International Journal of
Mental Health Promotion

Tech Science Press

http://doi.org/10.32604/ijmhp.2025.071999

ARTICLE

# Effects of Community Environmental Governance on Urban Mental Health: Evidence from the Yangtze River Delta, China

**Zhengliang Zhang[1], Shijian Wu[2], Xinna Tang[3] and Haowen Wu[3,*]**

[1]School of Government, Yunnan University, Kunming, 650500, China
[2]Faculty of Business, The Hong Kong Polytechnic University, Hong Kong SAR, China
[3]School of Government, Shenzhen University, Shenzhen, 518060, China
*Corresponding Author: Haowen Wu. Email: wuhaowen2018@szu.edu.cn

Received: 17 August 2025; Accepted: 28 November 2025; Published: 28 April 2026

**ABSTRACT: Objectives:** Amid accelerating urbanization, digitalization, and population aging, mental health issues have become increasingly salient among urban community residents. This study aims to examine how community environmental governance influences mental health (MH) by conceptualizing the community environment as comprising social capital (SC) and environmental perception (EP). Aging anxiety (AA) and digital usage tendency (DUT) are introduced as psychosocial background variables to analyze MH pathways under multifactor influences. **Methods:** Using data from the 2021 Chinese General Social Survey (CGSS), this study constructed a structural equation model (SEM) based on 362 urban residents from the Yangtze River Delta. Direct and indirect relationships among the key variables were assessed through path analysis. **Results:** Five statistically significant paths were identified. AA directly reduced MH ($\beta = -0.328$, $p < 0.001$). DUT negatively affected SC ($\beta = -0.173$, $p < 0.01$) and EP ($\beta = -0.212$, $p < 0.001$). SC positively influenced EP ($\beta = 0.260$, $p < 0.001$), and EP, in turn, positively affected MH ($\beta = 0.170$, $p < 0.05$). Mediation analysis confirmed three significant indirect pathways: DUT → EP → MH; DUT → SC → EP → MH; and SC → EP → MH. Other paths were not significant. **Conclusions:** The study clarifies how community environmental governance shapes urban residents' MH and highlights the mediating roles of SC and EP. MH reflects the positive interplay among social capital, environmental experience, and individual state; a supportive community environment is conducive to improved MH. As stressors arising from societal transformation, AA and DUT weaken MH via direct and indirect routes, respectively. Policy implications include positioning community environmental governance as a key entry point, promoting coordinated improvements in the community environment, and strengthening targeted psychosocial support for populations with elevated aging anxiety or digital dependence to provide sustained, multilayered support for urban mental health.

**KEYWORDS:** Community environmental governance; mental health; social capital; environmental perception; urban community; structural equation modeling

## 1 Introduction

The intersecting trajectories of urbanization and digitalization have drawn increasing attention to the mental health of urban populations [1]. Rising psychological distress not only threatens individual well-being but also undermines residents' sense of belonging and civic participation, thereby weakening the resilience and governance capacity of urban systems [2]. Especially in the post-pandemic era, the rapid transformation of social structures and the acceleration of daily life rhythms have jointly pushed mental health issues beyond the conventional boundaries of medicine and psychology, positioning them as critical concerns in public policy and social governance [3,4]. In this context, mental health is now widely understood as an embedded social construct, with its formation, evolution, and regulation deeply shaped by environmental settings and institutional frameworks. Accordingly, a growing body of research seeks to understand how public governance can serve as a mechanism for promoting mental health.

As a key intermediary between individuals and their surroundings, the community has become a central arena for exploring the mechanisms that shape mental health. It influences not only individuals' physiological activities but also their perceptual construction and emotional regulation. From a spatial perspective, the community functions both as a physical space that accommodates natural elements and as a social field that sustains interpersonal networks. Owing to this dual nature of social and ecological attributes, the community holds compound significance in the formation of mental states. Existing studies have demonstrated that favorable natural and social environments contribute positively to mental health [5–7]. Moreover, higher levels of community social capital can enhance individuals' perceptions of the natural environment, while positive experiences of that environment may, in turn, strengthen community cohesion and a sense of belonging [8–11]. However, some studies still regard these two factors as independent variables, overlooking their synergistic interaction and the dynamic logic embedded in governance processes. This limitation not only results in a fragmented understanding of how community mental health develops but also constrains public policy from designing integrated interventions. Therefore, the community environment should be conceptualized as a composite system that integrates social relationships, physical space, and governance structure, through which its multiple pathways of influence on mental health can be further explored.

Concurrently, the rise of the digital era is reshaping the spatial configuration and perceptual dynamics of community life [12–14]. The integration of smart platforms, digital interaction, and algorithmic governance tools has enabled communities to transcend physical boundaries, evolving into hybridized systems where social relations, environmental elements, and technological infrastructure are increasingly intertwined. In parallel, demographic transitions driven by population aging have heightened anxiety and uncertainty among middle-aged and older adults, and these concerns are further magnified by the uneven psychological adaptation to digital transformation. As a result, the community has become a multi-layered nexus of social, environmental, and technological forces whose influence on mental health is growing more complex and multifaceted.

