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Relative deprivation patterns in social and geographical references for health trajectories in China: Investigations of gender and urban-rural disparities

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ABSTRACT

Objective: A pervasive link between relative deprivation and health has been well-documented. However, prior studies suffered from inadequate relative deprivation measures that fail to define appropriate reference groups to which individuals compare themselves, and few provided longitudinal evidence. This study explores latent relative deprivation patterns based on multiple social and geographic reference groups, examining their impacts on health trajectories and variations by gender and urban-rural areas.
Methods: Using three waves (2013, 2015, & 2018) of the China Health and Retirement Longitudinal Study (n = 6035), we conducted latent class analysis (LCA) to identify the baseline latent relative deprivation patterns among five social and geographic reference groups (relatives, schoolmates, colleagues, neighbors, and other people in the city or county). The LCA results were linked to the latent growth curve parallel process modeling (PPM) to investigate the impacts of deprivation patterns on dual health trajectories (depressive symptoms and self-rated health), and the results were stratified to explore gender and urban-rural differences.
Results: The LCA revealed a relatively deprived group (36.39%) and a non-deprived group (63.61%). The PPM results indicated that the relatively deprived group showed a higher initial level of depressive symptoms and a lower initial level of self-rated health than the non-deprived group. However, the relatively deprived group showed a slower growth rate in depressive symptoms than the non-deprived group. These findings were particularly evident among women and rural residents.
Conclusions: Findings emphasize the negative impact of relative deprivation on health. Furthermore, there is a complex interplay in these effects intertwined with gender and locality. Policies aimed at promoting mental health should not only consider relatively deprived groups, but also non-deprived women and rural residents who are at higher risk for later-life depression.

1. Introduction

Economic prosperity in China has been accompanied by rising socioeconomic inequalities that lead to stressful social comparisons and an increased sense of relative deprivation (Subramanyam et al., 2009). Relative deprivation refers to the perception of disparity resulting from comparison with others (Smith et al., 2012), a concept that has been extensively used to explain a wide range of outcomes variables in social science research, such as collective action, intergroup attitude, and physical and mental health (reviewed in Smith et al., 2012). The relative deprivation hypothesis explains the underlying mechanism of the harmful effect of relative deprivation on health, that feeling worse off than others in social comparisons undermines social cohesion, social capital, trust, and well-being, in turn leading to negative psychosocial and physical outcomes (Wilkinson and Pickett, 2007).

Substantial empirical evidence supports this hypothesis, showing that relative deprivation is associated with adverse physical and mental health outcomes (e.g., Inoue et al., 2019; Lyu and Sun, 2020; Subramanyam et al., 2009). However, Adjaye-Gbewonyo and Kawachi (2012) identified two major research gaps. First, previous studies suffer

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from inadequate relative deprivation measures that fail to define appropriate reference groups to which individuals compare themselves. Second, longitudinal evidence is needed to reveal the long-term impact of relative deprivation on changes in health. Therefore, this study explored an innovative approach to capture relative deprivation and investigate its impact on health trajectories based on three waves of the China Health and Retirement Longitudinal Study (CHARLS). The study also examined related gender and urban-rural differences to take account of China's gender and urban-rural disparities (Wu, 2019).

1.1. Measures of relative deprivation

Although the measures of relative deprivation vary across studies, the operationalization could be generally divided into objective and subjective measures of relative deprivation (reviewed in Adjaye-Gbewonyo and Kawachi, 2012; Smith et al., 2012). Previous studies mainly used objective economic measures such as income (Yitzhaki, 1979) to assess relative deprivation (e.g., Eibner and Evans, 2005; Gero et al., 2022; Ling, 2009). Of these, the Yitzhaki index is the most frequently used, defined as *"a function of the cumulative difference between the income of an individual and that of all those with higher incomes within a reference group"* (Adjaye-Gbewonyo and Kawachi, 2012, p. 132). Other researchers have measured relative deprivation by subjective social status (Adler et al., 2000) or self-reported relative economic status (Mangyo and Park, 2011), which reflects individuals' assessment of their relative social standing. Smith and Huo (2014) suggest that subjective measures of relative deprivation are useful in predicting individual-level outcomes because they refer to negative emotions resulting from social comparisons involving inequality. This position is supported by a meta-analysis that compared the impacts of objective and subjective measures of relative deprivation, showing that subjective relative deprivation measures had larger effect sizes than objective measures (Smith et al., 2012). Despite this, subjective measures of relative deprivation are underexplored in Chinese contexts.

Another measurement challenge is precision and accuracy in choosing appropriate reference groups with which to make meaningful social comparisons when assessing individual relative deprivation. Although studies tend to use socio-demographic characteristics such as age, ethnicity, and education status as benchmarks when individuals reference their deprivation status to others (Subramanyam et al., 2009), it is unclear whether individuals make comparisons with these selected groups. Pham-Kanter (2009) suggests that individuals tend to compare themselves with people in their close networks whom they know personally. Empirical evidence from Mangyo and Park (2011) supports this argument, suggesting that people close to an individual (e.g., relatives, classmates, neighbors) form salient reference groups, particularly in the Chinese context. Additionally, evidence reveals that geographic reference groups also matter in the Chinese context (Inoue et al., 2019; Mangyo and Park, 2011). However, few studies have systematically included social relationships and geographical indicators to comprehensively assess one's relative deprivation.

There are concerns that the traditional index of relative deprivation (e.g., the Yitzhaki index) may not identify the relative importance of different reference groups as the comparison assessment varies across individuals (Eibner and Evans, 2005). Empirical evidence has also shown that the impacts of relative deprivation on health vary across different reference groups, although little is known about relative-deprivation patterns across multiple reference groups (Adjaye-Gbewonyo and Kawachi, 2012). Therefore, it is necessary to explore relative deprivation patterns across multiple reference groups and identify the relative importance of each reference group.

1.2. Relative deprivation and health

Research has shown that relative deprivation is associated with both physical and mental health outcomes. For physical health, relative deprivation has been associated with increased mortality (Eibner and Evans, 2005), poorer self-rated health (e.g., Inoue et al., 2019; Mishra and Carleton, 2015; Subramanyam et al., 2009), higher body mass index (Eibner and Evans, 2005), and functional disability (Kondo et al., 2009). Additionally, relative deprivation is significantly associated with poorer mental health (e.g., Beshai et al., 2017; Chang et al., 2020; Lyu and Sun, 2020), including a higher prevalence of depressive symptoms (Beshai et al., 2017) and a lower level of cognitive function (Lyu and Sun, 2020).

