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Local Fitness Accessibility and Mental Health: Evidence from China

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Abstract

This paper studies whether local fitness accessibility improves adults' mental health. We combine geocoded point-of-interest data on five categories of fitness amenities with longitudinal survey data from China and exploit within-person changes in local supply. The results show that greater fitness accessibility reduces depressive symptoms and the likelihood of clinically relevant symptom burdens. We use peer-city fitness supply within the same province as an instrumental variable and obtain similar results. We also find consistent evidence using an independent city-level measure of mental health related Baidu search behavior. Mechanism evidence suggests that fitness accessibility improves mental health partly by increasing physical activity and strengthening individuals' mental capital. The effects are stronger where facilities are spatially proximate and evenly distributed, and among groups that rely more on, or are better able to use, their local environment. Overall, local fitness accessibility emerges as an important nonmedical margin for improving mental health in aging societies.

JEL Classification: I12, R11

Keywords: Mental health; Fitness accessibility; Local amenities; Physical activity

Contents

1	Introduction	3
2	Institutional Background and Hypotheses Development	6
2.1	Institutional Background	6
2.2	Hypotheses Development	8
3	Data and Empirical Design	11
3.1	Data and Sample	11
3.2	Measuring Mental Health	12
3.3	Measuring Local Fitness Accessibility with POI Data	12
3.4	Control Variables	14
3.5	Empirical Model	14
4	Main Results	15
4.1	Baseline Estimates	15
4.2	Instrumental-Variable Estimates	16
4.3	Category-Specific Evidence	17
4.4	Complementary Evidence from Search Behavior	18
4.5	Robustness Tests	19
5	Underlying Mechanisms	20
5.1	Physical Activity	20
5.2	Mental Capital	21
6	Further Analyses	21
6.1	Spatial Structure of Fitness Supply	22
6.2	Heterogeneity by Individual Characteristics	23
7	Conclusion	25

1 Introduction

Nearly one billion people worldwide live with a mental disorder, and depression alone affects about 280 million ([World Health Organization, 2022](#)). Depressive and anxiety disorders are among the leading causes of years lived with disability. Their consequences also extend well beyond health by reducing labor supply, impairing decision making, and reinforcing poverty across generations ([Ridley et al., 2020](#)). Population aging is shifting an increasing share of this burden toward later life, when depressive symptoms often coincide with cognitive decline, shrinking social networks, and chronic disease. This challenge is particularly important in developing countries, where most of the world’s older adults will soon live.

The scale of the problem has increased the need for responses that can reach large populations. Effective treatments exist, yet more than three quarters of people with mental disorders in low- and middle-income countries receive no care ([World Health Organization, 2022](#)). The limited reach of clinical care has therefore increased interest in determinants of mental health that policy can influence outside the health care system, including income support, sleep, and the environments in which people live ([Ridley et al., 2020](#); [Bessone et al., 2021](#)). Prevention embedded in everyday environments is especially promising, because it can reach broad populations continuously without relying on scarce mental health professionals.

Empirical evidence shows that residential environments shape mental health. Moving to lower-poverty neighborhoods improves adult psychological well-being ([Kling et al., 2007](#); [Ludwig et al., 2012](#)), while air pollution worsens mental health and well-being ([Zhang et al., 2017](#)) and nearby green space has protective effects ([Krekel et al., 2026](#)). Other features of the local environment also matter. The digital environment can adversely affect mental health ([Braghieri et al., 2022](#)), whereas shared cycling infrastructure can improve both physical and mental health partly by facilitating exercise ([Li and Xia, 2026](#)). This evidence underscores the role of local environments in shaping mental health by influencing residents’ everyday opportunities and constraints.

However, one component of the urban environment has received much less attention. Cities contain a dense ecosystem of gyms, sports venues, swimming pools, equipment retailers, and training establishments that exists specifically to support physical activity. Urban economics recognizes consumption amenities as important determinants of location choice and city growth ([Glaeser et al., 2001](#); [Couture and Handbury, 2020](#)) and has valued them through housing prices and time use ([Su, 2022](#)). A related behavioral literature studies how gym members choose contracts and how attendance responds to incentives ([DellaVigna and Malmendier, 2006](#); [Royer et al., 2015](#); [Carrera et al., 2020](#)), while largely taking the surrounding supply of fitness facilities as given. Whether the local fitness environment improves the mental health of nearby residents remains an open question.

This paper studies whether local fitness accessibility can function as preventive mental health infrastructure. The argument rests on two well-established findings. First, exercise reduces depressive symptoms in randomized trials, with effects comparable in magnitude to first-line clinical treatments (Noetel et al., 2024). Second, exercise decisions are highly sensitive to relatively small frictions. Consumers overpredict their future attendance (DellaVigna and Malmendier, 2006; Acland and Levy, 2015), respond strongly to simple reminders (Calzolari and Nardotto, 2017), are deterred by the startup costs of beginning an exercise routine (Carrera et al., 2020), and require compensation for the immediate disutility of working out (Milkman et al., 2014). When exercise behavior is sensitive to such frictions, local conditions can meaningfully affect participation. A denser supply of fitness amenities reduces travel and attention costs, keeps physical activity salient in daily life, and provides opportunities for social interaction that can make exercise easier to sustain (Gershon et al., 2025). Thus, we anticipate that greater accessibility can improve mental health through behavioral channels that operate outside the clinical setting.

China provides an informative setting in which to examine this relationship. The country has the world’s largest population of middle-aged and older adults, among whom depressive symptoms are widespread (Lei et al., 2014), while professional mental health care remains scarce relative to need (World Health Organization, 2022). Rapid urbanization, the migration of adult children, and the weakening of traditional family support have further increased the importance of local environments for later-life well-being. These forces are also common across many developing countries undergoing similar demographic transitions. At the same time, fitness-related amenities expanded rapidly and unevenly across Chinese cities, generating substantial variation in local fitness environments. We measure this variation using geocoded point-of-interest (POI) records and link it to two independent measures of mental health. The first is the CES-D-10 depressive-symptom score for over 12,000 respondents observed across waves of the China Health and Retirement Longitudinal Study. The second is a city-level index of mental-health-related search activity on Baidu covering 251 cities.

Our measure of local fitness accessibility aggregates five categories of fitness-related amenities into a lagged density per 10,000 registered residents. The individual-level analysis relates within-person changes in depressive symptoms to changes in this density in the respondent’s city. We find that greater local fitness accessibility is associated with significantly lower depressive symptoms. One additional fitness-related amenity per 10,000 residents is associated with a 0.12-point decline in the CES-D-10 score, and greater accessibility also reduces the likelihood of crossing established depression screening thresholds. Although the use of lagged fitness density helps mitigate concerns about reverse causality, time-varying local conditions may still jointly affect fitness supply and mental health. We therefore use leave-one-out peer-city fitness supply, which captures province-level industry expansion, as an instrument for local fitness accessibility and estimate the relationship

using two-stage least squares. The instrumental-variable estimates remain negative and statistically significant, providing further support for the baseline finding.

We next decompose the aggregate fitness measure into five categories of amenities: sports facilities, fitness centers, aquatic and recreational facilities, sporting goods and cycling services, and sports training establishments. The estimated coefficients are negative across all five categories and statistically significant for the latter four, suggesting that the main relationship is not driven by a single type of fitness amenity. We then turn to an independent city-level measure of mental health based on Baidu search activity. Cities with more fitness accessibility also exhibit declining search intensity for depressive and anxious terms. The consistency of these results across amenity categories and across two distinct measures of mental health further supports the main finding.

The channels behind these effects match the theory. Greater fitness accessibility increases physical activity on margins available to most middle-aged and older adults. A one standard deviation increase in supply is associated with roughly ten additional days of light physical activity per year and about 13 percent higher total activity volume. Accessibility also improves several components of what we call mental capital. It strengthens episodic memory, increases the probability of high life satisfaction, and moves nightly sleep toward the seven-hour benchmark. Two further sets of results tie the findings to accessibility itself. The relationship is roughly three times stronger in cities where facilities are located closer together and more evenly distributed across the urban area, and it is statistically significant only in these settings. It is likewise strongest among residents aged 65 and older, those living apart from their children, urban residents, and those with pension coverage, the groups whose daily lives depend most on the local environment and who are best positioned to use it.

The paper makes three contributions. First, it extends the literature on the environmental determinants of mental health. Previous empirical evidence now covers neighborhood poverty and safety (Kling et al., 2007; Ludwig et al., 2012), air pollution (Zhang et al., 2017), green space (Krekel et al., 2026), the digital environment (Braghieri et al., 2022), and publicly provided exercise infrastructure such as shared cycling systems (Li and Xia, 2026). This literature has largely focused on ambient conditions or public programs. By contrast, the commercial amenity ecosystem that directly supports physical activity has received little attention, even though urban economics has long recognized such consumption amenities as important to city life and growth (Glaeser et al., 2001; Couture and Handbury, 2020). We bring this layer of the city into the study of mental health and provide the within-person panel evidence that the market-provided fitness environment protects mental health in the world’s largest aging population.

The second contribution is to establish what fitness accessibility does for mental health and to trace how and for whom it works. Greater local supply lowers depressive symptoms within individuals, reduces the probability of clinically relevant symptom burdens,

and yields consistent evidence from an independent city-level measure of mental health search behavior. This complementary measure follows the growing use of search data to capture attention, behavior, and well-being (Da et al., 2011; Stephens-Davidowitz, 2014; Baker and Fradkin, 2017; Brodeur et al., 2021) and is less vulnerable to stigma-related underreporting in surveys (Bharadwaj et al., 2017). The mechanism evidence points to greater physical activity and improvements in cognition, life satisfaction, and sleep, with stronger effects among older adults, those living apart from their children, urban residents, and those with pension coverage. In aging societies where most affected individuals receive no treatment (Ridley et al., 2020; World Health Organization, 2022), these findings highlight the local fitness environment as a nonmedical margin for reducing the population burden of depression.

Third, the paper contributes to the measurement of fitness accessibility. Existing work typically measures exercise environments using facility counts or public expenditure (Brechot et al., 2017; Steckenleiter et al., 2023), even though fitness amenities serve narrow spatial catchments and their health effects depend on proximity rather than city-wide abundance (Su, 2022; Krekel et al., 2026). Geocoded POI records, increasingly used to study urban change (Glaeser et al., 2018), allow us to move beyond aggregate supply measures by capturing both the composition and spatial configuration of fitness amenities. We construct measures of facility proximity and the extent to which supply is distributed across the urban area rather than concentrated in a few hubs, and show that these spatial characteristics govern where the mental health relationship is strongest. The same data source therefore captures the quantity, composition, and effective accessibility of local amenities in a way that can be extended to other settings.