Building on the above trends, this study adopts a social–ecological perspective to construct a three-layer analytical framework comprising social background, community environment, and mental health. The framework posits that mental health outcomes are embedded within multi-level environmental systems and shaped by the interplay of social structures, ecological settings, and interpersonal networks [15–17]. The analytical model proposed in this study includes five key variables: Social Capital (SC), Environmental Perception (EP), Aging Anxiety (AA), Digital Usage Tendency (DUT), and Mental Health (MH). Among them, the social background layer (AA and DUT) captures the socio-psychological characteristics that arise from demographic changes and technological transformation. Specifically, AA reflects the intergenerational tension and psychological burden associated with population aging, while DUT represents individuals' adaptive capacity and behavioral tendencies in the context of digital transformation. The community environment layer (SC and EP) embodies the dual operation of social and natural dimensions within community environmental governance: SC denotes the level of cohesion within social networks, and EP indicates residents' subjective perceptions and emotional responses to the quality of their living surroundings. Finally, the mental health layer (MH) serves as the outcome variable, reflecting the overall manifestation of the social–ecological system.

Accordingly, this study develops a multi-path structural equation model (SEM) to systematically identify the diverse pathways through which urban residents' mental health is influenced and to explore the roles and significance of community environmental governance within this process. Grounded in the intersection of community governance and social psychology, the model seeks to explain the complex relationships among social background, community environment, and mental health. The findings are expected to provide theoretical insight into how community environmental governance contributes to public psychological well-being and to offer policy guidance for optimizing community governance systems in the context of urban transformation.

## 2 Literature Review

### *2.1 The Rise of Urbanization and the Escalation of Mental Health Risks*

The accelerating pace of global urbanization has not only reshaped the spatial structure of modern societies but also prompted increasing scholarly concern for the mental health of urban populations [18]. As the proportion of urban residents continues to grow, urban life has become more closely linked to psychological vulnerability [19]. While cities offer superior medical and educational resources alongside greater economic opportunities, their complex ecological and social systems also give rise to a range of adverse conditions—such as deteriorating residential environments, limited access to public spaces, and weakened social support networks—that collectively intensify mental health stressors among urban dwellers [20,21].

Epidemiological studies have consistently shown that urban residents are more susceptible to anxiety, depression, and affective disorders than rural counterparts, a trend that has been observed across various national contexts [22–27]. For example, one study found a significant positive association between the degree of urbanization and depression risk in Austria [28]. In Russia, critical threats to psychological well-being have been linked to high population density, environmental degradation, and social inequality [29]. Research in Dhaka revealed that nearly 40% of respondents reported moderate to severe anxiety, while approximately 46% exhibited depressive symptoms; socioeconomic status, birthplace, and occupational status were significant predictors [30]. Similar dynamics have been documented in India, where rapid urban expansion and unequal resource distribution have disproportionately exposed vulnerable groups—including the elderly, adolescents, and women—to increased psychological risk [31,32]. In China, census data and cross-sectional surveys have demonstrated the complex and multifaceted interactions between urbanization and mental health [33].

However, not all studies present a uniformly negative assessment of urbanization's mental health consequences. One study suggests that urban residents, on average, report better mental health outcomes than those living in rural or small-town settings [34]. Another finding indicates that urbanization has contributed positively to the psychological well-being of specific population groups in China [35]. For example, urbanization has been shown to enhance life satisfaction among middle-aged and older adults [36], and a similar outcome has been observed among adolescents [37].

Overall, the relationship between urbanization and mental health is neither unidirectional nor linear, but shaped by the interplay of socioeconomic structures, institutional arrangements, and environmental conditions, with significant variation across contexts. Socially and economically marginalized populations are particularly vulnerable within the urbanization process [38–40], as rapid urban growth often exacerbates income disparities, undermines equitable resource allocation, and disrupts service provision. These structural challenges intensify psychological distress and exacerbate serious obstacles to the effectiveness and inclusiveness of public governance systems [41,42].

### *2.2 Impacts of Urban Environmental Factors on Mental Health*

The urban environment, as the fundamental spatial framework of daily life, not only shapes individuals' behavioral patterns but also subtly influences how psychological experiences unfold. Recent studies have commonly divided the influence of urban environments on mental health into two dimensions: the physical and the social. The former refers to objective conditions such as natural resources and infrastructure, while the latter relates to social attributes like neighborhood relations and interpersonal interactions. This classification helps to systematically understand how environmental factors influence psychological states through emotional responses and cognitive evaluations.

On the physical dimension, variables such as the layout of green and blue spaces, access to recreational resources, streetscape aesthetics, and pollution levels have been widely identified as critical determinants of mental health. Green spaces, as key venues for nature contact and stress reduction, have been consistently validated for their positive psychological effects [43–45]. Urban forests further promote psychological restoration by enhancing individuals' perception of nature [46]. Moreover, activity support and environmental quality are recognized as two essential dimensions through which open spaces contribute to mental health [47]. Additional research has revealed that streetscape greening improves psychological well-being indirectly by fostering place attachment, with effects varying across demographic groups [48]. Among older adults, higher green space coverage is associated with reduced stress and lower risks of depression [49], while the availability of leisure facilities correlates with reduced psychological distress [50]. Similarly, access to blue spaces has been confirmed to positively impact mental health outcomes [51]. In contrast, urban environmental pollution has been consistently linked to adverse psychological effects [52]. These findings collectively underscore the importance of a well-designed physical environment, particularly the equitable distribution of natural resources, in establishing the foundation for mental well-being in urban settings.

