis in this study limits the applicability of the results across regions. Future comparative regional studies are needed to explore the moderating role of sociocultural contexts.

6.Conclusion

Based on health production function theory, this study analyzed CFPS 2022 data (N = 3,666) using relative weight analysis and restricted cubic spline methods-two data science-driven approaches that address limitations of traditional statistical tools-to identify multidimensional determinants of SRH among young-old adults. These data science techniques extracted more granular insights than conventional regression: RWA quantified variance decomposition among correlated predictors; RCS captured nonlinear dose-response patterns without parametric constraints. Chronic disease was the dominant factor (relative weight: 48.79%, β =-0.300), validating its role in health capital depreciation. Mental health factors showed particular significance: depression (12.86%) was a major negative determinant, while psychological flourishing indicators-subjective well-being (9.39%), meaning in life (7.58%), and life satisfaction (6.22%)-collectively contributed nearly one-quarter of explained variance. Income contributed 11.00% (β =0.120). Psychological flourishing demonstrated dose-response relationships with varying marginal effects across the range, with the most robust positive association in the central score range.

These findings suggest health interventions for China's young-old adults should adopt stratified priorities: strengthen chronic disease prevention systems, develop mental health services, and improve income security. Resource allocation should prioritize chronic disease management while addressing low psychological flourishing levels and depression to promote health equity. Maintaining high-flourishing individuals' well-being also yields noteworthy health returns. This stratified approach balances health security baselines with promotion efficiency, advancing healthy aging goals. Looking forward, future research could integrate multi-source longitudinal data (e.g., electronic health records, wearable device data) and advanced machine learning algorithms to deepen the mechanism analysis of the health production function, providing more precise data science support for personalized and targeted health policies.

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