The remainder of the paper proceeds as follows. Section 2 presents the institutional background and develops the hypotheses. Section 3 describes the data, measurement, and empirical design. Section 4 reports the main results. Section 5 examines the underlying mechanisms. Section 6 presents further analyses of spatial structure and individual heterogeneity. Section 7 concludes.

2 Institutional Background and Hypotheses Development

2.1 Institutional Background

Mental disorders affect roughly one person in eight worldwide, with depression accounting for a substantial share of the burden (World Health Organization, 2022). Depressive and anxiety disorders are among the leading causes of years lived with disability across nearly every region, and their consequences extend well beyond health. More than 700,000 people die by suicide each year, while depression and anxiety impose an estimated annual loss of one trillion dollars on the global economy through reduced productivity. Poor

mental health also lowers labor supply, impairs cognition and decision making, and can transmit disadvantage across generations (Ridley et al., 2020).

This burden is particularly severe in low- and middle-income countries, where most people with mental disorders live but treatment resources remain limited. The majority of affected individuals receive no treatment. Governments allocate, on average, less than 2% of health spending to mental health, and the specialist workforce remains extremely limited. Low-income countries have a median of fewer than two mental health workers per 100,000 people, compared with more than sixty in high-income countries (World Health Organization, 2022). Services are also concentrated in large urban hospitals, leaving rural residents and older adults with particularly limited access to care. Population aging compounds this challenge as many developing countries are aging faster than their mental health systems can expand.

China reflects these pressures at especially large scale. By the end of 2025, China had 323.38 million people aged 60 and above, and is aging rapidly. Depressive symptoms are widespread among middle-aged and older adults, with substantial differences by socioeconomic status, household registration, and family structure (Lei et al., 2014). Several demographic and social changes have increased vulnerability in later life. Urbanization and the migration of adult children have weakened the traditional multigenerational household as a source of companionship and care, leaving more older adults living apart from their children. Meanwhile, the rising prevalence of chronic disease has lengthened the period over which physical and psychological burdens accumulate. Similar demographic transitions are occurring across many developing countries, making China informative for understanding the mental health challenges associated with population aging.

Mental health treatment capacity in China has not kept pace with these needs. Psychiatric professionals and specialized services remain scarce relative to the affected population and are concentrated in major cities. As a result, many older adults with clinically relevant symptoms are never diagnosed or treated (World Health Organization, 2022). Stigma further limits treatment by discouraging individuals from reporting psychological distress or seeking formal care (Bharadwaj et al., 2017). These constraints make it difficult for clinical expansion alone to address the growing burden of late-life depression. They also increase the importance of preventive approaches that operate through the environments in which people live and conduct their daily activities.

The local fitness environment in China has also changed substantially. Traditionally, physical activity relied heavily on public sports grounds and dedicated venues. As exercise options have diversified, commercial gyms, training studios, swimming and recreational facilities, sporting goods retailers, and cycling services have expanded alongside public facilities, supporting more flexible and self-directed activity. This expansion has varied across cities, generating meaningful differences in local fitness opportunities. Point-of-interest (POI) records allow these amenities to be measured consistently by type and

location.

China therefore combines a substantial and undertreated mental health burden among older adults with marked variation in local fitness opportunities. This setting allows us to examine whether greater access to fitness amenities is associated with better mental health and through which channels such a relationship may arise.

2.2 Hypotheses Development

We organize the analysis around two sets of hypotheses that link local fitness accessibility to mental health, identify the mechanisms through which this relationship operates, and characterize the conditions under which it should be strongest.

The starting point is that physical exercise improves mental health. Randomized trials show that exercise reduces depressive symptoms, with effects comparable in magnitude to first-line clinical treatments (Noetel et al., 2024; Pearce et al., 2022). Economic studies also document that sustained physical activity is associated with better health, subjective well-being, and labor market outcomes over longer horizons (Lechner, 2009; Humphreys et al., 2014). Experimental evidence further strengthens this link, as providing free access to a gym increases exercise and improves downstream performance (Cappelen et al., 2026). More broadly, residential environments have been shown to affect psychological well-being through neighborhood conditions and access to local amenities (Kling et al., 2007; Bilger and Carrieri, 2013; Krekel et al., 2026). An environment that facilitates physical activity is therefore a natural candidate for improving mental health.

The key link is that exercise decisions are highly responsive to behavioral frictions. Gym members often overpredict future attendance, while participation responds to reminders, startup costs, and the immediate enjoyment of exercise (DellaVigna and Malmendier, 2006; Acland and Levy, 2015; Milkman et al., 2014; Calzolari and Nardotto, 2017; Carrera et al., 2020). Local fitness accessibility can reduce these frictions by shortening travel distances, lowering search costs, increasing the salience of exercise opportunities, and expanding the range of nearby options. This is particularly important because fitness amenities serve narrow spatial catchments and their value declines rapidly with distance (Su, 2022). Fitness facilities may also support social interaction, and exercising with others can increase attendance through accountability and enjoyment (Gershon et al., 2025). Greater local fitness accessibility should therefore encourage exercise and, in turn, reduce depressive symptoms.

The first mechanism operates through physical activity. If greater accessibility lowers the time, monetary, and attention costs of exercise, local fitness supply should increase actual participation. Existing evidence has shown that residents living in areas with denser sports facilities participate more in sports (Brechot et al., 2017), exposure to better school sports facilities increases physical activity into adulthood (Black et al., 2019), and

experimentally removing access barriers directly raises exercise (Cappelen et al., 2026). By contrast, public spending on sports facilities does not necessarily translate into greater participation (Steckenleiter et al., 2023). This distinction suggests that what matters for behavior is the effective supply of exercise opportunities that residents can access, rather than expenditure alone.

The relevant activity margin should also reflect the population studied. For middle-aged and older adults, local fitness opportunities are likely to affect light and routine forms of activity such as walking and community exercise, which require relatively little skill, equipment, or expenditure. Older adults may also have greater discretionary time to incorporate nearby exercise opportunities into their daily routines. Sporting goods and cycling services can support this margin by facilitating self-directed activity outside formal venues. In a health production framework, greater accessibility lowers the effective price of physical activity. Both the frequency of light activity and overall activity volume should therefore increase (Lechner, 2009; Humphreys et al., 2014).

The second mechanism operates through mental capital. Regular physical activity can strengthen the stock of cognitive and emotional resources that individuals use to function, adapt, and cope with adverse circumstances (Beddington et al., 2008). These resources are particularly relevant in later life, when depressive symptoms often coincide with declining cognition, lower subjective well-being, and disrupted sleep. One important component is cognitive function. Exercise supports brain structure and function at older ages, with episodic memory among the domains that respond to physical activity (Hillman et al., 2008). Preserved cognition can in turn support the autonomy and engagement that are important for psychological well-being.

Mental capital also has evaluative and restorative dimensions. Improvements in residential environments can raise life satisfaction, as documented for safer neighborhoods and nearby green space (Kling et al., 2007; Ludwig et al., 2012; Krekel et al., 2026). Physical activity also improves sleep (Kredlow et al., 2015), while better sleep generates substantial psychological and economic benefits (Gibson and Shrader, 2018; Bessone et al., 2021). Cognition, life satisfaction, and sleep are all resources through which adverse economic and social conditions can influence mental health (Ridley et al., 2020). Greater fitness accessibility may therefore reduce depressive symptoms not only by increasing contemporaneous physical activity, but also by strengthening these broader cognitive, evaluative, and restorative resources. This reasoning yields the paper's first three hypotheses.

Hypothesis 1a. Main hypothesis. *Greater local fitness accessibility reduces residents' depressive symptoms.*

Hypothesis 1b. Physical activity mechanism. *Greater local fitness accessibility increases residents' physical activity.*

Hypothesis 1c. Mental capital mechanism. *Greater local fitness accessibility strengthens residents' mental capital.*

The strength of these effects should also depend on how fitness supply is arranged in space. Facility counts alone provide an incomplete measure of effective access because exercise decisions depend on the cost of reaching available opportunities. Urban density creates value by placing consumption amenities within easy reach of residents (Glaeser et al., 2001), and proximity to amenities is an important source of the benefits of dense urban living (Couture and Handbury, 2020). This is especially relevant for fitness amenities, which serve relatively narrow spatial catchments (Su, 2022). Evidence from comparable amenities such as green space also shows that health benefits depend on proximity rather than citywide abundance (Krekel et al., 2026). More generally, exercise responds to relatively small costs of attention and convenience (Milkman et al., 2014; Calzolari and Nardotto, 2017), making travel distance a particularly important component of effective access.

Two features of spatial configuration are therefore likely to matter for a given quantity of supply. The first is proximity. When facilities are located closer together, fitness opportunities form a more spatially compact local configuration. Such configurations may improve effective access when they overlap with where residents live and conduct daily activities. The second is decentralization. When facilities are distributed across neighborhoods rather than concentrated in a few hubs, a larger share of residents is more likely to have nearby opportunities. By contrast, highly centralized supply benefits residents close to the hub while imposing longer travel on others. Therefore, we propose the following hypothesis.

Hypothesis 2a. *The mental health effect of local fitness accessibility is stronger where facilities are spatially proximate and evenly distributed across the city.*

The strength of the relationship should also vary across individuals. One source of heterogeneity is dependence on the local environment. Activity spaces tend to contract with age, making nearby opportunities more important for older adults. Retirement may also provide more discretionary time to incorporate local exercise into daily routines. Family structure can further shape this dependence. Family arrangements are strongly associated with depressive symptoms among older Chinese adults (Lei et al., 2014). Those living apart from their children may have less regular companionship and interaction at home, increasing the value of local venues as spaces for social contact. This channel is consistent with evidence that exercising with others increases participation through accountability and enjoyment (Gershon et al., 2025).

A second source of heterogeneity is the capacity to translate nearby supply into actual use. City-level amenity density is more likely to imply convenient access for urban residents, which mirrors the supply-side logic of Hypothesis 2a. Economic security may also

matter. Financial insecurity can worsen mental health directly (Ridley et al., 2020) and limit investment in leisure-time health activities, while stable pension income can relax these constraints. This interpretation is consistent with evidence on the health benefits of pension coverage in China (Cheng et al., 2018). Health orientation may further shape responses because health behaviors tend to cluster within individuals, and those already investing in their health may respond more strongly to additional opportunities (Cutler and Lleras-Muney, 2010). Cognitive capacity could also affect the ability to recognize and organize routines around new opportunities. Because light and routine physical activity places relatively limited cognitive demands, however, we treat cognition as a capacity check rather than as a directional prediction. Thus, we propose the following hypothesis.