Social environmental factors, by contrast, influence mental health through alternative pathways. Deficits in neighborhood trust, weakened social support systems, and intensified social exclusion can trigger feelings of loneliness, anxiety, and helplessness. A sense of neighborhood safety contributes to better mental health through increased social cohesion, higher life satisfaction, and reduced stress [53]. However, these benefits are unequally distributed: urban hukou residents experience them more prominently than rural migrants or *in-situ* urbanized populations [54]. Housing market volatility also affects psychological well-being. Rising housing prices, while contributing to improvements in physical health, can simultaneously undermine psychological well-being, as inequality in housing wealth often translates into disparities in mental health [55]. Moreover, multidimensional energy deprivation has been shown to significantly impair mental health, particularly in resource-scarce regions [56]. Policy interventions play a critical buffering role in addressing structural vulnerabilities. For instance, urban regeneration programs have been found to alleviate psychological distress among disadvantaged populations during economic downturns [57]. One study reported that higher levels of urban development are associated with improved mental health among healthcare professionals, suggesting a broader link between urban affluence and psychological resilience [58].

Crucially, the physical and social environments do not operate in isolation; they are interconnected and mutually reinforcing. One study suggests that the social interaction potential of green spaces makes them critical nodes within the dual-pathway framework, where engaging in physical activity in natural environments facilitates social bonding and, in turn, promotes mental well-being [59]. Perceptions of street-level environmental features affect mental health through both physical and social mechanisms, with social elements often serving as mediators [60]. One study emphasized that neighborhood greening can substantially enhance mental well-being by improving walkability, strengthening social cohesion, and increasing life satisfaction [61]. In this context, Healthy City policies that foster environmentally friendly urban spaces may contribute to emotional stability and psychological resilience [62].

Beyond the physical and social environments, the widespread adoption of digital technology has become an increasingly important factor influencing mental health. Evidence from the CFPS 2020 data indicates that there is substantial mental health inequality between urban and rural residents in China, while Internet use plays a positive mediating role that helps alleviate this disparity [63]. Wang and Li (2025) further support this finding, showing that digital participation significantly enhances the mental health of Chinese adults and, to some extent, reduces mental health inequalities across gender and urban–rural groups [64]. In addition, research on social media suggests that healthy information flows and favorable communication environments contribute to improving residents' psychological well-being [65].

The physical, social, and informational environments jointly influence residents' mental health through multiple pathways. However, most existing studies focus on a single dimension, lacking a comprehensive perspective from community governance. Therefore, it is essential to conceptualize the community environment as an integrated governance system encompassing social relations, natural spaces, and digital media, and to further examine its mechanisms from a social–ecological perspective.

### *2.3 The Role of Community Governance in Shaping Mental Health*

In recent years, the focus of mental health research has gradually shifted from macro-level structures and individual characteristics to the meso-level domain of community governance, reflecting growing interest in community-based psychological intervention frameworks. Urban communities have evolved from being settings for daily life and social interaction to becoming key spaces for the formation, regulation, and restoration of psychological well-being. Residents' perceptions of the community environment, neighborhood interactions, institutional trust, and satisfaction with local governance have emerged as key variables in explaining disparities in mental health outcomes.

Empirical studies have shown that community-level environmental perceptions and neighborhood engagement can effectively reduce mental health inequalities associated with differences in socioeconomic status. The mechanisms, however, differ across urban and rural settings: social interaction plays a dominant role in cities, whereas rural areas rely more on environmental perception pathways [6,66]. Multiple factors—such as the physical environment, social capital, and institutional trust—jointly constitute the foundation of community governance and collectively shape residents' psychological conditions [5,67]. These findings suggest that the community is not merely a physical space but a psychosocial nexus at the intersection of governance systems and social relationships.

Housing conditions represent a foundational determinant of mental well-being. Research conducted in urban villages in China has revealed that housing quality and affordability indirectly affect mental health by strengthening community attachment, underscoring the psychological vulnerability of low-income populations in undergoverned areas [7]. Case studies from Guangzhou also demonstrate that housing tenure, neighborhood infrastructure, and opportunities for civic participation are significant determinants of community-based psychological well-being [5]. Similar findings have been reported in studies on public housing communities, where the development trajectory of housing and the quality of neighborhood interactions are closely linked to residents' satisfaction and psychological well-being [68].

The social capital dimension of community governance has also garnered increasing scholarly attention. Research suggests that community-level social capital can enhance subjective well-being by promoting psychological enrichment, with particularly strong effects observed among lower-educated groups [69]. In Seoul, neighborhood social networks among housewives provided both emotional support and social pressure, revealing the ambivalent nature of community-based social networks [70]. Survey data from Indonesia during the COVID-19 pandemic indicate that urban residents experienced greater psychological distress but also benefited from stronger community-based social support [71]. These findings highlight the dual psychological effects of community governance, which may simultaneously empower and burden residents.

The mental health effects of governance mechanisms on specific populations appear especially complex. Due to limited mobility, older adults are particularly sensitive to their immediate neighborhood conditions, and disadvantaged neighborhood environments have been shown to exacerbate their symptoms of depression and stress [72]. Meanwhile, internal migrants in China—constrained by the hukou (household registration) system—often struggle to access social capital and public services, thereby limiting the positive effects of community governance [73]. These findings suggest that, in addition to access to resources, equitable participation is essential in creating a fair opportunity structure for mental health promotion.