However, the current evidence base primarily reflects cross-sectional data, where the measures of relative deprivation are mainly focused on objective (e.g., the Yitzhaki index) rather than subjective (e.g., self-rated relative economic status) indicators (e.g., Gero et al., 2022). Research has also centered on high-income countries, and it is unclear how the effects of relative deprivation in health operate in middle-/low-income countries. Given these research gaps, Adjaye-Gbewonyo and Kawachi (2012) call for more longitudinal studies to examine the long-term impacts of relative deprivation on health, paying particular attention to middle-/low-income countries.

1.3. The Chinese context

Gender and urban-rural disparities are obvious in China (Cai et al., 2022; Wu, 2019). Patriarchal traditions rooted in Confucian culture have had long-term impacts on Chinese society, shaping gender norms and leading to females' disadvantaged positions in many areas of Chinese society (He and Wu, 2017; Shi et al., 2022). The gender gap has been magnified by rapid marketization and accelerated economic growth, which pushes women to a more disadvantaged position in the labor market because of the emphasis on efficiency, productivity, and profit orientation that exacerbates discrimination against women (He and Wu, 2018). Evidence has revealed varied aspects of gender inequality, including wage discrimination in the labor market (He and Wu, 2018), social mobility chances (Xie et al., 2022), career advancement (He and Wu, 2021), and health (Lei et al., 2014).

Urban-rural inequalities in China have widened in the past few decades because urban areas have faster development and growth rates than rural areas (Ling, 2009; Wu, 2019). Therefore, urban residents are more likely to have higher living standards than rural residents. Research has indicated that urban residents are advantaged compared to rural residents in terms of income, social mobility chances, and health (Lei et al., 2014; Wu, 2019; Wu and Treiman, 2007; Xie et al., 2022). However, little is known about how gender disparities and the urban-rural divide translate into relative deprivation when affecting health.

1.4. The present study

This study advances the current evidence in three ways. First, we considered social relationships and geographical referencing indicators together (i.e., relatives, schoolmates, colleagues, neighbors, and other people, in the city or county) to measure relative deprivation with latent class analyses (LCA) in order to explore patterns in relative deprivation. Compared to the traditional index approach that combines all indicators, LCA has advantages in capturing the nuanced differences across each referencing indicator by classifying individuals into distinct patterns that share similar endorsements in relative deprivation. This could assist in identifying the relative importance of each indicator among individuals. Second, we examined how the patterns of relative deprivation might simultaneously affect trajectories of depressive symptoms and self-rated health, including initial health status and longitudinal changes. Lastly, we investigated the intersectionality of relative deprivation, gender, and urban-rural differences on health trajectories to uncover if and how the relative deprivation-health nexus varies across gender and locality.

We hypothesized that relative deprivation is associated with poor initial health status and accelerated health deterioration. Moreover, this association differs by gender and locality in the Chinese context. The following hypotheses were proposed in this study:

H1a. Relative deprivation is associated with poor initial health status (i.e., more depressive symptoms and lower self-rated health)

H1b. Relative deprivation is associated with accelerated health deterioration (i.e., worsening depressive symptoms and decline in self-rated health)

H2a. The association between relative deprivation and initial health status differs by gender and locality

H2b. The association between relative deprivation and over-time health deterioration differs by gender and locality

2. Methods

2.1. Data and sample

Data were drawn from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative panel survey of individuals aged 45 years and older. The survey began in 2011, with subsequent waves in 2013, 2015, and 2018. The original harmonized dataset across all waves included 25,586 cases (see Zhao et al. (2012) for detailed information on sampling and cohort profiles). We used CHARLS 2013 (referred to as baseline hereafter) when information on relative deprivation began to be systematically collected and included respondents participating in at least two waves from 2013 to 2018 that contained 12,471 samples. Those aged 45 at baseline and with information about relative deprivation, depressive symptoms, and self-rated health were included in the study (n = 6689). Among the remaining 6689 respondents, 654 proxy respondents were excluded. The final analytical sample comprised 6035 respondents. The results of Little's missing completely at random (MCAR) test ($p > 0.05$) indicated that patterns of missing values were MCAR (Li, 2013). Thus, we handled missing values by creating 20 imputed datasets using multiple imputations with chained equations (White et al., 2011).

2.2. Measures

Health outcomes. We modeled the changes in self-rated health and depressive symptoms using CHARLS 2013, 2015, and 2018, controlling for the lagged self-rated health and depressive symptoms in CHARLS 2011. Depressive symptoms were evaluated with the Chinese version of the ten-item Center for Epidemiologic Studies Depression Scale (CESD-10) (Andresen et al., 1994). CESD-10 is a four-point (1 = *rarely*, 4 = *most of the time*) self-assessed tool to report feelings and behaviors related to depressive symptoms during the week. Two positive items (e.g.," happy" and "hopeful") were reverse-coded and summed (*range* = 0–30), with higher scores indicating greater depressive symptoms. The reliability and validity of the CESD-10 have been established in Chinese samples (Cheng et al., 2006; Lei et al., 2014). Cronbach's α values were acceptable across all waves (0.78–0.84), which indicates reasonable levels of internal consistency. Self-rated health was assessed by a single question: "*would you say your health in general is very good, good, fair, poor, or very poor?*" The responses were reverse-coded so that higher scores indicated better self-rated health. Self-rated health is a widely used measure of health (Jylhä, 2009) and is a robust predictor of objective health outcomes (e.g., mortality, cardiovascular disease, and multiple biomarkers; Idler and Benyamini, 1997; May et al., 2006; Vie et al., 2014). Self-rated health is reported as a reliable and valid measure in Chinese contexts (Qi, 2014).