Hypothesis 2b. *The mental health effect of local fitness accessibility is stronger among residents who depend more on the local environment, or are better positioned to use it.*

3 Data and Empirical Design

3.1 Data and Sample

Our individual-level analysis draws on the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative panel survey of Chinese residents aged 45 and above modeled on the Health and Retirement Study (Zhao et al., 2014). CHARLS provides detailed information on mental and physical health, cognition, household economic conditions, employment, and social participation, together with the prefecture-level city of each sampled community. We use the 2013, 2015, and 2018 waves. The 2011 baseline predates the first year of our fitness facility data, while 2018 is the last completed wave before the pandemic disrupted the survey operations.

To measure local fitness supply, we obtain raw geocoded point-of-interest (POI) records from 2012 to 2023 covering fitness-related establishments across Chinese cities. City-level covariates and registered population are obtained from the CSMAR city database. To complement the survey-based measure of mental health, we also collect city-level Baidu Search Index data after identifying a set of mental health related keywords. The estimation sample includes respondents aged 45 or older with complete responses to all ten depressive-symptom items, complete personal controls, and available fitness and city-level covariates. Because the empirical analysis relies on within-individual variation, we further require each respondent to be observed in at least two survey waves. These restrictions yield 31,544 person-year observations for 12,539 individuals across 107 cities.

3.2 Measuring Mental Health

Our primary measure of mental health is based on the ten-item Center for Epidemiologic Studies Depression scale (CES-D-10), a short form of the instrument developed by Radloff (1977). The scale has been widely validated for population screening (Andresen et al., 1994) and for older Chinese adults in particular (Boey, 1999; Chen and Mui, 2014).

Each item records how often during the previous week the respondent experienced a particular symptom, such as depressed mood, restless sleep, loneliness, or difficulty concentrating, on a four-point scale from 0 to 3. The two positively worded items are reverse coded,¹ and the ten responses are summed to construct our Mental Health Index (*MHI*). The index ranges from 0 to 30, with higher values indicating more severe depressive symptoms. We calculate *MHI* only when all ten items are valid, ensuring a consistent measure across survey waves. The CES-D-10 is widely used to measure depressive symptoms in research based on CHARLS, such as Lei et al. (2014).

To complement this survey-based measure, we construct a city-level index of mental-health-related search activity using Baidu, the dominant search engine in China. Search data can capture concerns that individuals may be reluctant to disclose in surveys (Stephens-Davidowitz, 2014) and have been widely used in economics to measure attention, behavior, and well-being at fine geographic and temporal resolution (Da et al., 2011; Choi and Varian, 2012; Baker and Fradkin, 2017; Brodeur et al., 2021). Our measure, denoted *MHI_Search*, averages annual Baidu search intensity across 17 Chinese-language keywords in two groups. The first group contains eight terms describing core psychological symptoms, including depression, anxiety, melancholy, feeling suppressed, feeling gloomy, feeling depressed, low mood, and despair. The second contains nine terms capturing broader negative affect, including feeling lost, helplessness, emotional breakdown, palpitations with anxiety, mental agitation, irritability, feeling vexed, irascibility, and bad temper.² This measure provides a complementary city-level indicator of mental health related distress that is constructed independently of individual survey responses.

3.3 Measuring Local Fitness Accessibility with POI Data

We measure local fitness accessibility using geocoded point-of-interest (POI) records. POI data identify individual establishments by name, functional category, and geographic

¹The two positively worded items ask whether the respondent felt hopeful about the future and was happy during the previous week.

²The eight psychological symptom terms are 抑郁 (*yiyu*, depression), 焦虑 (*jiaolv*, anxiety), 忧郁 (*yoyu*, melancholy), 压抑 (*yayi*, feeling suppressed), 郁闷 (*yumen*, feeling gloomy), 心情郁闷 (*xinqing yumen*, feeling depressed), 情绪低落 (*qingxu diluo*, low mood), and 绝望 (*juewang*, despair). The nine broader negative affect terms are 失落 (*shiluo*, feeling lost), 无奈 (*wunai*, helplessness), 崩溃 (*bengkui*, emotional breakdown), 心慌 (*xinhuang*, palpitations with anxiety), 心烦意乱 (*xinfan yiluan*, mental agitation), 烦躁 (*fanzao*, irritability), 烦闷 (*fanmen*, feeling vexed), 易怒 (*yinu*, irascibility), and 脾气暴躁 (*piqi baozao*, bad temper).

coordinates, and have become an important source for measuring urban amenities at fine spatial resolution (Glaeser et al., 2018; Li and Xia, 2026). We assemble annual POI records from 2012 to 2023 and harmonize administrative names to a consistent prefecture-level framework, allowing us to track changes in local fitness supply across Chinese cities over time.

We classify each fitness-related POI into one of five mutually exclusive categories. Sports facilities include venues where physical activity takes place directly, such as stadiums, courts, ordinary swimming pools, and outdoor fitness spaces. Fitness centers consist of dedicated commercial gyms. Aquatic and recreational facilities include water-sports and aquatic activity centers, water parks, amusement parks, and related recreational venues, but exclude ordinary swimming pools, which are classified as sports facilities. Sporting goods and cycling services include retailers and service establishments that provide exercise equipment, outdoor gear, and bicycles. Sports training includes establishments that offer instruction in specific sports. Together, these categories capture the venues, equipment, and services that support physical activity in urban areas.

Figure 1 illustrates the spatial evolution of local fitness supply. Panels A and B report the number of fitness-related POIs in 2012 and 2017, while Panels C and D report POIs per 10,000 registered residents in the same years. Both measures show a substantial expansion in fitness supply over this period, with higher levels in 2017 concentrated mainly in eastern and coastal cities. To account for differences in city population and improve comparability in local access, we use POI density per 10,000 registered residents as our primary measure of fitness accessibility.

[INSERT FIGURE 1 HERE]

For each category g and city c , we calculate the number of POIs per 10,000 registered residents using registered population in year $t - 1$. To reduce the influence of extreme city-year observations, each category-specific density is winsorized at the 1st and 99th percentiles. Local fitness accessibility is defined as the sum of the five winsorized densities,

$$Fitness_{c,t-1} = \sum_{g=1}^5 \mathcal{W}_{1,99} \left(\frac{POI_{g,c,t-1}}{Pop_{c,t-1}} \right), \quad (1)$$

where $\mathcal{W}_{1,99}(\cdot)$ denotes winsorization and $Pop_{c,t-1}$ is registered population measured in units of 10,000. This measure captures the density of fitness opportunities available to local residents, consistent with facility-density measures of exercise environments (Brechot et al., 2017). Directly measuring amenities is preferable to relying on public sports expenditure, which does not necessarily translate into the supply residents actually face (Steckenleiter et al., 2023). This distinction is particularly important for fitness amenities because they tend to serve narrow spatial catchments (Su, 2022). Local density there-

fore provides a meaningful measure of the fitness opportunities embedded in residents' everyday environments.

3.4 Control Variables

Our specifications include control variables at both the individual and city levels. At the individual level, we control for socioeconomic and demographic characteristics associated with depressive symptoms in later life (Lei et al., 2014; Ridley et al., 2020). *Education* is a four-category measure of educational attainment entered linearly. *Partnered* indicates whether the respondent is married or cohabiting, *Agricultural hukou* indicates agricultural household registration, and *Employed* indicates current employment. At the city level, we include *Fiscal Spending*, defined as the natural logarithm of lagged fiscal expenditure per registered resident. This measure captures local public resources that may co-move with both amenity provision and public services, while broader local economic conditions can affect health behavior and health outcomes (Ruhm, 2000).

[INSERT TABLE 1 HERE]

Table 1 reports summary statistics for the individual and city-level samples. In the CHARLS sample, *MHI* has a mean of 8.0 and a standard deviation of 6.2, with a median of 6 and a 90th percentile of 17, indicating substantial variation in depressive symptom burdens. *Fitness* averages 1.77 amenities per 10,000 registered residents and ranges from 0.45 at the 10th percentile to 3.50 at the 90th percentile. Residents near the top of the accessibility distribution therefore face substantially greater local fitness supply than those near the bottom. Most respondents are partnered, hold agricultural hukou, and remain employed, broadly reflecting the socioeconomic profile of middle-aged and older adults in China. Panel B reports corresponding summary statistics for the Baidu city sample. Table A.1 provides definitions of all variables used in the analysis.

3.5 Empirical Model

To test **Hypothesis 1a**, which predicts that greater local fitness accessibility reduces depressive symptoms, we follow the literature (Bilger and Carrieri, 2013; Krekel et al., 2026; Li and Xia, 2026) and estimate

$$MHI_{i,c,t} = \beta Fitness_{c,t-1} + X'_{i,t}\gamma + W'_{c,t-1}\delta + \alpha_i + \lambda_t + \varepsilon_{i,c,t}, \quad (2)$$

where i indexes individuals, c indexes cities, and t indexes survey years. The dependent variable $MHI_{i,c,t}$ is the Mental Health Index for individual i in city c and year t , while $Fitness_{c,t-1}$ measures lagged local fitness accessibility. The vector $X_{i,t}$ contains the

individual-level controls for education, partnership status, agricultural hukou, and employment, and $W_{c,t-1}$ contains the lagged city-level control, *Fiscal Spending*. Individual fixed effects, α_i , absorb time-invariant individual characteristics,³ while survey-year fixed effects, λ_t , absorb shocks and policy changes common to all respondents in a given year. Hypothesis 1a implies $\beta < 0$.

The coefficient β is identified from within-individual changes in depressive symptoms associated with changes in lagged fitness accessibility in the respondent’s city across survey waves. The individual fixed effects remove persistent differences across respondents, including stable health endowments, early-life conditions, and other time-invariant characteristics, while the year fixed effects account for common temporal variation. Standard errors are clustered at the city level because fitness accessibility varies at the city-year level and observations within a city may be correlated over time (Abadie et al., 2023).

Although using one-year-lagged fitness accessibility helps reduce concerns about reverse causality, endogeneity may still arise if time-varying local factors jointly affect fitness supply and mental health. To address this concern, we later use leave-one-out peer-city fitness supply, which captures province-level industry expansion, as an instrument for local fitness accessibility. We then estimate the relationship using two-stage least squares (2SLS) to assess whether the baseline results remain robust to these remaining endogeneity concerns.

4 Main Results

This section presents the evidence on **Hypothesis 1a**. We first report baseline fixed-effects estimates, then address remaining endogeneity concerns with an instrumental-variable strategy, decompose the relationship across amenity categories, corroborate it with city-level evidence from search behavior, and close with robustness tests.

4.1 Baseline Estimates

We begin by estimating Equation (2), and Table 2 reports three specifications. Column (1) includes *Fitness* together with individual and year fixed effects. Column (2) adds the individual-level controls, and Column (3) further includes the city-level control, which is our preferred specification.