At the institutional level, conflict and responsiveness within community governance exert considerable influence on psychological states. Studies have revealed that resident–government conflicts over urban planning and property management are significantly associated with depressive symptoms [3], challenging the prevailing assumption that community-building necessarily enhances mental health. These findings suggest that governance quality, institutional responsiveness, and relational coordination form the essential foundation for effective community-based psychological interventions. Furthermore, variation in residents' satisfaction with community renovation and micro-renewal projects has also been found to significantly affect mental health outcomes [74].

Community governance is emerging as a vital theoretical lens for explaining mental health disparities and guiding intervention strategies. Spanning housing environments, social capital, and institutional arrangements, these dimensions collectively shape individual psychological well-being. This trend also resonates with international practices. For instance, the Community Health Promotion Program in the United States enhances mental health equity through multi-level social participation and collaborative interventions [75]. In Europe, the GreenME Project centers on "green care" and examines how nature-related interventions can be expanded across different settings, assessing their potential impacts on adult mental health and mental health equity [76]. These experiences further demonstrate that the community is not merely a physical space but also a psychological carrier where governance systems and social relations intersect, providing important international insights into the relationship between community governance and mental health in urban China.

### *2.4 Research Questions and Hypotheses*

Recent research has increasingly examined the relationship between urbanization and residents' mental health (MH), highlighting the roles of community environmental factors and governance characteristics as critical variables shaping individual psychological conditions. As a core component of urban governance, community environmental governance offers a meso-level analytical lens that helps contextualize mental health within broader environmental and social dynamics. Although existing studies suggest that factors such as neighborhood interaction and environmental perception (EP) may indirectly affect psychological outcomes [6], much of the literature remains focused on macro-level socioeconomic disparities and offers limited structural explanations within urban communities. In particular, prior work often adopts a single-dimensional perspective and lacks systematic exploration of the collaborative pathways through which social and natural environments jointly influence mental health.

To fill these gaps, this study constructs a multi-path theoretical framework (Fig. 1) grounded in the social–ecological framework, which conceptualizes individual mental health as an outcome of interactions among multiple environmental systems [15,16]. Within this framework, social background factors, community environmental conditions, and individual mental health correspond to three analytical levels: the macrosystem, the exo–mesosystem, and the microsystem. The macrosystem reflects the overarching characteristics of social structural transformation and the broader digital–technological context. The exo–mesosystem serves as the intermediate layer of the social–ecological structure, transmitting institutional and environmental influences from the outer systems through interpersonal and social interactions at the community level. The microsystem, in turn, captures individuals' psychological and emotional states.

Within the context of urban governance, the community environment constitutes the core com-ponent of this exo–mesosystem. The community level integrates institutional and physical conditions with residents' social relationships and interaction networks, forming a crucial linkage between structural conditions and individual psychological responses. Accordingly, social capital (SC) and environmental perception (EP) are conceptualized as mediating mechanisms within the social–ecological system that absorb macro-level influences and transmit them to individual mental health (MH), reflecting residents' subjective experiences of the community's social and natural environments, respectively. Higher levels of SC are likely to enhance public participation and environmental satisfaction, thereby improving EP and subsequently promoting MH [8,77,78]. Together, SC and EP constitute a bridging mechanism between the social and psychological domains, functioning as a "transmission layer" within the social–ecological framework and helping to explain how macro-level social contexts influence mental health through the community level. This conceptualization is consistent with Stokols's formulation of social–ecological theory, which emphasizes multilevel person–environment relationships and their dynamic interactions [17].

Aging anxiety (AA) and digital usage tendency (DUT) are defined as psychosocial variables at the macrosystem level, reflecting typical social responses to structural transformation and lifestyle change. As population ageing accelerates, middle-aged and older adults experience growing anxiety about their future quality of life, which has become an important source of psychological stress within communities. This anxiety may indirectly influence MH by reshaping individuals' environmental perceptions and social interaction patterns. At the same time, the deep penetration of digital technologies into community governance and everyday life has made media-use behaviors increasingly central to social connection, information acquisition, and subjective experience. While digital engagement can strengthen social ties, it may also weaken emotional bonds as opportunities for offline interaction decline. Through their combined influence on community interaction and environmental appraisal, AA and DUT indirectly affect MH.

At the exo–mesosystem level, SC and EP link macro-level social structures to individual psychological outcomes through the dual dimensions of social relations and subjective experience. MH, situated at the microsystem level, represents individuals' ultimate psychological responses emerging from the interaction between social and environmental contexts. Together, these elements form a three-layer transmission chain—spanning the macro-, exo–meso-, and micro-systems—expressed as AA and DUT $\rightarrow$ SC and EP $\rightarrow$ MH. This hierarchical mapping aligns with the multilayered logic of the social–ecological framework and provides the theoretical foundation for the multi-path structural model of "social psychology–community environment–mental health" proposed in this study. Guided by this framework, the study addresses the following research questions:

**RQ1.** Do EP and SC, representing natural and social dimensions of community governance, significantly influence residents' MH?