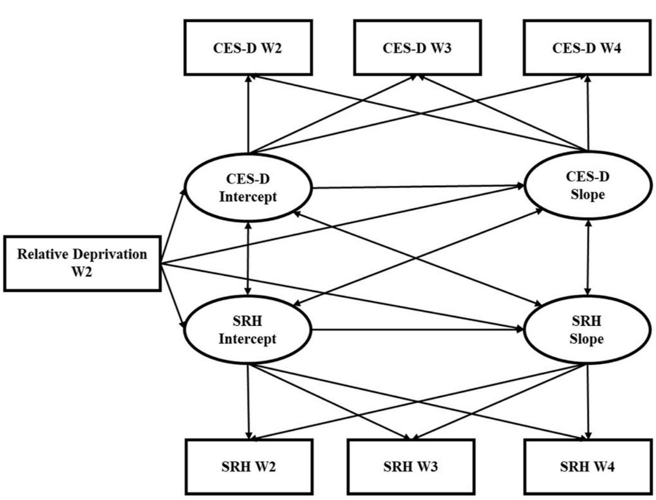

Fig. 1. Conceptual diagram of the parallel process model. CES-D = Center for Epidemiologic Studies Depression Scale; SRH = self-rated health; W2–W4 = the wave 2 -wave 4 of CHARLS.

Relative deprivation. Relative deprivation was measured by respondents' perceptions of how their own living standards compared to five social and geographic reference groups at 2013 CHARLS ("*Compared to the average living standard of [your relatives, your schoolmates, your colleagues, your neighbors, and others in your city or county], how would you rate your standard of living?*") Responses using a 5-point scale from "*much better*" to "*much worse*" were coded from 1 to 5. Due to the skewness of the distribution and few respondents in the distribution tails in each item, the five response categories were collapsed into three levels: "relatively worse" (coded as 1), "about the same" (coded as 2), and "relatively better" (coded as 3). The recoded 3-point scales were correlated strongly with the original 5-point scores ($r_{relatives} = 0.93$; $r_{schoolmates} = 0.93$; $r_{colleagues} = 0.93$; $r_{neighbors} = 0.93$, $r_{others\ in\ your\ city\ or\ county} = 0.90$).

Covariates. This study selected three sets of control variables related to mental and physical health. The first set included demographic characteristics (Lei et al., 2014) measured by age (continuous), gender (1 = *male*), residency area (1 = *rural*), family size (continuous), and marital status (1 = *married*). The second set contained socioeconomic factors (Braveman et al., 2011; Inoue et al., 2019; Steiber, 2019) and social participation (Lyu and Sun, 2020), including quartile household income constructed by total income from all family members and income from government transfer, which provides a comprehensive reflection of an individual's economic status, individual income (1 = *yes*) for accessing whether individuals have income, assets (continuous), education level (1 = *less than lower secondary*; 2 = *upper secondary*; 3 = *tertiary*), parental education level (1 = *less than lower secondary*; 2 = *upper secondary*; 3 = *tertiary*) measured by the highest level of parental education, employment status (1 = *employed*) and social participation (1 = *yes*). The third set described health behaviors (Petrovic et al., 2018), including alcohol consumption (1 = *yes*) and smoking (1 = *yes*). We also used lagged design to control for depressive symptoms and self-rated health in CHARLS 2011and address health selection (Kröger et al., 2015). An attrition variable was created and controlled to model the missingness over time.

2.3. Analysis

Two parts of the analyses were conducted. The first part described outcomes and tested for gender and locality differences (χ^2 test using design-based F distribution and independent-sample t-tests). All analyses were weighted using longitudinal weights provided in CHARLS. R software was used to conduct preliminary analysis and multiple imputations using the MICE package.

The second part of the analysis involved using M*plus* for latent modeling. First, the LCA was used to characterize unobserved relative deprivation patterns based on respondents' subjective feelings of relative economic status compared with five reference groups for the full sample. The procedures were applied to each subsample by gender and

Table 1
Weighted sample characteristics (Total $N = 6035$).