[INSERT TABLE 2 HERE]

The coefficient on *Fitness* is -0.113 in Column (1) and remains stable as controls are added. In the preferred specification, the coefficient is -0.122 and statistically significant

³Because each respondent is observed in a single city, α_i also absorbs time-invariant city characteristics, including geography, climate, and persistent features of the local economy and culture. This limits confounding from residential sorting based on stable preferences (Bilger and Carrieri, 2013).

at the 5% level. The consistency of the estimates across specifications indicates that the negative relationship is not sensitive to the inclusion of observed individual and city-level characteristics. These results support **Hypothesis 1a**, which predicts that greater local fitness accessibility reduces depressive symptoms.

The estimated magnitude is also economically meaningful. One additional fitness-related amenity per 10,000 registered residents is associated with a 0.12-point reduction in the CES-D-10 score. A one standard deviation increase in *Fitness* corresponds to a decline of about 0.19 points, or roughly 3 percent of a standard deviation of *MHI*. These magnitudes are comparable to the mental health effects documented for other features of the urban environment, including shared cycling infrastructure and nearby green space (Krekel et al., 2026; Li and Xia, 2026).

The control variables are also broadly consistent with established patterns in late-life mental health. Being partnered is associated with a 1.36-point lower *MHI* score and employment with a 0.42-point lower score, while agricultural hukou is associated with a 0.80-point higher score. These patterns are consistent with the socioeconomic gradient in depressive symptoms among middle-aged and older adults (Lei et al., 2014; Ridley et al., 2020).

4.2 Instrumental-Variable Estimates

Although the baseline specification uses lagged fitness accessibility, remaining endogeneity concerns may arise from time-varying local conditions. For example, improvements in local economic conditions may stimulate the expansion of fitness amenities while also affecting employment, income, and psychological well-being (Ruhm, 2000). Local fitness supply may also respond to changes in demand that are correlated with residents' health. In addition, POI counts may measure the underlying supply of fitness opportunities with error. We address these concerns using a two-stage least squares approach.

Our instrument exploits common province-year shifts in the broader fitness-supply environment. Province-level policy and market conditions can generate correlated changes in fitness supply across cities within the same province. For city c in province p , we construct the instrument as the leave-one-out mean of raw fitness-related POI counts in all other cities within the same province and year,

$$Z_{c,t-1} = \frac{\sum_{j \in p, j \neq c} POI_{j,t-1}}{1000 (N_{p,t-1} - 1)}, \quad (3)$$

where $POI_{j,t-1}$ denotes the total five-category POI count in city j , and $N_{p,t-1}$ is the number of cities in province p . The instrument captures province-level changes in fitness supply while excluding the focal city's own POI count. The identifying assumption is that, conditional on the fixed effects and observed controls, changes in fitness supply in

other cities within the same province affect an individual’s mental health only through changes in fitness accessibility in the individual’s own city.⁴ Table 3 reports the first-stage estimates in Column (1) and the second-stage estimates for *MHI* in Column (2).

[INSERT TABLE 3 HERE]

The first-stage results show a strong positive relationship between peer-city fitness supply and local fitness accessibility. The coefficient on the instrument is 1.09 and is statistically significant at the 1% level. The Kleibergen–Paap rk LM test rejects under-identification ($p < 0.001$), and the Kleibergen–Paap rk Wald F statistic of 28.3 exceeds the conventional rule-of-thumb threshold of 10, indicating a strong first stage. In the second stage, the coefficient on instrumented *Fitness* is -0.254 and statistically significant at the 5% level. The IV estimate therefore preserves the negative and statistically significant relationship between local fitness accessibility and depressive symptoms.

The two-stage least squares estimate is roughly twice the fixed-effects estimate. The larger magnitude is consistent with attenuation from measurement error in a POI-based measure of fitness supply (Angrist and Krueger, 2001), as well as with a local effect among cities whose fitness supply responds more strongly to common provincial shifts. Overall, the IV estimates help address the remaining endogeneity concerns and provide further support for **Hypothesis 1a**.

4.3 Category-Specific Evidence

The analysis so far combines different types of fitness amenities into a composite measure. Because these amenities differ in how residents use them, we next examine each category separately. Each column of Table 4 re-estimates Equation (2) using the winsorized lagged density of one fitness category as the explanatory variable, while retaining the baseline controls and fixed effects.

The estimated coefficients are negative across all five categories. Fitness centers, aquatic and recreational facilities, sporting goods and cycling services, and sports training are all statistically significant, while the coefficient on general sports facilities is negative but not statistically distinguishable from zero. Sporting goods and cycling services show the strongest statistical evidence, with a coefficient of -0.324 that is significant at the 1% level. Fitness centers, aquatic and recreational facilities, and sports training have coefficients of -0.60 , -1.01 , and -1.07 , respectively, each significant at the 10% level. In terms of point estimates, the largest associations are observed for sports training and aquatic and recreational facilities.

⁴The four provincial-level municipalities are excluded because they have no other prefecture-level cities within the same province from which to construct the leave-one-out measure. The resulting IV sample contains 30,483 observations for 12,118 individuals across 103 cities.

[INSERT TABLE 4 HERE]

The pattern across categories is informative. The negative relationship appears not only for facilities where exercise takes place directly, such as fitness centers and aquatic venues, but also for training services and establishments that support self-directed activity. In particular, sporting goods and cycling services facilitate relatively flexible forms of exercise that can be incorporated into daily routines, a margin on which reductions in behavioral frictions can increase participation (Calzolari and Nardotto, 2017; Carrera et al., 2020). Overall, the results suggest that the aggregate relationship reflects several components of the local fitness environment rather than a single type of amenity.

4.4 Complementary Evidence from Search Behavior

We next examine whether the relationship also appears in a measure of mental health constructed independently of the CHARLS survey.

MHI_Search is based on the Baidu Search Index and captures city-level search intensity for the mental-health-related terms defined above. The available city-level series span 2016 to 2020, which determines the estimation period. Search-based measures provide a complementary view of population mental health because they capture behavior outside the survey setting and are not subject to interviewer effects or recall error (Stephens-Davidowitz, 2014; Brodeur et al., 2021). We estimate the city-level specification

$$MHI_Search_{c,t} = \beta Fitness_{c,t-1} + W'_{c,t-1}\delta + \mu_c + \lambda_t + e_{c,t}, \quad (4)$$

where c indexes cities and t indexes years. $MHI_Search_{c,t}$ denotes city-level mental health related search intensity, and $Fitness_{c,t-1}$ is lagged local fitness accessibility. The vector $W_{c,t-1}$ contains lagged city-level controls, μ_c denotes city fixed effects, and λ_t denotes year fixed effects. Standard errors are clustered at the city level. The estimation sample contains 1,141 city-year observations across 251 cities. Table 5 reports three specifications. Column (1) includes city and year fixed effects only. Column (2) adds *Fiscal Spending*, the same city-level control used in the individual analysis. Because city-level search behavior may also respond to broader local socioeconomic and health conditions, Column (3) further controls for lagged measures of income, population, fiscal capacity, health care supply, insurance coverage, retail activity, wages, unemployment, and financial development.

[INSERT TABLE 5 HERE]

As reported in Table 5, greater fitness accessibility is consistently associated with lower mental health related search intensity. The coefficient on *Fitness* is -0.245 in Column (1), remains nearly unchanged after adding *Fiscal Spending*, and is -0.266 with

the broader set of city controls in Column (3). All three estimates are statistically significant at the 5% level. This evidence complements the individual-level results in two important respects. The outcome is generated from observed search behavior rather than self-reported survey responses, and it captures mental health related concerns across a broader urban population and a substantially larger set of cities. The persistence of the negative relationship across these distinct measurement settings suggests that the baseline finding is not specific to the CHARLS survey or to its middle-aged and older respondents. The search-based evidence therefore provides an independent source of support for **Hypothesis 1a**.

4.5 Robustness Tests

We next examine whether the baseline relationship is robust to alternative outcome definitions, measure construction, inference procedures, and control sets. Table 6 reports five specifications, each modifying one element of the baseline model. Columns (1) and (2) use alternative indicators of depressive symptom severity, Column (3) modifies the fitness accessibility measure, Column (4) changes the clustering procedure, and Column (5) expands the set of city-level controls.

Columns (1) and (2) define indicators for *MHI* scores of at least 12 and at least 16, thresholds commonly used to identify clinically relevant depressive symptom burdens. Using the full baseline specification, a one standard deviation increase in *Fitness* lowers the probability of exceeding these thresholds by 1.3 and 1.5 percentage points, respectively, with the latter estimate significant at the 1 percent level. These results indicate that greater fitness accessibility is also associated with a lower likelihood of more severe depressive symptoms.

Column (3) reconstructs *Fitness* using four categories by excluding sports training. The coefficient remains negative at -0.133 and statistically significant at the 5 percent level, showing that the baseline result is not driven by the inclusion of training establishments. Column (4) applies two-way clustering by city and individual (Cameron et al., 2011), and the estimated relationship remains statistically significant. Column (5) adds *GDP per capita* together with additional lagged city-level controls for fiscal revenue, retail activity, wages, employment intensity, unemployment, hospital capacity, pension coverage, and health insurance coverage. The coefficient is -0.156 and remains significant at the 5 percent level in the resulting sample of 28,466 observations.

[INSERT TABLE 6 HERE]

Overall, the negative relationship between local fitness accessibility and depressive symptoms is stable across alternative outcome definitions, measurement choices, inference procedures, and control specifications.

5 Underlying Mechanisms

The results in [Section 4](#) show a robust negative relationship between local fitness accessibility and depressive symptoms, consistent with **Hypothesis 1a**. We next examine the mechanisms underlying this relationship. **Hypothesis 1b** predicts that greater accessibility improves mental health by increasing physical activity, while **Hypothesis 1c** predicts an additional channel through stronger mental capital, including cognitive and emotional resources that support psychological well-being. For each mechanism, we replace *MHI* in equation (2) with the corresponding intermediate outcome while retaining the baseline fixed effects, controls, clustering, and lag structure.⁵

5.1 Physical Activity

We first examine physical activity as a mechanism linking local fitness accessibility to mental health, as proposed in **Hypothesis 1b**. We consider two measures of physical activity. *Light physical activity* is the number of days in the previous week with at least ten minutes of light activity, ranging from 0 to 7. *Total physical activity* is the natural logarithm of one plus total metabolic-equivalent expenditure across vigorous, moderate, and light activity.

[Table 7](#) reports the results. Columns (1) and (2) examine light physical activity, while Columns (3) and (4) examine total physical activity. Within each pair, the first specification includes *Fitness* together with individual and year fixed effects, and the second adds the full set of baseline controls. Columns (2) and (4) are our preferred specifications. In the preferred specifications, the coefficient on *Fitness* is positive and statistically significant at the 5% level for both measures of physical activity. One additional fitness-related amenity per 10,000 residents increases light physical activity by 0.12 days per week and total activity volume by about 8%. In economic terms, a one standard deviation increase in *Fitness* raises light activity by 0.19 days per week, equivalent to roughly ten additional active days per year, and increases total activity volume by about 13%.