**RQ2.** Do AA and DUT significantly influence SC and EP?

**RQ3.** How do AA and DUT exert both direct and indirect effects on MH?

Accordingly, we develop sixteen testable hypotheses (Table 1) and empirically examine them in the subsequent analysis.

**Table 1:** Hypothesis statements and path relationships in the theoretical model.

| RQ | No. | Hypothesis | Path |
|---|---|---|---|
| RQ1 | H1 | SC significantly affects EP. | SC → EP |
| | H2 | EP significantly affects MH. | EP → MH |
| | H3 | SC significantly affects MH. | SC → MH |
| | H4 | SC indirectly affects MH through EP. | SC → EP → MH |
| RQ2 | H5 | AA significantly affects EP. | AA → EP |
| | H6 | AA significantly affects SC. | AA → SC |
| | H7 | DUT significantly affects EP. | DUT → EP |
| | H8 | DUT significantly affects SC. | DUT → SC |
| RQ3 | H9 | AA significantly affects MH. | AA → MH |
| | H10 | DUT significantly affects MH. | DUT → MH |
| | H11 | AA indirectly affects MH through EP. | AA → EP → MH |
| | H12 | AA indirectly affects MH through SC and EP. | AA → SC → EP → MH |
| | H13 | AA indirectly affects MH through SC. | AA → SC → MH |
| | H14 | DUT indirectly affects MH through EP. | DUT → EP → MH |
| | H15 | DUT indirectly affects MH through SC and EP. | DUT → SC → EP → MH |
| | H16 | DUT indirectly affects MH through SC. | DUT → SC → MH |

Note: H1–H3 and H5–H10 represent direct effect hypotheses in the structural model, while H4 and H11–H16 refer to indirect effect hypotheses examining the mediating roles of Environmental Perception (EP) and Social Capital (SC) in the relationships between background variables (AA, DUT) and Mental Health (MH). All indirect effects were tested using the Bootstrap method.

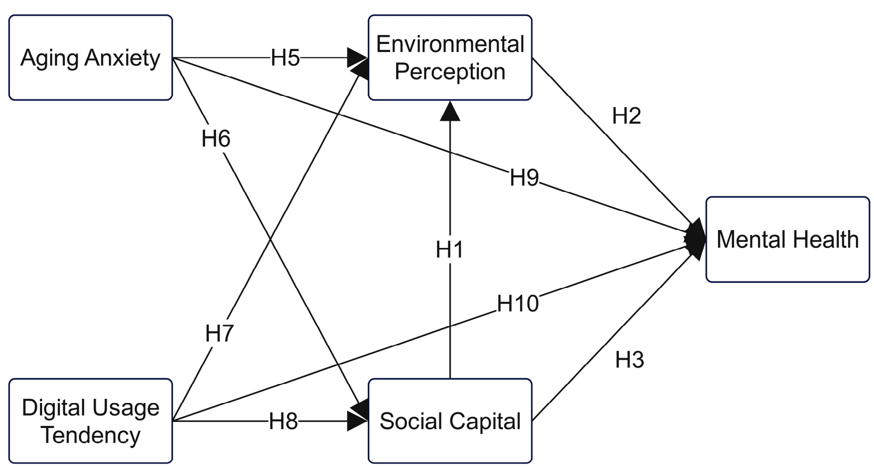


**Figure 1:** Theoretical model and hypothesized relationships.

These theoretical assumptions are grounded in the functional roles of each variable within the broader "community governance–mental health" pathway, rather than in conventional linear models of independent and dependent variables. In the empirical analysis, if any hypothesized directions or significance levels are not supported by the data, the model will be revised and reinterpretations will be provided, guided by both theoretical reasoning and empirical evidence.

## 3 Methods

### *3.1 Data Source*

This study used data from the 2021 Chinese General Social Survey (CGSS), conducted by the National Survey Research Center (NSRC) at Renmin University of China. Since its launch in 2003, the CGSS has completed 15 rounds of nationally representative surveys covering social, economic, cultural, and political dimensions, and is widely recognized as one of the most authoritative social surveys in China. The 2021 wave collected 8148 valid responses, with several modules designed according to international frameworks such as the International Social Survey Programme (ISSP) and the East Asian Social Survey (EASS), enhancing the data's comparability and cross-national relevance. The dataset is publicly available at http://cgss.ruc.edu.cn/English/Home.htm (accessed on 25 March 2025).

### *3.2 Sample Selection and Processing*

To examine the mental health of urban community residents and the pathways through which it is shaped, this study focuses on respondents living in urban areas of the Yangtze River Delta (YRD) region. As one of China's most economically developed and highly urbanized areas, the YRD is recognized for strong community governance, public service provision and civic participation, making it a representative setting for this research [79]. It is also among the regions at highest risk of severe population aging [80] and has taken the lead in aging governance and social security reform. Meanwhile, the YRD is a pioneer in smart-city development and digital governance, using digital technologies to improve the efficiency of social governance and forming a benchmark for institutional innovation [81]. These features mean that the YRD's community governance patterns and resident characteristics provide a theoretically informative context for examining links between community environments and mental health. Studying this region helps to clarify the multi-path relationships between psychosocial factors and community environments—and their combined impacts on residents' psychological well-being—under conditions of high urbanization, strong governance capacity, advanced aging, and extensive digital penetration. Although the analysis is based on data from the YRD, the theoretical framework and analytical approach are generalizable and can inform community governance research in other rapidly urbanizing areas.