	Total *M* (*SD*)/*N* (%)	Gender			Residency Area		
		Women *M* (*SD*)/*N* (%)	Men *M* (*SD*)/*N* (%)	Design-based *F* distribution/ *t*-test	Urban M (SD)/N (%)	Rural *M* (*SD*)/*N* (%)	Design-based *F* distribution/ *t*-test
Age (45–103)	59.20 (8.63)	58.28 (8.7)	60.05 (8.48)	$t = -5.73$***	59.58 (8.88)	58.75 (8.31)	$t = 2.73$**
Family size (1–14)	3.60 (1.72)	3.61 (1.72)	3.60 (1.73)	$t = 0.17$	3.42 (1.55)	3.81 (1.88)	$t = -7.18$***
Marital status (Married)	5438 (90%)	2515 (90.04%)	2923 (93.1%)	$F = 47.69$***	2341 (89.92%)	3097 (90.1%)	$F = 0.04$
Others	596 (10%)	370 (9.96%)	226 (6.9%)		264 (10.08%)	332 (9.9%)	
Household income quartiles							
Lowest 25%	882 (21.81%)	443 (22.34%)	439 (21.29%)	$F = 1.65$	148 (8.64%)	734 (33.82%)	$F = 156.16$***
25%–50%	903 (23.39%)	422 (21.75%)	481 (24.97%)		253 (15.58%)	650 (30.52%)	
50%–75%	836 (25.78%)	399 (25.41%)	437 (26.14%)		416 (31.71%)	420 (20.37%)	
Highest 25%	833 (29.02%)	412 (30.49%)	421 (27.59%)		534 (44.08%)	299 (15.29%)	
Assets (in log form)	11.7 (0.45)	11.72 (0.67)	11.68 (0.59)	$t = -0.46$	12.27 (0.66)	11.12 (0.4)	$t = 15.02$***
Individual income (Yes)	2921 (63.68%)	1364 (59.29%)	1557 (68.42%)	$F = 22.74$***	1413 (74.71%)	1508 (52.29%)	$F = 128.2$***
No	1858 (36.32%)	1119 (40.71%)	739 (31.58%)		540 (25.29%)	1318 (47.71%)	
Education level							
Less than lower secondary	5081 (81.27%)	2551 (84.57%)	2530 (78.19%)	$F = 5.04$*	1989 (73.83%)	3092 (89.9%)	$F = 99.9$***
Upper secondary	830 (15.51%)	293 (12.66%)	537 (18.17%)		512 (20.66%)	318 (9.53%)	
Tertiary	124 (3.22%)	42 (2.77%)	82 (3.64%)		105 (5.51%)	19 (0.57%)	
Parental education level							
Less than lower secondary	5730 (94.04%)	2724 (92.88%)	3006 (95.13%)	$F = 2.93$	2400 (91.48%)	3330 (97.01%)	$F = 25.95$***
Upper secondary	225 (4.56%)	120 (5.47%)	105 (3.7%)		146 (6.32%)	79 (2.51%)	
Tertiary	69 (1.4%)	38 (1.65%)	31 (1.17%)		55 (2.2%)	14 (0.47%)	
Social participation (Yes)	3442 (60.13%)	1632 (59.16%)	1810 (61.38%)	$F = 1.78$	1656 (66.99%)	1786 (52.54%)	$F = 79.66$***
No	2577 (39.69%)	1248 (40.84%)	1329 (38.62%)		945 (33.01%)	1632 (47.46%)	
Employment status (Employed)	4146 (64.68%)	1797 (59.56%)	2349 (69.46%)	$F = 26.35$***	1405 (51.09%)	2741 (80.32%)	$F = 346.19$***
Unemployed	1862 (35.32%)	1071 (40.44%)	791 (30.54%)		1181 (48.91%)	681 (19.68%)	
Alcohol consumption (Yes)	2329 (40.19%)	469 (17.83%)	1860 (61.11%)	$F = 609.98$***	1009 (41.45%)	1320 (38.73%)	$F = 2.44$
No	3688 (59.81%)	2409 (82.17%)	1279 (38.89%)		1592 (58.55%)	2096 (61.27%)	
Smoking (Yes)	762 (16%)	85 (2.49%)	677 (38.13%)	$F = 812.78$***	286 (13.14%)	476 (19.51%)	$F = 15.45$***
No	3727 (84%)	2700 (97.51%)	1027 (61.87%)		1703 (86.86%)	2024 (80.49%)	
Relative economic status							
Compared with relatives							
Relative worse	2050 (34.68%)	1044 (17.89%)	1006 (16.78%)	$F = 6.13$**	859 (18.39%)	1191 (16.28%)	$F = 9.1$***
About the same	3394 (55.43%)	1594 (26.51%)	1800 (28.93%)		1440 (28.83%)	1954 (26.6%)	
Relative better	539 (9.89%)	217 (3.88%)	322 (6.01%)		287 (6.48%)	252 (3.41%)	
Compared with schoolmates							
Relative worse	2297 (39.56%)	1087 (18.96%)	1210 (20.6%)	$F = 4.74$**	959 (20.46%)	1338 (19.11%)	$F = 1.48$
About the same	2968 (52.71%)	1429 (26.11%)	1539 (26.6%)		1271 (28.08%)	1697 (24.63%)	
Relative better	452 (7.72%)	183 (3.08%)	269 (4.65%)		222 (4.4%)	230 (3.33%)	
Compared with colleagues							
Relative worse	2054 (35.47%)	990 (16.89%)	1064 (18.58%)	$F = 1.73$	888 (19.22%)	1166 (16.25%)	$F = 0.46$
About the same	3436 (58.34%)	1643 (28.51%)	1793 (29.84%)		1466 (30.94%)	1970 (27.4%)	
Relative better	375 (6.19%)	157 (2.61%)	218 (3.58%)		178 (3.46%)	197 (2.73%)	
Compared with neighbors							
Relative worse	1812 (31.7%)	931 (16.03%)	881 (15.67%)	$F = 6.47$**	766 (17.39%)	1046 (14.3%)	$F = 1.95$
About the same	3561 (59.88%)	1696 (29.05%)	1865 (30.83%)		1505 (30.88%)	2056 (29%)	
Relative better	530 (8.43%)	195 (3.25%)	335 (5.18%)		235 (4.24%)	295 (4.18%)	
Compared with people live in the same city or county							
Relative worse	3672 (61.68%)	1773 (29.64%)	1899 (32.04%)	$F = 4.27$*	1398 (29.02%)	2274 (32.66%)	$F = 44.03$***

(*continued on next page*)

Table 1 (*continued*)

	Total *M* (*SD*)/*N* (%)	Gender			Residency Area		
		Women *M* (*SD*)/*N* (%)	Men *M* (*SD*)/*N* (%)	Design-based *F* distribution/ *t*-test	Urban M (SD)/N (%)	Rural *M* (*SD*)/*N* (%)	Design-based *F* distribution/ *t*-test
About the same	1762 (33.68%)	840 (16.67%)	922 (17.02%)		885 (20.89%)	877 (12.8%)	
Relative better	240 (4.63%)	89 (1.68%)	151 (2.96%)		142 (3.21%)	98 (1.43%)	
CES-D (range: 0–30)							
Wave 2 (2013)	7.11 (5.37)	7.92 (5.72)	6.34 (4.9)	$t = 9.27$***	6.52 (5.02)	7.78 (5.67)	$t = -7.69$***
Wave 3 (2015)	7.02 (6.00)	8.02 (6.37)	6.1 (5.49)	$t = 9.33$***	6.2 (5.66)	7.93 (6.24)	$t = -8.75$***
Wave 4 (2018)	7.85 (6.15)	8.76 (6.57)	7 (5.6)	$t = 8.56$***	7.06 (5.81)	8.76 (6.4)	$t = -8.82$***
Self-rated health (range: 1–5)							
Wave 2 (2013)	3.13 (0.90)	3.05 (0.89)	3.2 (0.9)	$t = -5.06$***	3.18 (0.87)	3.08 (0.94)	$t = 3.34$**
Wave 3 (2015)	3.14 (0.94)	3.07 (0.94)	3.19 (0.94)	$t = -3.96$***	3.21 (0.91)	3.05 (0.97)	$t = 5.32$***
Wave 4 (2018)	3.07 (0.99)	3 (0.96)	3.13 (1.01)	$t = -3.72$***	3.14 (0.95)	2.99 (1.03)	$t = 4.78$***

Note. *M* = weighted mean; *SD* = weighted standard deviation, *N* = unweighted count, % = weighted percentage; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. *Weighted at individual longitudinal weight.*

locality. LCA is a model-based approach used to classify individuals into distinct subgroups (i.e., different latent classes) based on their responses to multiple categorical or ordinal indicators (Wang and Wang, 2012). The number of latent classes was assessed using several objective model fit indices, including the Bayesian information criterion (BIC), Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMRT), and parametric bootstrapped likelihood ratio test (BLRT) (Nylund et al., 2007). Specifically, a lower BIC value indicates a better model fit (Nylund et al., 2007), and a statistically significant *p*-value for the VLMRT or BLRT indicates that the *k* class LCA model is better than the *k*-1 class LCA model (Lo et al., 2001). As model interpretability and practical discretions are also critical to identifying the number of latent classes (Collins and Lanza, 2009), both objective indices and model interpretability were used to determine the optimal LCA model of relative deprivation patterns.