[INSERT [TABLE 7](#) HERE]

The results show that greater local fitness accessibility increases both the frequency of light activity and overall activity volume, two margins closely related to the health returns from physical activity ([Lechner, 2009](#); [Humphreys et al., 2014](#)). This evidence supports **Hypothesis 1b**.

⁵Sample sizes vary across outcomes because the detailed physical activity modules and some outcome questions are available only for subsets of respondents. Each outcome-specific sample is restricted to respondents observed at least twice.

5.2 Mental Capital

We next examine mental capital as a second mechanism linking local fitness accessibility to mental health (Beddington et al., 2008), as proposed in **Hypothesis 1c**. We focus on three dimensions. *Episodic memory* is the mean of immediate and delayed ten-word recall, ranging from 0 to 10. *High life satisfaction* is an indicator equal to one for a rating of 4 or 5 on the reverse-coded five-point scale, with higher values indicating greater life satisfaction. *Sleep-duration deviation* is the absolute difference between nightly sleep duration and seven hours, with lower values indicating sleep closer to the benchmark.

Table 8 reports the results. Columns (1) and (2) examine episodic memory, Columns (3) and (4) examine high life satisfaction, and Columns (5) and (6) examine sleep-duration deviation. Within each pair, the first specification includes *Fitness* together with individual and year fixed effects, while the second adds the full set of baseline controls. The even-numbered columns are our preferred specifications.

[INSERT TABLE 8 HERE]

The three dimensions of mental capital move consistently in the predicted direction. Greater local fitness accessibility is associated with better episodic memory, a higher probability of reporting high life satisfaction, and a smaller deviation of sleep duration from the seven-hour benchmark. In our preferred specifications, the coefficient on *Fitness* is statistically significant at the 5% level for episodic memory and at the 10% level for both life satisfaction and sleep-duration deviation. The magnitudes are also economically meaningful. One additional fitness-related amenity per 10,000 residents increases episodic memory by 0.088 words, raises the probability of high life satisfaction by about 1 percentage point, and reduces sleep-duration deviation by approximately 0.02 hours. A one standard deviation increase in *Fitness* corresponds to an increase of about 0.14 words in episodic memory and 1.6 percentage points in the probability of high life satisfaction.

These patterns are consistent with evidence linking physical activity and supportive residential environments to cognition, subjective well-being, and sleep (Hillman et al., 2008; Kling et al., 2007; Ludwig et al., 2012; Krekel et al., 2026; Kredlow et al., 2015; Gibson and Shrader, 2018; Bessone et al., 2021). Overall, the results show that greater local fitness accessibility is associated with improvements across the cognitive, evaluative, and restorative dimensions of mental capital (Ridley et al., 2020), providing support for **Hypothesis 1c**.

6 Further Analyses

The final analyses examine where and for whom the local fitness environment matters most. **Hypothesis 2a** predicts stronger effects where the spatial arrangement of supply

delivers greater effective access, and **Hypothesis 2b** predicts stronger effects among residents whose daily lives depend most on the local environment and who are best positioned to use it.

6.1 Spatial Structure of Fitness Supply

In this subsection, we examine whether the mental health relationship varies with the spatial configuration of fitness supply, as predicted by **Hypothesis 2a**. We characterize the spatial configuration of fitness supply along three dimensions: facility proximity, scale-adjusted proximity, and network centralization.

The first measure captures proximity among fitness facilities and therefore characterizes the spatial compactness of local fitness supply rather than resident-specific travel distance. For city c , we compute the median nearest-neighbor distance

$$d_c^{NN} = \text{median}_{k \in c} \left[\min_{l \in c, l \neq k} \text{dist}(k, l) \right], \quad (5)$$

where k and l index fitness-related facilities and $\text{dist}(k, l)$ denotes straight-line distance (Clark and Evans, 1954). We define spatial proximity using the inverse ordering of d_c^{NN} , so higher values indicate that facilities are located closer together. Because cities with more facilities mechanically tend to have shorter nearest-neighbor distances, we also construct a scale-adjusted proximity measure. Using the 2012, 2014, and 2017 city-year observations, we residualize $d_{c,t}^{NN}$ on the logarithm of one plus the facility count and POI-source-year fixed effects, and standardize the resulting residual. Scale-adjusted proximity is defined by the inverse ordering of this standardized residual, so cities with smaller residual distances have higher scale-adjusted proximity.

The third measure captures how concentrated or decentralized fitness supply is within the city. We connect any two facilities located within two kilometers of each other and compute the degree centralization of the resulting network (Freeman, 1979),

$$C_c^D = \frac{\sum_{k \in c} (d_c^{\max} - d_k)}{(N_c - 1)(N_c - 2)}, \quad (6)$$

where d_k is the number of facilities within two kilometers of facility k , $d_c^{\max}$ is the maximum degree in city c , and N_c is the number of facilities. Higher values indicate a more centralized network, while lower values indicate that facilities are more evenly distributed across the city. We adjust this measure for facility counts in the same manner as the proximity measure.

Figure 2 provides an illustrative view of these spatial measures using selected cities in Shandong Province. Dezhou and Weihai show contrasting levels of spatial proximity, while Weifang and Binzhou illustrate more decentralized and more centralized network

structures. The examples highlight that cities with comparable local fitness supply can differ substantially in how facilities are arranged, motivating the empirical analysis of whether these spatial characteristics shape the relationship between fitness accessibility and mental health.

[INSERT **Figure 2** HERE]

For each dimension, cities are divided at the sample median based on their 2012 spatial configuration, and equation (2) is estimated separately for the two groups using the full baseline specification. Respondents retain the classification of their city at sample entry. [Table 9](#) reports the results. Columns (1) and (2) split cities by spatial proximity, Columns (3) and (4) by scale-adjusted proximity, and Columns (5) and (6) by network centralization, with the group predicted to exhibit the stronger relationship shown first.

[INSERT **TABLE 9** HERE]

The results are consistent across all three measures. In cities with high spatial proximity, the coefficient on *Fitness* is -0.259 and statistically significant at the 5% level, compared with -0.089 and statistically insignificant in low-proximity cities. The scale-adjusted proximity split yields a similar contrast, with coefficients of -0.317 and -0.076 , respectively. The network measure shows the same pattern. The coefficient is -0.177 and significant at the 1% level where fitness supply is more decentralized, compared with -0.076 where facilities are more concentrated.

Across all three comparisons, the estimated relationship is substantially stronger when facilities are located closer together and more evenly distributed across the urban area. These findings indicate that the spatial arrangement of fitness supply matters for its effective accessibility. The pattern is consistent with evidence that exercise responds to small costs of travel and convenience ([Milkman et al., 2014](#); [Calzolari and Nardotto, 2017](#)) and that fitness amenities serve narrow spatial catchments ([Su, 2022](#)). Overall, the results support **Hypothesis 2a**.

6.2 Heterogeneity by Individual Characteristics

We next examine how the relationship between local fitness accessibility and mental health varies across individual characteristics, as predicted by **Hypothesis 2b**. Respondents are classified at sample entry along six dimensions organized into three pairs, and Equation (2) is estimated separately for each subgroup using the full baseline specification. [Tables 10](#), [11](#), and [12](#) each report results for two dimensions, with the same controls, fixed effects, and city-level clustering as in the baseline analysis.

[Table 10](#) examines heterogeneity by age and coresidence with children. Columns (1) and (2) split respondents by age at entry, while Columns (3) and (4) distinguish those

living with and without their children. The relationship is substantially stronger among older respondents and those living apart from their children. For respondents aged 65 and older, the coefficient on *Fitness* is -0.240 and statistically significant at the 1% level, compared with -0.084 among those aged 45 to 64. Similarly, the coefficient is -0.211 and significant at the 1% level among respondents not living with their children, compared with -0.072 among those who coreside with children. These patterns are consistent with local fitness amenities being particularly relevant for individuals whose daily activities and social interactions depend more heavily on their surrounding environment.

[INSERT TABLE 10 HERE]

Table 11 considers urban residence and pension coverage, two dimensions related to individuals' ability to make use of nearby fitness opportunities. Columns (1) and (2) compare rural and urban residents, while Columns (3) and (4) split the sample by pension coverage. The coefficient among urban residents is -0.133 and statistically significant at the 10% level, compared with -0.034 among rural residents. The relationship is also stronger among respondents with pension coverage. Their coefficient is -0.165 and significant at the 5% level, compared with -0.065 among those without coverage. The urban pattern is consistent with the spatial evidence in Section 6.1, while the pension results suggest that economic security may complement access to local fitness opportunities. This interpretation is consistent with evidence linking economic resources and pension income to mental and later-life health (Ridley et al., 2020; Cheng et al., 2018).

[INSERT TABLE 11 HERE]

Table 12 examines smoking status and cognitive function. Columns (1) and (2) split respondents by current smoking status, while Columns (3) and (4) divide respondents according to whether entry-year cognition is below or above the sample median. Among non-smokers, the coefficient on *Fitness* is -0.128 and statistically significant at the 5% level, compared with -0.071 among smokers, consistent with complementarity across health-related behaviors (Cutler and Lleras-Muney, 2010). By contrast, the estimates are similar across the two cognition groups, at -0.123 below the median and -0.149 above it, with both significant at the 10% level. The association with local fitness accessibility therefore extends across the cognitive distribution rather than being concentrated among respondents with higher cognitive function.

[INSERT TABLE 12 HERE]

Overall, the relationship is stronger among older adults, those living apart from their children, urban residents, and respondents with pension coverage, while remaining broadly similar across cognitive groups. Together, these patterns indicate that the

mental health benefits of local fitness accessibility are more pronounced for groups that depend more on their local environment or are better positioned to use nearby fitness opportunities, providing support for **Hypothesis 2b**.

7 Conclusion

This paper examines whether local fitness accessibility is related to mental health among middle-aged and older adults in China. Linking geocoded fitness amenities to longitudinal CHARLS data, we find that greater local fitness supply is consistently associated with fewer depressive symptoms within individuals. One additional fitness-related amenity per 10,000 registered residents reduces the CES-D-10 score by about 0.12 points, while a one standard deviation increase in *Fitness* lowers the probability of exceeding commonly used depression screening thresholds by 1.3 to 1.5 percentage points. The relationship remains negative and statistically significant in the instrumental-variable analysis using leave-one-out fitness supply in other cities within the same province. Independent city-level evidence from mental health related search behavior yields the same negative relationship.

We also find that this pattern is not confined to a single component of the fitness environment. The estimated coefficients are negative across all five amenity categories. The mechanism evidence points to both behavioral and mental-capital channels. Greater fitness accessibility increases light physical activity and total activity volume, while also improving episodic memory, life satisfaction, and sleep. Thus, these results indicate that the local fitness environment is associated with several dimensions of everyday behavior and psychological functioning that are relevant to mental health.