During data preprocessing, only respondents from urban communities were retained, identified by the organizational type of their communities, to ensure a consistent governance context and focus on typical urban residents. Cases with invalid responses on selected items (e.g., "don't know" or "unable to answer") were removed, yielding 362 valid samples. To verify that this sample size met the statistical requirements for structural equation modeling (SEM), a priori power analysis was conducted using G*Power 3.1. The most complex equation in the model was approximated as a multiple regression with four predictors. With a medium effect size ($f^2 = 0.15$), a significance level ($\alpha = 0.05$), and a statistical power of 0.80, the required minimum sample size was 85, demonstrating that the study sample ($N = 362$) provides sufficient statistical power. Although the CGSS employed a stratified three-stage probability sampling design, this study aims to examine structural relationships among variables rather than population parameters; weighting and design effects were not applied in model estimation.

In addition, all included items were harmonized in terms of scale levels and coding direction to ensure consistency and comparability in subsequent analyses. Specifically, every variable was standardized to a five-point Likert scale ranging from 1 (strongly negative) to 5 (strongly positive) and reverse-coded items were recoded to align their direction with other items. These procedures ensured measurement consistency and provided a robust basis for reliability testing and SEM-based hypothesis analysis.

### *3.3 Variable Construction and Measurement*

Drawing on CGSS 2021 data, five core latent constructs were developed around mental health and its potential determinants: mental health (MH), social capital (SC), environmental perception (EP), aging anxiety (AA), and digital usage tendency (DUT). All constructs were theoretically grounded and measured through multiple survey items.

MH, the dependent variable in the model, reflects recent negative emotional states and their impact on daily functioning. It was measured using three items: depression or frustration in the past four weeks (MH1), emotional interference with work and daily life (MH2) and reduced concentration ability (MH3). These items capture emotional distress and role limitations consistent with mental health dimensions commonly employed in public health research [82,83], and have been widely applied in CGSS-based studies of subjective mental health [84,85].

Community environmental governance, the main explanatory construct, comprises two components. EP measures individuals' subjective evaluations of the natural environment, including air quality (EP1), water quality (EP2), noise levels (EP3), and lighting conditions (EP4). Environmental psychology and health research commonly use these factors to represent subjective environmental quality and examine its impact on health [86,87]. SC reflects the quality of community social relationships and perceived safety, including neighborly interaction (SC1), perceived trust (SC2), and evaluation of community safety (SC3). The SC items were selected from existing CGSS questions and informed by Putnam's work on trust and reciprocity [88], Harpham et al.'s concept of cognitive social capital [89], and Phongsavan et al.'s research on social capital and mental health [90], supporting the use of these three indicators to measure SC. The validity of both sets of indicators has been empirically verified in previous CGSS-based studies [91].

For psychosocial antecedents, AA reflects concerns about later-life well-being, including self-care ability (AA1), independent decision-making capacity (AA2), and financial security (AA3). Its conceptual content aligns with the relevant dimensions of the classic Anxiety about Aging Scale [92]. DUT reflects engagement with digital media and was measured using three items: preference for internet-based media (DUT1), use of personalized mobile content (DUT2), and frequency of internet use during leisure time (DUT3). These indicators are widely used in communication and social media research to measure digital usage tendencies [93,94]. All items were extracted from CGSS classifications, and their measurement stability has been supported by multiple empirical studies [95–97]. The original survey items and coding scheme are detailed in the Supplementary Materials (Table S1).

### *3.4 Analytical Strategy*

This study employs SEM to examine the pathways through which community environmental governance affects urban residents' mental health. The analysis included specifying and validating the measurement model, estimating structural paths, and testing mediation effects. SEM estimation was based on covariance-based Structural Equation Modeling (CB-SEM), and all main analyses were conducted in AMOS 28.0 (IBM Corp., Armonk, NY, USA) using Maximum Likelihood Estimation (MLE).

Before model estimation, descriptive statistics and normality tests were conducted to ensure data suitability. Guided by the theoretical framework and variable definitions, the measurement model was specified and its reliability assessed, followed by confirmatory factor analysis (CFA) to evaluate construct validity. Model fit was evaluated using multiple indices, including $\chi^2$/df, CFI, TLI, and RMSEA.

Composite reliability and convergent validity were then examined, with the latter evaluated using average variance extracted (AVE) and standardized factor loadings. Upon validation of the measurement model, the structural model was estimated with MH as the dependent variable, and AA, DUT, SC, and EP as predictors. Given the potential for indirect effects, mediation was tested using the bootstrap method, with both bias-corrected and percentile confidence intervals applied to ensure robustness.

To further assess the robustness of the CB-SEM results, Partial Least Squares Structural Equation Modeling (PLS-SEM) was introduced as a cross-validation tool. PLS-SEM was implemented using SmartPLS 4.0 by re-estimating the measurement and structural models in a form fully consistent with those specified in AMOS. A total of 5000 bootstrap resamples were used to obtain the t-values and significance levels of the path coefficients. Consistent path estimation performance between PLS-SEM and CB-SEM was taken as evidence of model robustness.