The LCA results were subsequently linked to the parallel process latent growth curve model (PPM) to model dual health trajectories (initial health status [i.e., intercept] and longitudinal changes [i.e., slopes]) for self-rated health and depressive symptoms (Wickrama, 2016). These investigations considered how relative deprivation patterns affected health trajectories in the entire sample and in subgroups of gender and location (see Fig. 1). The PPM was conducted sequentially. First, the unconditional latent growth curve modeling (LGCM) for self-rated health and depressive symptoms were conducted separately to identify the best fit model for changes, and the results were combined to perform a parallel model for dual health trajectories. The parallel model was conditioned on the LCA results and covariates to examine how relative deprivation patterns influence health trajectories. Lastly, these results were further stratified by gender and locality. The PPM analyses were based on 20 imputed data sets (using the R program) and estimated using Rubin's rule (Rubin, 2004). Using the "imputation" syntax built within M*plus*, the results were averaged estimates based on 20 imputed data by pooling the 20 imputed data together and adjusted coefficients and standard errors for the variability between imputations. The model fit was assessed using model χ^2, the comparative fit index (CFI), the Tucker Lewis Index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) metrics. The recommended cut-offs for acceptable model fit were a CFI and TLI above 0.90 and an RMSEA and SRMR below 0.08 (Hu and Bentler, 1999).

3. Results

3.1. Descriptive statistics and bivariate analysis

Table 1 presents the descriptive statistics of the full sample and bivariate analyses stratified by gender and locality. The average age of the full sample was 59.2 years ($SD = 8.63$), and the average family size was 3.6 ($SD = 1.72$). About 90% of respondents were married, and more than 60% had an individual income. Over 60% of respondents participated in social activities, and only 3.2% held a higher education degree. More than 40% of respondents consumed alcohol, and 16% smoked. For relative economic status, approximately 30% of respondents felt their living standards were worse than others, whilst over 60% felt their living standards were worse than others living in the same city or county location. Over time, depressive symptoms increased, whereas self-rated health decreased.

Bivariate analyses showed that compared with men, women in the sample were more likely to be younger, not married, employed, consumed alcohol or smoked, had no individual income, lower levels of education, and worse health outcomes over time. Women tended to rate their relative economic status lower than men in every aspect (except when compared to colleagues). Compared to their urban counterparts, rural adults were much older, with a large family, fewer assets, less income, lower levels of education, and smoked. Considering relative deprivation, rural adults rated their economic status more poorly compared to their relatives or people who lived in the same city or county. There was a clear health divide, as rural adults had higher depressive symptoms and lower self-rated health than urban adults.

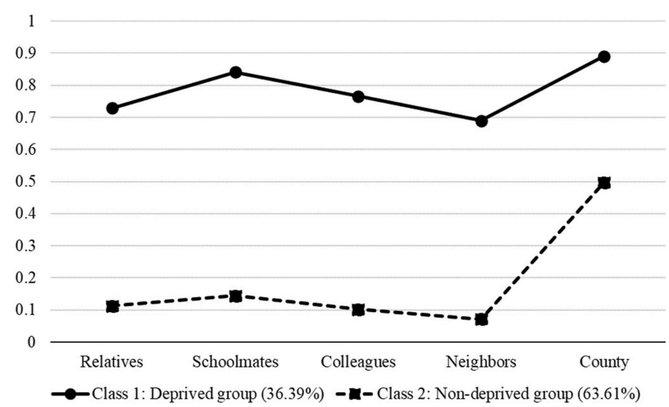

Fig. 2. Latent class analysis of relative deprivation patterns for the full sample. Note: the numbers on the vertical axis indicate the probability of endorsement in attaining "relatively worse" in relative economic status assessment.

3.2. Latent class analysis

Fig. 2 presents the results of the LCA of relative deprivation based on five social and geographic reference groups. The fit indices showed that

Table 2
Weighted demographics by latent classes for the full sample.

	Relatively deprived group *M (SD)/N* (%)	Non-deprived group *M (SD)/N* (%)	Design-based *F* distribution/*t*-test *M (SD)/N* (%)
Age (45–103)	59.09 (8.56)	59.26 (8.67)	$t = -0.17$
Gender (Men)	1108 (50.83%)	2041 (52.18%)	$F = 0.5$
Women	1088 (49.17%)	1798 (47.82%)	
Residency Area (Rural)	1278 (53.24%)	2151 (53.99%)	$F = 0.17$
Urban	918 (46.76%)	1688 (46.01%)	
Family size (1–14)	3.65 (1.7)	3.57 (1.73)	$t = 0.75$
Marital status (Married)	1940 (88.62%)	3498 (90.81%)	$F = 4.97^{*}$
Others	256 (11.38%)	340 (9.19%)	
Household income quartiles			
Lowest 25%	355 (23.98%)	527 (20.56%)	$F = 18.86^{***}$
25%–50%	395 (29.19%)	505 (20.04%)	
50%–75%	286 (26.38%)	550 (25.44%)	
Highest 25%	209 (20.45%)	624 (33.97%)	
Assets (in log form)	11.31 (0.64)	11.9 (0.55)	$t = -7.05^{***}$
Individual income (Yes)	994 (60.44%)	1927 (65.59%)	$F = 6.69^{**}$
No	760 (39.56%)	1098 (34.41%)	
Education level			
Less than lower secondary	1895 (84.28%)	3186 (79.52%)	$F = 7.18^{***}$
Upper secondary	276 (14.02%)	554 (16.37%)	
Tertiary	25 (0.17%)	99 (4.11%)	
Parental education level			
Less than lower secondary	2091 (94.89%)	3639 (93.54%)	$F = 1.51$
Upper secondary	80 (4.14%)	145 (4.8%)	
Tertiary	20 (0.97%)	49 (1.65%)	
Social participation (Yes)	1160 (57.76%)	2282 (61.79%)	$F = 5.19^{*}$
No	1033 (42.24%)	1544 (38.21%)	
Employment status (Employed)	1502 (64.2%)	2644 (64.95%)	$F = 0.14$
Unemployed	683 (35.8%)	1179 (35.05%)	
Alcohol consumption (Yes)	804 (38.41%)	1525 (41.23%)	$F = 2.01$
No	1385 (61.59%)	2303 (58.77%)	
Smoking (Yes)	294 (16.11%)	468 (15.93%)	$F = 0.02$
No	1338 (83.89%)	2389 (84.07%)	