Spatial configuration and individual characteristics further shape this relationship. The association is substantially stronger where facilities are located in closer proximity and distributed more evenly across the urban area, suggesting that the effective accessibility of amenities depends on more than their aggregate quantity. The relationship is also stronger among adults aged 65 and older, those living apart from their children, urban residents, and respondents with pension coverage, while remaining broadly similar across cognitive groups. These patterns highlight the importance of both the spatial organization of local supply and residents' ability to make use of nearby fitness opportunities.

The findings have direct implications for mental health policy in aging societies. Local fitness accessibility offers a complementary nonmedical margin alongside clinical care, particularly when facilities are conveniently located and broadly distributed across neighborhoods. The stronger associations among older adults and those living apart from their children further suggest that such investments may be especially valuable for groups that rely most on their immediate local environment. More broadly, fitness accessibility is an important feature of urban design through which cities can support healthier aging.

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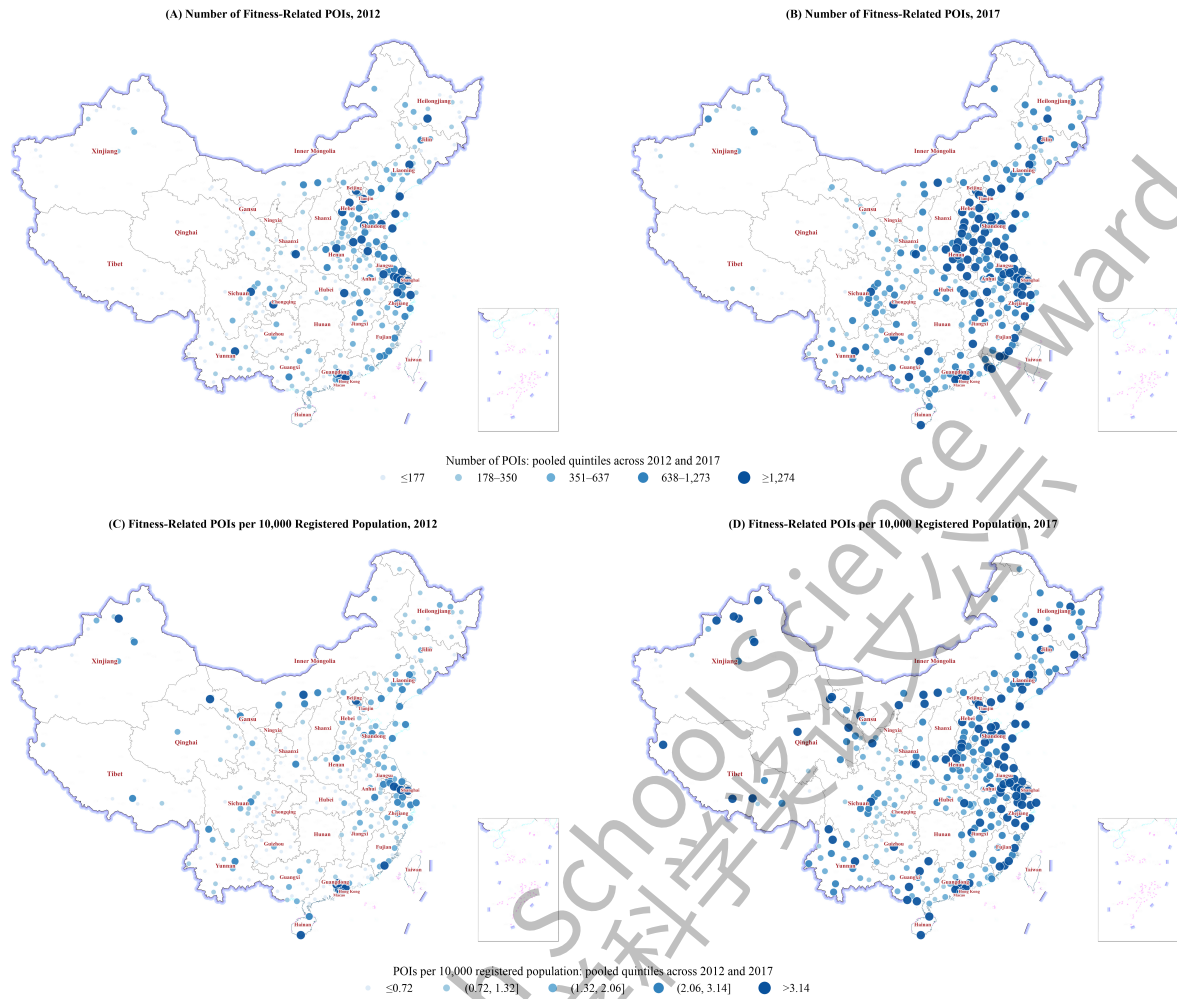


Figure 1: Spatial Distribution of Fitness-Related POIs in China

Notes: Panels A and B show the number of fitness-related POIs across cities in 2012 and 2017, respectively. Panels C and D show fitness-related POIs per 10,000 registered residents in the corresponding years. Marker colors indicate pooled quintiles constructed jointly across 2012 and 2017, with darker shades representing higher values.

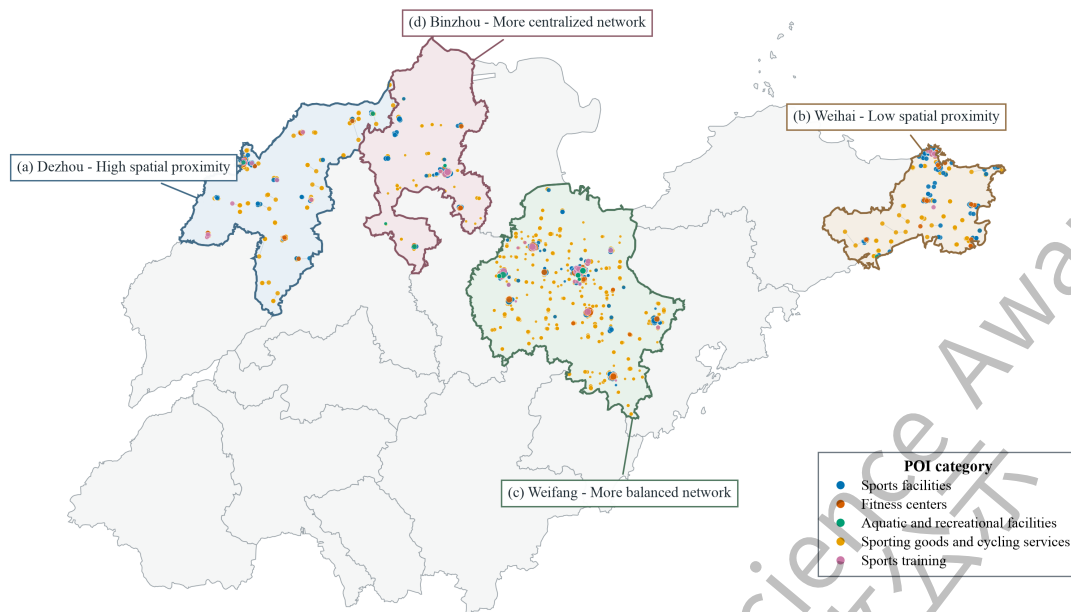


Figure 2: Examples of Fitness-Supply Network Structure

Notes: The figure uses selected cities in Shandong Province to illustrate different spatial characteristics of local fitness supply in 2012. Dezhou and Weihai provide examples of high and low spatial proximity, respectively, while Weifang and Binzhou illustrate more balanced and more centralized network structures. Colored markers distinguish the five categories of fitness-related POIs.

Table 1: Summary Statistics

Variable	Obs.	Mean	S.D.	P10	Median	P90
Panel A. Individual-Level Sample						
<i>MHI</i>	31,544	8.0274	6.2346	1.0000	6.0000	17.0000
<i>Fitness</i>	31,544	1.7660	1.6019	0.4519	1.3125	3.5007
<i>Education</i>	31,544	2.0422	1.0561	1.0000	2.0000	4.0000
<i>Partnered</i>	31,544	0.8830	0.3214	0.0000	1.0000	1.0000
<i>Agricultural hukou</i>	31,544	0.7811	0.4135	0.0000	1.0000	1.0000
<i>Employed</i>	31,544	0.6817	0.4658	0.0000	1.0000	1.0000
<i>Urban residence</i>	31,544	0.3940	0.4886	0.0000	0.0000	1.0000
<i>Fiscal Spending</i>	31,544	8.8360	0.4991	8.2558	8.7634	9.4695
Panel B. City-Level Sample						
<i>MHI_Search</i>	1,346	23.2379	25.3258	3.2924	14.4003	58.0347
<i>Fitness</i>	1,346	3.7140	2.8615	1.2309	2.8668	7.6385
<i>Fiscal Spending</i>	1,346	9.2429	0.5297	8.6645	9.1419	10.0161

Notes: Panel A reports the individual-level sample for 2013, 2015, and 2018, and Panel B reports the city-level sample for 2016–2020. The columns report the number of observations, mean, standard deviation, 10th percentile, median, and 90th percentile. Variable definitions are provided in [Appendix Table A1](#).