### *3.5 Common Method Bias Test*

To assess potential common method bias (CMB), Harman's single-factor test was first conducted [98,99]. An unrotated exploratory factor analysis including all measurement items extracted five factors with eigenvalues greater than one. The first factor accounted for 21.004% of the variance, well below the 40% threshold, indicating that CMB was not a serious concern. To address the limitations of a single diagnostic method, a confirmatory single-factor model was then tested by loading all items onto one latent variable and comparing it with the hypothesized five-factor measurement model. The single-factor model showed poor fit ($\chi^2$/df = 14.277, RMSEA = 0.192, SRMR = 0.148, CFI = 0.275, TLI = 0.163, IFI = 0.281), which was substantially worse than that of the five-factor model (Table 2). The large difference in fit confirmed that common method bias was not a serious issue in this study.

**Table 2:** Model fit indices of the measurement model.

| Fit Index | CMIN/DF | RMSEA | SRMR | GFI | AGFI | IFI | TLI | CFI |
|---|---|---|---|---|---|---|---|---|
| Reference Standards | <3 | <0.08 | <0.08 | >0.9 | >0.9 | >0.9 | >0.9 | >0.9 |
| Test Results | 1.534 | 0.038 | 0.050 | 0.954 | 0.933 | 0.974 | 0.966 | 0.974 |

Note: CMIN/DF = Normed Chi-Square; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; GFI = Goodness-of-Fit Index; AGFI = Adjusted Goodness-of-Fit Index; IFI = Incremental Fit Index; TLI = Tucker–Lewis Index; CFI = Comparative Fit Index.

## 4 Results

### *4.1 Descriptive Statistics and Normality Test*

This study analyzed a sample of 362 urban residents from the YRD, whose demographic characteristics are summarized in the Supplementary Materials (Table S2). The gender distribution was balanced, with 177 males (48.9%) and 185 females (51.1%). Regarding age, most respondents were of working age (18–59 years): 53 aged 18–29 (14.6%), 82 aged 30–44 (22.7%), 88 aged 45–59 (24.3%), and 139 aged 60 and above (38.4%), covering key life stages of urban residents. Regionally, participants were drawn from Anhui (n = 90; 24.9%), Jiangsu (n = 130; 35.9%), and Zhejiang (n = 142; 39.2%), providing balanced geographic coverage. Most respondents were Han Chinese (n = 361 participants, 99.7%), with only one person (0.3%) reporting ethnic minority status. Educational attainment was diverse: 28.7% (n = 104) had primary education or below, 29.3% (n = 106) completed junior high school, 16.6% (n = 60) had senior high school or technical secondary education, and 0.3% (1) had vocational school experience. Additionally, 23.8% (n = 86) held an associate or bachelor's degree, and 1.4% (n = 5) had postgraduate education, providing a solid contextual foundation for subsequent analysis.

Before structural modeling, descriptive statistics and normality tests were performed on the main measurement variables (Supplementary Materials, Table S3). Among the five latent constructs, MH had the highest score (Mean = 4.076), suggesting generally positive emotional states. SC (Mean = 3.957) and

EP (Mean = 3.818) followed, reflecting favorable evaluations of social and environmental conditions. DUT averaged 3.172, slightly above the midpoint, while AA had the lowest mean (Mean = 3.166), indicating a moderate level of concern about later life.

Regarding variability, DUT had the highest standard deviation (SD = 1.331), indicating considerable variation in digital behavior. AA had an SD of 0.923, suggesting notable variation in aging-related concerns. EP (SD = 0.742), SC (SD = 0.674), and MH (SD = 0.785) showed lower variability, reflecting relatively consistent perceptions across respondents.

Skewness and kurtosis were calculated to assess normality. According to Kline's criteria [100], absolute skewness less than 3 and absolute kurtosis less than 8 indicate approximate normality. As shown in the table, all items fell within acceptable ranges, with no significant skew or excess kurtosis. This indicates approximate normality, meeting the assumptions of maximum likelihood estimation (MLE) and supporting SEM analysis. To address minor departures from normality, maximum likelihood (ML) was supplemented with Bootstrap robust standard errors based on 5000 resamples to ensure stable results.

### *4.2 Measurement Model Assessment*

#### *4.2.1 Reliability Analysis*

Internal consistency was assessed using Cronbach's alpha, with $\alpha \geq 0.70$ considered acceptable [101, 102]. As shown in Table 3, all five latent constructs meet this criterion (AA = 0.732, DUT = 0.774, EP = 0.754, SC = 0.713, MH = 0.765), indicating satisfactory internal reliability.

**Table 3:** Reliability statistics of the latent constructs.

| Dimension | Cronbach's Alpha | N of Items |
|---|---|---|
| Aging Anxiety (AA) | 0.732 | 3 |
| Digital Usage Tendency (DUT) | 0.774 | 3 |
| Environmental Perception (EP) | 0.754 | 4 |
| Social Capital (SC) | 0.713 | 3 |
| Mental Health (MH) | 0.765 | 3 |

#### *4.2.2 Convergent Validity and Composite Reliability*

Composite reliability (CR) for all constructs exceeds the recommended threshold of 0.70 [103], indicating strong internal consistency. Convergent validity, assessed using Average Variance Extracted (AVE), reflects that DUT (0.631), SC (0.510), and MH (0.576) all exceed the 0.50 benchmark.

Although AVE values for AA (0.479) and EP (0.444) fall slightly below 0.50, their CR values are above 0.70 and their items are conceptually coherent. Thus, they are considered to exhibit borderline but acceptable convergent validity [103]. Table 4 presents detailed CR and AVE results.