Note. M = weighted mean; SD = weighted standard deviation, N = unweighted count, % = weighted percentage; ***$p < 0.001$, *$p < 0.05$; *Weighted at individual*. Longitudinal weight.

models with more latent classes were favored (smaller BIC values and significant VLMRT or BLRT tests; see online supplementary materials, Table S1). After plotting the output of these models, we found that the two-class model showed distinct and meaningful classes compared to others. Thus, we selected the two-class model based on acceptable model fit and model interpretability. In Fig. 2, the horizontal axis indicates relative economic status among the five reference groups, and the vertical axis indicates the propensity to report "relatively worse" relative economic status. Given that respondents in class 1 (36.39%) were more likely to have relatively worse living standards in every relative deprivation indicator, this class was labeled the "deprived group". Similarly, respondents in class 2 (63.61%) were labeled the "non-deprived group" because of the lower probabilities of having relatively worse living standards except when compared with people in the same city or county. The latent class patterns in the whole sample were also observed in the gender and locality subsamples (see online supplementary materials, Fig. S1). Therefore, the two-class model was applied throughout. Bivariate analyses of latent classes by demographics for the whole sample (Table 2) and gender and locality subgroups (Table S2) showed that deprived, compared to non-deprived, respondents were more likely to be unmarried, have fewer assets, lower income, lower levels of education, and not engaged in social participation.

3.3. Parallel process latent growth curve model

The unconditional LGCM results for dual health trajectories showed significant linear change for both depressive symptoms and self-rated health, with depressive symptoms increasing and self-rated health declining over time (see online supplementary materials, Table S3). Table 3 and Fig. 3 report the conditional PPM results of the estimates of relative deprivation patterns (*ref*: non-deprived group, class 2) on two health trajectories on the whole sample and subsamples, with all models showing satisfactory model fits. Among the whole sample, the deprived group had higher initial depressive symptoms ($\beta = 0.168$, $p < 0.001$) and lower self-rated health ($\beta = -0.133$, $p < 0.001$), and the relatively deprived patterns were longitudinally associated with the depressive symptom trajectory. The negative association ($\beta = -0.09$, $p < 0.05$) of relatively deprived patterns on the increasing depression trajectory showed a decelerating effect, indicating that the deprived group, compared to the non-deprived group, had a *slower* increase in depressive symptoms across time. Subgroups of women and rural adults had similar results to the whole sample. Compared to non-deprived women and rural adults, deprived women and rural adults had worse initial depressive symptoms ($\beta_{women} = 0.179$ and $\beta_{rural} = 0.212$, $p < 0.001$) and self-rated health ($\beta_{women} = -0.149$ and $\beta_{rural} = -0.128$, $p < 0.001$), and a slower increase in depressive symptoms over time ($\beta_{women} = -0.17$ and $\beta_{rural} = -0.1$, $p < 0.05$). However, deprivation patterns were only associated with initial depressive symptoms ($\beta_{men} = 0.155$ and $\beta_{urban} = 0.131$, $p < 0.001$) and self-rated health ($\beta_{men} = -0.119$ and $\beta_{urban} = -0.145$, $p < 0.001$) among men and urban adults, and were not significantly associated with self-rated health trajectories in the whole sample and subsamples.

Regarding the impact of covariates on dual health trajectories among the whole sample, women ($\beta = -0.116$, $p < 0.001$), married adults ($\beta = -0.051$, $p < 0.01$), and respondents not participating in social activities ($\beta = -0.091$, $p < 0.001$) had higher initial depressive symptoms. Unemployed respondents ($\beta = 0.107$, $p < 0.001$) and those who consumed alcohol ($\beta = 0.075$, $p < 0.001$) showed lower initial self-rated health. Compared to those not married, married adults ($\beta = 0.095$, $p < 0.05$) had a faster increase in depressive symptoms over time. The negative association of age ($\beta = -0.221$, $p < 0.01$) on accelerated self-rated health deterioration patterns indicated that older adults have a faster decline in self-rated health than younger people (see online supplementary materials, Table S4). Detailed conditional PPM results of the impacts of covariates on the dual health trajectories among the gender and location subsamples are presented in online supplementary materials, Table S4.

4. Discussion

This study used an innovative approach to capture the heterogeneous clusters of relative deprivation in China. It thus adds new information to the current global evidence base. Drawing on panel data from the 2013–2018 waves of CHARLS, this study investigated associations between relative deprivation patterns with depression and self-rated health dual trajectories, and whether associations change in gender and locality subgroups. Consistent with previous research (Lei et al., 2014; Shi et al., 2022; Wu, 2019; Wu and Treiman, 2007), our analyses showed that women and rural residents are in a relatively disadvantaged position in terms of objective socioeconomic status (e.g., educational attainment, employment status), relative economic status, and health, which reflects the gender and urban-rural inequalities in China.

Unlike the prior studies, which used an index approach to measure

Table 3
Standardized estimates for conditional parallel process model for the full sample and subsamples.

Model paths	Full sample		Women		Men		Urban		Rural	
	β	SE	β	SE	β	SE	β	SE	β	SE
RD → $I_{(CES-D)}$	0.168***	0.02	0.179***	0.025	0.155***	0.033	0.131***	0.032	0.212***	0.021
RD → $S_{(CES-D)}$	−0.09*	0.043	−0.17*	0.066	0.004	0.056	−0.054	0.069	−0.1*	0.05
RD → $I_{(SRH)}$	−0.133***	0.018	−0.149***	0.026	−0.119***	0.026	−0.145***	0.029	−0.128***	0.022
RD → $S_{(SRH)}$	0.024	0.042	0.074	0.053	−0.048	0.081	0.089	0.102	−0.001	0.043
Model fit										
$\chi^2_{(df)}$	$193.102_{(43)}$		$106.001_{(41)}$		$114.633_{(41)}$		$139.066_{(41)}$		$107.89_{(41)}$	
CFI	0.985		0.987		0.984		0.976		0.99	
TLI	0.957		0.964		0.954		0.931		0.972	
RMSEA	0.024		0.023		0.014		0.03		0.022	
SRMR	0.013		0.014		0.018		0.018		0.011	