Table 2: Local Fitness Accessibility and Mental Health

Variable	(1)	(2)	(3)
<i>Fitness</i>	-0.1129*	-0.1219**	-0.1216**
	(0.0608)	(0.0590)	(0.0590)
<i>Education</i>		0.0614	0.0613
		(0.4191)	(0.4193)
<i>Partnered</i>		-1.3625***	-1.3628***
		(0.2924)	(0.2922)
<i>Agricultural hukou</i>		0.8006**	0.8005**
		(0.3750)	(0.3749)
<i>Employed</i>		-0.4154***	-0.4154***
		(0.1069)	(0.1069)
<i>Fiscal Spending</i>			-0.0642
			(0.4242)
Individual FEs	YES	YES	YES
Year FEs	YES	YES	YES
Obs.	31,544	31,544	31,544
Adj. R^2	0.533	0.534	0.534

Notes: This table examines the relationship between local fitness accessibility and mental health. The dependent variable is *MHI*, and the key explanatory variable is *Fitness*. Column (1) includes individual and year fixed effects. Column (2) adds individual-level controls, and Column (3) further adds *Fiscal Spending*. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Instrumental Variable Estimates

Dependent variable	(1) First stage <i>Fitness</i>	(2) Second stage <i>MHI</i>
<i>Peer-city fitness supply</i>	1.0922*** (0.2055)	
<i>Fitness</i>		-0.2545** (0.1288)
Individual controls	YES	YES
City controls	YES	YES
Individual FEs	YES	YES
Year FEs	YES	YES
Obs.	30,483	30,483
Kleibergen–Paap rk Wald F statistic		28.252
Kleibergen–Paap rk LM statistic		21.344

Notes: This table examines the relationship between local fitness accessibility and mental health using an instrumental-variable approach. The dependent variable of interest is *MHI*, and the key explanatory variable is *Fitness*. Column (1) reports the first-stage estimate, and Column (2) reports the second-stage estimate. The instrument is *Peer-city fitness supply*, defined as the leave-one-out mean of fitness-related POIs in other cities within the same province and POI source year, divided by 1,000. Controls are the same as those in Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Fitness Accessibility and Mental Health by Amenity Category

Variable	(1)	(2)	(3)	(4)	(5)
<i>Sports facilities</i>	-0.2491 (0.1905)				
<i>Fitness centers</i>		-0.5954* (0.3547)			
<i>Aquatic and recreational facilities</i>			-1.0057* (0.5650)		
<i>Sporting goods and cycling services</i>				-0.3235*** (0.1218)	
<i>Sports training</i>					-1.0674* (0.5979)
<i>Education</i>	0.0617 (0.4195)	0.0658 (0.4198)	0.0612 (0.4193)	0.0578 (0.4186)	0.0633 (0.4187)
<i>Partnered</i>	-1.3603*** (0.2919)	-1.3586*** (0.2921)	-1.3582*** (0.2922)	-1.3647*** (0.2928)	-1.3588*** (0.2924)
<i>Agricultural hukou</i>	0.7946** (0.3749)	0.7954** (0.3756)	0.7937** (0.3747)	0.8001** (0.3752)	0.7987** (0.3744)
<i>Employed</i>	-0.4138*** (0.1068)	-0.4142*** (0.1069)	-0.4154*** (0.1071)	-0.4153*** (0.1067)	-0.4129*** (0.1068)
<i>Fiscal Spending</i>	-0.1016 (0.4277)	-0.0873 (0.4261)	-0.1210 (0.4261)	-0.0017 (0.4286)	-0.1067 (0.4284)
Individual FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES
Obs.	31,544	31,544	31,544	31,544	31,544
<i>Adj. R</i> ²	0.534	0.534	0.534	0.535	0.534

Notes: This table examines the relationship between different categories of local fitness accessibility and mental health. The dependent variable is *MHI*, and the key explanatory variable in each column is the lagged density of the corresponding fitness category. Columns (1)–(5) examine sports facilities, fitness centers, aquatic and recreational facilities, sporting goods and cycling services, and sports training, respectively. Controls are the same as those in Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Fitness Accessibility and Mental Health Search Intensity

Variable	(1)	(2)	(3)
<i>Fitness</i>	-0.2448** (0.0997)	-0.2428** (0.0991)	-0.2663** (0.1123)
<i>Fiscal Spending</i>		0.6770 (1.6742)	0.4507 (1.8350)
Additional city controls	NO	NO	YES
City FEs	YES	YES	YES
Year FEs	YES	YES	YES
Obs.	1,141	1,141	1,141
<i>Adj. R</i> ²	0.985	0.985	0.985

Notes: This table examines the relationship between local fitness accessibility and mental health related search intensity. The dependent variable is *MHI_Search*, and the key explanatory variable is *Fitness*. Column (1) includes city and year fixed effects. Column (2) adds *Fiscal Spending*, the same city-level control used in Column (3) of Table 2. Column (3) further adds lagged GDP per capita, population, physician supply, hospital-bed supply, healthcare-facility supply, health insurance coverage, retail sales per capita, average wage, unemployment, bank deposits per capita, and employment. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Robustness Checks

Specification	(1)	(2)	(3)	(4)	(5)
	Cutoff = 12	Cutoff = 16	Four-category measure	Two-way clustering	Expanded controls
<i>Fitness</i>	-0.0082** (0.0040)	-0.0093*** (0.0027)	-0.1325** (0.0642)	-0.1216** (0.0590)	-0.1557** (0.0730)
Individual controls	YES	YES	YES	YES	YES
City controls	YES	YES	YES	YES	YES
Individual FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES
Obs.	31,544	31,544	31,544	31,544	28,466
<i>Adj. R</i> ²	0.388	0.351	0.534	0.534	0.536

Notes: This table examines the robustness of the relationship between local fitness accessibility and mental health. The key explanatory variable is *Fitness*. Columns (1) and (2) use indicators for *MHI* scores of at least 12 and 16 as the dependent variables. Column (3) uses *MHI* and a four-category fitness measure that excludes sports training. Column (4) uses *MHI* with two-way clustering by city and individual. Column (5) uses *MHI* and augments the baseline controls with lagged *GDP per capita*, fiscal revenue per capita, retail sales per capita, average wage, employment intensity, unemployment, hospital-bed supply, pension coverage, and health insurance coverage. Columns (1)–(4) otherwise use the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level except in Column (4). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Underlying Mechanism: Physical Activity

Variable	<i>Light physical activity</i>		<i>Total physical activity</i>	
	(1)	(2)	(3)	(4)
<i>Fitness</i>	0.1175** (0.0581)	0.1199** (0.0586)	0.0755* (0.0393)	0.0826** (0.0376)
<i>Education</i>		0.1290 (0.3080)		0.2093 (0.3416)
<i>Partnered</i>		-0.2535 (0.2194)		0.3516 (0.2162)
<i>Agricultural hukou</i>		-0.1019 (0.2956)		-0.2363 (0.2683)
<i>Employed</i>		0.3324*** (0.0965)		0.8771*** (0.1010)
<i>Fiscal Spending</i>		-0.3463 (0.5342)		-0.2158 (0.3515)
Individual FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Controls	NO	YES	NO	YES
Obs.	13,827	13,827	13,611	13,611
<i>Adj. R²</i>	0.158	0.160	0.232	0.244

Notes: This table examines physical activity as a potential mechanism linking local fitness accessibility to mental health. The dependent variable is light physical activity in Columns (1)–(2) and total physical activity in Columns (3)–(4). The key explanatory variable is *Fitness*. Columns (1) and (3) include individual and year fixed effects, while Columns (2) and (4) additionally include the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Underlying Mechanism: Mental Capital

Variable	<i>Episodic memory</i>		<i>Life satisfaction</i>		<i>Sleep deviation</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Fitness</i>	0.0865** (0.0338)	0.0876** (0.0339)	0.0091 (0.0055)	0.0097* (0.0056)	-0.0208* (0.0116)	-0.0208* (0.0115)
<i>Education</i>		-0.0882 (0.1749)		-0.0199 (0.0413)		0.0061 (0.0943)
<i>Partnered</i>		0.3315*** (0.0890)		0.0153 (0.0200)		-0.1259* (0.0676)
<i>Agricultural hukou</i>		0.3120*** (0.0928)		-0.0341 (0.0304)		-0.1790** (0.0769)
<i>Employed</i>		0.1292*** (0.0309)		0.0376*** (0.0091)		-0.0055 (0.0247)
<i>Fiscal Spending</i>		-0.0100 (0.2386)		-0.0652 (0.0413)		0.0365 (0.1042)
Individual FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
Controls	NO	YES	NO	YES	NO	YES
Obs.	29,016	29,016	31,414	31,414	31,157	31,157
<i>Adj. R</i> ²	0.476	0.477	0.290	0.291	0.366	0.366

Notes: This table examines mental capital as a potential mechanism linking local fitness accessibility to mental health. The dependent variables are episodic memory in Columns (1)–(2), high life satisfaction in Columns (3)–(4), and sleep-duration deviation in Columns (5)–(6). The key explanatory variable is *Fitness*. Odd-numbered columns include individual and year fixed effects, while even-numbered columns additionally include the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Spatial Attributes of Fitness Accessibility

Variable	Spatial proximity		Scale-adjusted proximity		Network centralization	
	High	Low	High	Low	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Fitness</i>	-0.2594** (0.1074)	-0.0887 (0.0628)	-0.3172* (0.1619)	-0.0762 (0.0611)	-0.1773*** (0.0454)	-0.0760 (0.1114)
<i>Education</i>	0.1474 (0.4907)	-0.0209 (0.6831)	0.0966 (0.4837)	0.0256 (0.6806)	0.2795 (1.0282)	-0.0225 (0.3921)
<i>Partnered</i>	-1.5338*** (0.4026)	-1.1727*** (0.4264)	-1.3195*** (0.4352)	-1.3961*** (0.3990)	-1.4215*** (0.4361)	-1.3289*** (0.3946)
<i>Agricultural hukou</i>	-0.0044 (0.5360)	1.5659*** (0.3686)	-0.0518 (0.6756)	1.3264*** (0.3840)	1.0882** (0.4115)	0.5617 (0.6017)
<i>Employed</i>	-0.4435*** (0.1520)	-0.3835** (0.1534)	-0.3854** (0.1506)	-0.4368*** (0.1541)	-0.3675** (0.1491)	-0.4581*** (0.1549)
<i>Fiscal Spending</i>	0.5860 (0.6227)	-0.5593 (0.6097)	0.0460 (0.6291)	-0.4017 (0.5641)	0.3249 (0.7074)	-0.3960 (0.5033)
Individual FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Obs.	16,446	15,098	15,843	15,701	14,966	16,578
<i>Adj. R</i> ²	0.540	0.529	0.532	0.535	0.539	0.530

Notes: This table examines whether the relationship between local fitness accessibility and mental health varies with the spatial structure of fitness supply. The dependent variable is *MHI*, and the key explanatory variable is *Fitness*. Columns (1)–(2), (3)–(4), and (5)–(6) split cities at the 2012 median of spatial proximity, scale-adjusted proximity, and network centralization, respectively. All columns use the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Heterogeneity by Age and Coresidence with Children

Variable	Age		Coresidence with children	
	Age 45–64 (1)	Age 65+ (2)	No (3)	Yes (4)
<i>Fitness</i>	-0.0839 (0.0757)	-0.2401*** (0.0698)	-0.2110*** (0.0659)	-0.0722 (0.0758)
<i>Education</i>	-0.5618 (0.4566)	1.6259* (0.9227)	0.4363 (0.6028)	-0.2306 (0.6350)
<i>Partnered</i>	-1.4493*** (0.3900)	-1.2980*** (0.4006)	-1.5809*** (0.4021)	-1.1897*** (0.3856)
<i>Agricultural hukou</i>	0.9362** (0.4573)	0.3677 (0.6632)	1.4731*** (0.4713)	0.2852 (0.4732)
<i>Employed</i>	-0.4122*** (0.1207)	-0.4341** (0.1673)	-0.6016*** (0.1396)	-0.2182 (0.1354)
<i>Fiscal Spending</i>	-0.0382 (0.5319)	-0.0599 (0.6847)	-0.3726 (0.6234)	0.1110 (0.6279)
Individual FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Obs.	23,641	7,903	13,992	17,029
<i>Adj. R</i> ²	0.535	0.531	0.539	0.532