Note. $I_{(CES-D)}$ = intercept of CES-D depressive symptoms score; $S_{(CES-D)}$ = slope of CES-D depressive symptoms score; $I_{(SRH)}$ = intercept of self-rated health score; $S_{(SRH)}$ = slope of self-rated health score; RD = relative deprivation (deprived group vs. non-deprived group); $\chi2$ = chi-square test of model fit; CFI = comparative fit index; TLI = Tucker Lewis Index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; β = standardized coefficient; SE = standard error; ***$p < 0.001$, *$p < 0.05$. Results are combined using 20 imputed datasets. Results are based on models adjusted for selection and control variables given in Table 1.

relative deprivation, our study identifies the typology of relative deprivation by using LCA based on social relationships and geographical indicators. We identified two distinct parsimonious and meaningful groups: the “deprived group” and the “non-deprived group.” Our analysis showed that in China, approximately 30% of respondents were relatively deprived, and these individuals tended to report being worse off in all the deprivation indicators. Furthermore, both deprived and non-deprived groups were more likely to report “relatively worse” in relative economic status assessment when compared to the greater geographic areas (city and county). These findings concurred with those of Mangyo and Park (2011).

We also found that relative deprivation patterns are detrimental to *initial* health, with people classified as deprived showing lower self-rated health and higher depressive symptoms than non-deprived respondents, regardless of the level of analysis (overall or subgroups). Therefore, hypothesis 1a was supported, but hypothesis 2a was not supported. This concurs with the findings of Inoue et al. (2019), who reported that higher relative deprivation is associated with poorer self-rated health using the 2015 China Health and Nutrition Survey. However, hypothesis 1 b was not supported as relative deprivation was not associated with the self-rated health trajectory. Economic reform could partly explain this finding, as rapid economic growth in China has been accompanied by poverty reduction and significant improvement in access to health (Hao et al., 2020). Such economic transitions may affect people’s perception of health and counterbalance the influence of relative deprivation on self-rated health deterioration.

Our study found that relative deprivation was associated with the trajectory of depression, as deprived people, compared to non-deprived people, had a slower increase in depressive symptoms over time. This is counter-intuitive, despite being observed among the whole sample and, in particular, among women and rural adults. These findings are inconsistent with earlier studies applying intersectionality perspectives, where acceleration in health decline was observed for respondents with multiple risk exposures or disadvantages linked to social status (e.g., being an economically disadvantaged woman or living in rural areas, see (Bauer, 2014; Zeng et al., 2022). On the other hand, we found no significant association between relative deprivation and the trajectory of depressive symptoms among men and urban adults. Therefore, hypothesis 2 b was supported as the association between relative deprivation and health changes differs by gender and locality. This finding should be interpreted with caution. We confirmed a clear health divide by gender and locality (Lei et al., 2014), where women and rural adults have worse initial health, manifested by higher depressive symptoms and lower self-rated health (see Table 1). This potentially suggests that the slower over-time increase in depression for women and rural adults indicates the limited opportunity for depression to increase.

Conversely, the significant effects of relative deprivation on depressive symptoms may imply that gender and urban-rural inequalities are at play in these associations in contemporary China, though these assumptions are not directly tested in this study. Additional testing by flipping the reference coding (using the non-deprived group compared to the deprived group) showed that non-deprived women and rural residents were at higher risk of depression in the long term, as they experienced a faster increase in depressive symptoms over time. Our findings suggest that non-deprived women and rural residents may experience discrimination due to gender and urban-rural inequalities when they attempt to maintain their relatively higher social status (He and Wu, 2017; Shi et al., 2022; Xie et al., 2022). This may put double pressure on this group, resulting in a steeper growth rate of depressive symptoms. For example, public (gender inequality or unfair workplace practices) or private barriers (traditional gender roles in the family) may pose challenges for non-deprived women to maintain their status, which may accelerate their depression levels over time. For non-deprived rural residents, on the one hand, urban-rural inequalities such as the household resignation system (*hukou)* (Wu, 2019) may hinder them from moving to urban areas and achieving higher social status. Moreover, due to lagging development in rural areas, fewer high-paying jobs are available in rural areas, which leads to high competition in positions, which may result in a faster increase in depressive symptoms of non-deprived rural residents. A growing body of evidence suggests that structural barriers, such as sexism, racism, or geographically-based discrimination, have detrimental impacts on mental health (Vargas et al., 2020).

A sensitivity test was conducted for women living in rural areas to validate our main findings, as rural women exposed to multiple risks (i.e., gender and urban-rural inequalities) are in a particularly disadvantaged position in China (Xie et al., 2022). The results were consistent with the findings from the whole sample, and for rural and women subsamples, as similar relative deprivation patterns (i.e., a relatively deprived group and a non-deprived group) were identified through LCA. Additionally, PPM results showed that deprived rural women had worse initial health (i.e., lower self-rated health and higher depressive symptoms) and a slower increase in depressive symptoms over time, than non-deprived rural women. Another sensitivity test was conducted to examine whether the trajectories of self-rated health and depressive symptoms were influenced by the initial level of health (i.e., intercept of self-rated health and depressive symptoms measured in 2013) rather than health in 2011. The results showed that initial health (measured in 2013) did not significantly affect the self-rated health trajectory ($\beta = 0.007$, $p = 0.434$) or the trajectory of depressive symptoms ($\beta = -0.038$, $p = 0.723$).

The following limitations of the study should be noted. First, due to

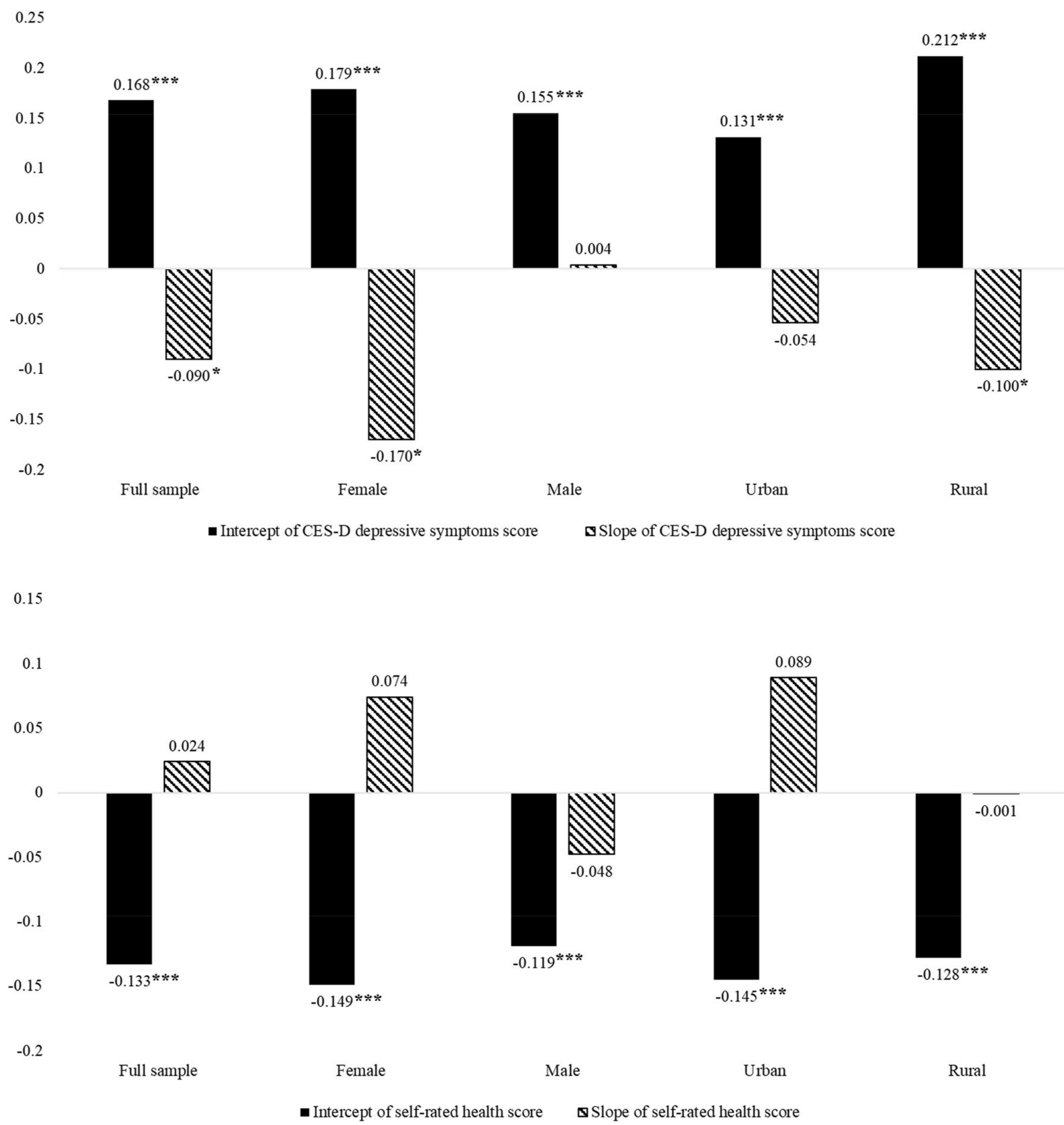

Fig. 3. Standardized estimates of associations between relative deprivation (deprived group vs. non-deprived group) and growth parameters (W2–W4) of CES-D and self-rated health in the conditional parallel process model. CES-D = Center for Epidemiologic Studies Depression Scale; ***$p < 0.001$, *$p < 0.05$. Results are combined using 20 imputed datasets. Results are based on models adjusted for selection and control variables given in Table 2.

the study window with three-time points, our study could only identify a linear trajectory for depressive symptoms and self-rated health based on this methodological constraint. However, these linear trajectories are population-average estimates without exploring the heterogeneity. Nevertheless, the significant variability in depression and self-rated health trajectories (see online Table S3) suggests that differential trajectories for subgroups could be further identified. Future studies that aim to explore health heterogeneity should use a growth mixture model approach, such as the latent class growth model, to investigate how different patterns of health trajectories may respond to relative deprivation (e.g., stable low or high depression). Second, estimates of the measures of relative deprivation were constrained by the available social and geographical indicators. Other potential salient reference groups for relative deprivation, such as province and nation, were not measured in the CHARLS; therefore, their effects could not be considered. Third, these relative deprivation measures were only available in 2013 CHARLS, which precludes modeling longitudinal changes in relative deprivation. Fourth, both depressive symptoms and self-rated health were self-reported and could be influenced by recall bias. Future studies should aim to examine impacts on actual health measures such as biomarkers and diagnosis of diseases to avoid potential recall bias. Lastly, although the longitudinal design strengthens a causal argument, the observational design may compromise the causal inference.

Despite these limitations, this study has several strengths. It is one of the first attempts to identify the typology of relative deprivation using the LCA approach. Understanding the heterogeneous patterns of relative deprivation may not only assist in understanding the implications of targeting marginalized populations suffering from multiple social and geographical deprivations, but also advance the current literature, where most studies use a combined index approach that cannot distinguish the relative importance of each indicator. Furthermore, this study provides initial evidence that a complex interplay across relative deprivation, gender, and locality may be critical in influencing long-term health.

Our study findings have implications for research and policy. Unlike prior studies that mainly adopted cross-sectional data and were confined to high-income countries, our study investigated the long-term impacts of relative deprivation on health in a middle-income country, China. This study addresses the paucity of longitudinal studies in middle-/low-income countries and provides a template for other studies in other middle-/low-income countries. Our study suggests that health could be improved by reducing relative deprivation resulting from inequalities across gender and locality. Therefore, the government is urged to introduce policies that care for individuals who are in a disadvantaged position to reduce people's feelings of relative deprivation, thereby improving mental and physical health. Additionally, programs should be promoted that target women, redress unfair treatment in public or private spheres, and re-allocate resources to develop rural infrastructure. This is especially important for non-deprived women and rural residents, as they may be at greater risk for depression in the long term.

In conclusion, our findings suggest that relative deprivation negatively affects mental and physical health status. The impacts of relative deprivation on mental health trajectories vary by gender and urban-rural locality, indicating that an interplay between relative deprivation and structural factors may affect the trajectory of Chinese people's mental health. Policies aimed at promoting mental health should consider non-deprived females and rural residents who are at higher risk for depression in the long term.

Credit author statement

Songyun Shi: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Visualization. Yu-Chih Chen: Conceptualization, Methodology, Writing – original draft, reviewing & editing. Paul S.F. Yip: Conceptualization, Methodology, reviewing & editing.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115589.

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