Notes: This table examines heterogeneity in the relationship between local fitness accessibility and mental health by age and coresidence with children. The dependent variable is *MHI*, and the key explanatory variable is *Fitness*. Columns (1)–(2) split respondents by age 45–64 and age 65 or older, while Columns (3)–(4) split respondents by coresidence with children. Groups are defined at sample entry. All columns use the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Heterogeneity by Residence and Pension Coverage

Variable	Residence		Pension coverage	
	Rural (1)	Urban (2)	No pension (3)	Pension (4)
<i>Fitness</i>	-0.0342 (0.0708)	-0.1326* (0.0717)	-0.0654 (0.0649)	-0.1648** (0.0738)
<i>Education</i>	-0.0656 (0.7529)	0.1696 (0.3682)	-0.6680 (0.6776)	1.3416** (0.6500)
<i>Partnered</i>	-1.3459*** (0.3680)	-1.4154*** (0.4307)	-2.2607*** (0.4484)	-1.0542*** (0.3617)
<i>Agricultural hukou</i>	0.8495* (0.4821)	0.7597 (0.5443)	0.5168 (0.5000)	0.6863 (0.5037)
<i>Employed</i>	-0.3597*** (0.1305)	-0.5351*** (0.1873)	-0.5647*** (0.1697)	-0.4546*** (0.1575)
<i>Fiscal Spending</i>	-0.2997 (0.5232)	0.3358 (0.4834)	-0.6394 (0.5796)	0.4376 (0.5259)
Individual FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Obs.	19,116	12,428	15,608	12,463
<i>Adj. R²</i>	0.525	0.529	0.516	0.544

Notes: This table examines heterogeneity in the relationship between local fitness accessibility and mental health by residence and pension coverage. The dependent variable is *MHI*, and the key explanatory variable is *Fitness*. Columns (1)–(2) split respondents by rural and urban residence, while Columns (3)–(4) split respondents by pension coverage. Groups are defined at sample entry. All columns use the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Heterogeneity by Smoking and Cognition

Variable	Smoking status		Cognition	
	Not smoking (1)	Smoking (2)	Low (3)	High (4)
<i>Fitness</i>	-0.1284** (0.0635)	-0.0709 (0.0949)	-0.1227* (0.0687)	-0.1492* (0.0876)
<i>Education</i>	-0.3457 (0.7481)	-0.1448 (0.7137)	-0.5380 (0.7860)	0.3587 (0.5566)
<i>Partnered</i>	-1.3050*** (0.3555)	-2.6683*** (0.7572)	-1.3524*** (0.4125)	-1.2499*** (0.4054)
<i>Agricultural hukou</i>	1.3397*** (0.4074)	0.1789 (0.7706)	0.5934 (0.6833)	1.1143*** (0.3516)
<i>Employed</i>	-0.3713*** (0.1191)	-0.4807 (0.2912)	-0.3376* (0.1770)	-0.5253*** (0.1410)
<i>Fiscal Spending</i>	-0.2903 (0.4575)	1.0285 (0.9366)	-0.4110 (0.7172)	0.7006 (0.6426)
Individual FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Obs.	20,418	5,456	13,752	13,728
<i>Adj. R</i> ²	0.549	0.465	0.518	0.511

Notes: This table examines heterogeneity in the relationship between local fitness accessibility and mental health by smoking status and cognition. The dependent variable is *MHI*, and the key explanatory variable is *Fitness*. Columns (1)–(2) split respondents by current smoking status, while Columns (3)–(4) split respondents by whether cognition at sample entry is at or below versus above the median. Groups are defined at sample entry. All columns use the same controls as Column (3) of Table 2. Standard errors in parentheses are clustered at the city level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.1: Variable Definitions

Variable	Definition
Panel A. Outcomes	
<i>MHI</i>	CES-D-10 depressive symptom score constructed as the sum of ten items coded from 0 to 3, with the two positively worded items reverse coded. The score ranges from 0 to 30, with higher values indicating more severe depressive symptoms, and is computed only when all ten items are valid.
<i>MHI_Dummy</i>	Indicator equal to one when <i>MHI</i> is at least 12 or at least 16, as specified in the relevant column.
<i>MHI_Search</i>	Annual mean of the combined desktop and mobile Baidu Search Index across the 17 mental-health-related keywords, measured at the city-year level.
Panel B. Fitness Accessibility	
<i>Fitness</i>	Sum of five category-specific fitness POI densities per 10,000 registered residents in year $t-1$, with each category separately winsorized at the 1st and 99th percentiles before aggregation.
Sports facilities	Density of venues where sports and exercise are directly undertaken, including stadiums, courts, ordinary swimming pools, and outdoor fitness spaces.
Fitness centers	Density of dedicated commercial gyms and fitness centers.
Aquatic and recreational facilities	Density of water-sports and aquatic activity centers, water parks, amusement parks, and related recreational venues. Ordinary swimming pools are excluded and classified as sports facilities.
Sporting goods and cycling services	Density of retail and service establishments supplying exercise equipment, outdoor gear, bicycles, and related cycling services.
Sports training	Density of establishments providing instruction or training in specific sports.
Peer-city fitness supply	Leave-one-out mean of raw five-category fitness POI counts across all other cities in the same province and POI source year, divided by 1,000.
Panel C. Individual Controls	
<i>Education</i>	Educational attainment measured in four ordered categories from below primary school to high school or above, entered linearly.
<i>Partnered</i>	Indicator equal to one if the respondent is married or cohabiting.
<i>Agricultural hukou</i>	Indicator equal to one if the respondent holds an agricultural household registration.
<i>Employed</i>	Indicator equal to one if the respondent is currently employed.

Table A.1: Variable Definitions (continued)

Variable	Definition
Panel D. City Controls	
<i>Fiscal Spending</i>	Natural logarithm of fiscal expenditure per registered resident in year $t-1$.
Panel E. Mechanism Outcomes	
Light physical activity	Days in the previous week with at least ten minutes of light physical activity, ranging from 0 to 7.
Total physical activity	Natural logarithm of one plus total metabolic-equivalent expenditure across vigorous, moderate, and light activity, winsorized within survey year at the 1st and 99th percentiles before transformation.
Episodic memory	Mean of immediate and delayed ten-word recall scores, ranging from 0 to 10.
High life satisfaction	Indicator equal to one for a rating of 4 or 5 on the reverse-coded five-point scale, with higher values indicating greater satisfaction.
Sleep-duration deviation	Absolute difference between nightly sleep duration and seven hours.
Panel F. Individual Subgroup Classifications	
Age group	Age 45–64 versus 65 or older at sample entry.
Coresidence with children	Living with children versus not at sample entry.
Residence	Rural versus urban residence at sample entry.
Pension coverage	With versus without pension coverage at sample entry.
Smoking status	Currently smoking versus not at sample entry.
Cognition	Total cognition score, ranging from 0 to 21, equal to the sum of episodic memory and executive function scores. Low and high groups are defined at or below versus above the entry-year sample median.
Panel G. Spatial Configuration Measures	
Spatial proximity	Inverse ordering of the median nearest-neighbor distance between fitness-related facilities. Higher values indicate greater proximity. Groups are split at the median of the 2012 value.
Scale-adjusted proximity	Inverse ordering of the standardized residual from regressing median nearest-neighbor distance on log facility count and POI-source-year fixed effects using 2012, 2014, and 2017 city-year observations. Groups are split at the median of the 2012 value.
Network centralization	Freeman degree centralization of the two-kilometer fitness-facility network, adjusted for facility count. Higher values indicate greater centralization. Groups are split at the median of the 2012 value.

Acknowledgments

I have always enjoyed exercise, especially strength training and mountain biking. After a workout, I usually feel calmer, more energetic, and happier. This personal experience made me curious about a broader question: if regular exercise can improve my mood, what might happen if more people had convenient opportunities to exercise? Conversations with my grandparents also made me realize that older adults often face fewer opportunities for physical activity and social interaction, even though both may be important for their well-being. This question seemed especially relevant in China, a rapidly aging society in which the mental health of older adults is becoming increasingly important. These considerations led me to study whether access to nearby fitness facilities is related to mental health among middle-aged and older adults in China.

I am grateful to my advisor, Zhiliang Ying, Professor of Statistics in the Department of Statistics at Columbia University. He provided academic guidance as my initial idea developed into an empirical study. His advice covered the research question, hypotheses, empirical strategy, data analysis, interpretation of statistical results, endogeneity concerns, and robustness checks. After reading my first draft, he also commented on the structure, logical flow, and clarity of the writing. He helped me identify arguments that needed revision or removal while leaving the substance of the project in my hands. His guidance helped me understand how a personal observation can become a researchable question and how evidence should determine the conclusion.

I conducted the project as the sole student researcher. I proposed the topic, assembled the datasets, and wrote the first draft. The study combined CHARLS survey data, fitness-related point-of-interest records, city statistics from CSMAR, and Baidu search indices. I wrote Python and Stata scripts for data cleaning, matching records across cities and years, constructing variables, and estimating regressions. I examined the main relationship and conducted additional analyses of possible mechanisms, differences across groups, spatial patterns, instrumental variables, and robustness. I prepared the tables and figures, revised the discussion, and checked the final presentation. The research used existing data and did not involve an experiment or new

participant recruitment.

The most difficult task was making information from different sources comparable. City identifiers, measurement units, missing observations, and survey coding required attention before the datasets could be combined. I addressed these problems by checking variable definitions, comparing records, and revising my scripts. Keeping clear records helped me trace mistakes and understand each result. I also had to learn that my own experience could motivate a question but could not establish the answer. I therefore explored alternative explanations and checked how estimates changed across specifications. This process taught me to distinguish associations from causal evidence and to interpret results close to conventional significance thresholds with care. It also showed me why transparent data processing matters as much as the final regression table.

The project changed the way I think about exercise and research. I began with a simple question from my daily life, but answering it required patience with data, careful definitions, and repeated checks. The evidence cannot show that every person will experience the same benefit from a fitness facility. It can, however, help clarify whether local opportunities for exercise are associated with mental health and which groups may be more likely to benefit. That distinction has made me more cautious and more interested in using data to study practical questions.

For the completed paper, I used ChatGPT (GPT-5.6-SOL) on five occasions after finishing the manuscript in early September 2026. Its role at that stage was proofreading the English for grammar and clarity. I remain responsible for the accuracy of the submitted work and the account of my contribution.

My advisor was the only other person who provided research guidance. I thank him for his time, patience, and careful comments, and I thank the researchers and data providers whose work made this study possible. I also appreciate the personal experiences that first encouraged me to ask this question. I hope to continue learning how evidence can inform accessible opportunities for exercise and better mental health.