**Table 4:** Convergent validity and composite reliability of the latent constructs.

| Path | Estimate | AVE | CR |
|---|---|---|---|
| AA → AA1 | 0.670 | 0.479 | 0.734 |
| AA → AA2 | 0.719 | | |
| AA → AA3 | 0.686 | | |
| DUT → DUT1 | 0.966 | 0.631 | 0.819 |
| DUT → DUT2 | 0.360 | | |
| DUT → DUT3 | 0.911 | | |

**Table 4:** *Cont.*

| Path | Estimate | AVE | CR |
|---|---|---|---|
| EP → EP1 | 0.712 | | |
| EP → EP2 | 0.757 | 0.444 | 0.759 |
| EP → EP3 | 0.604 | | |
| EP → EP4 | 0.576 | | |
| SC → SC1 | 0.820 | | |
| SC → SC2 | 0.836 | 0.510 | 0.742 |
| SC → SC3 | 0.399 | | |
| MH → MH1 | 0.498 | | |
| MH → MH2 | 0.912 | 0.576 | 0.794 |
| MH → MH3 | 0.805 | | |

Note: AA = Aging Anxiety; DUT = Digital Usage Tendency; EP = Environmental Perception; SC = Social Capital; MH = Mental Health; AVE = Average Variance Extracted; CR = Composite Reliability.

#### *4.2.3 Discriminant Validity*

Discriminant validity was assessed using the Fornell and Larcker criterion [103], which requires that the square root of each construct's AVE exceed its correlations with other constructs.

Table 5 presents the correlation matrix among the latent constructs, with the square roots of AVE shown in bold on the diagonal. All constructs meet this criterion, indicating that the latent variables are statistically distinct and that the model has adequate discriminant validity.

**Table 5:** Discriminant validity assessment of the latent constructs.

| Construct | AA | DUT | EP | SC | MH |
|---|---|---|---|---|---|
| AA | **0.692** | | | | |
| DUT | 0.027 | **0.666** | | | |
| EP | −0.104 | −0.259 | **0.794** | | |
| SC | 0.034 | −0.172 | 0.292 | **0.714** | |
| MH | −0.340 | 0.022 | 0.208 | 0.119 | **0.759** |

Note: Bold diagonal elements represent the square roots of AVE; off-diagonal elements are the inter-construct correlations. AA = Aging Anxiety; DUT = Digital Usage Tendency; EP = Environmental Perception; SC = Social Capital; MH = Mental Health; AVE = Average Variance Extracted.

#### *4.2.4 Model Fit Evaluation*

Model fit was evaluated using eight standard fit indices: $\chi^2$/df, RMSEA, SRMR, CFI, TLI, IFI, GFI, and AGFI. Following established guidelines, $\chi^2$/df < 3, RMSEA and SRMR < 0.08, and values above 0.90 for the remaining indices indicate good fit [100,102,104–106]. As presented in Table 2, all indices met these thresholds, confirming that the measurement model fits the data well and providing a solid basis for subsequent analysis. Fig. 2 illustrates the CFA path diagram, with standardized loadings and links between items and constructs, visually summarizing the measurement structure.

Overall, the measurement model satisfies statistical and theoretical criteria for reliability, convergent and discriminant validity, and model fit, supporting its use in the structural modeling stage.

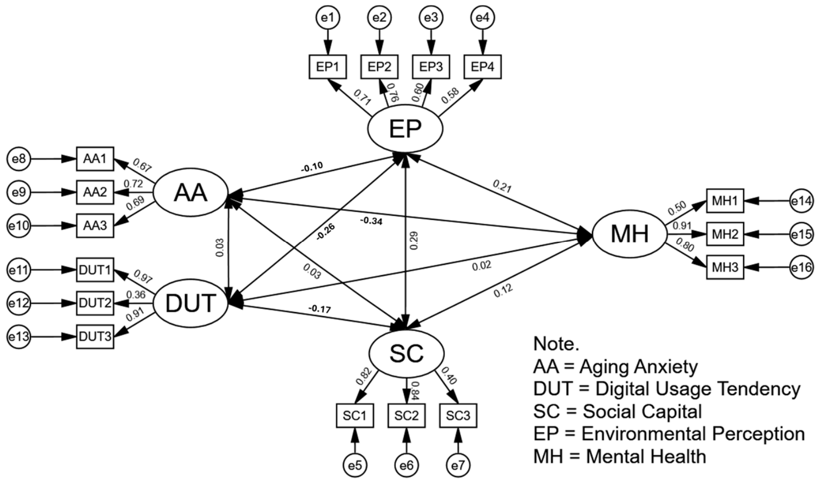


**Figure 2:** Path diagram of the measurement model.

### *4.3 Structural Model Estimation*

Building on the measurement model, SEM (Fig. 3) was specified to test the hypothesized relationships and underlying pathways. The model included nine structural paths covering both direct and indirect effects. The overall model fit was satisfactory ($\chi^2$/df = 1.534, RMSEA = 0.038, SRMR = 0.050, CFI = 0.974, TLI = 0.966, IFI = 0.974, GFI = 0.954, and AGFI = 0.933), with all indices meeting recommended thresholds (Table 6).

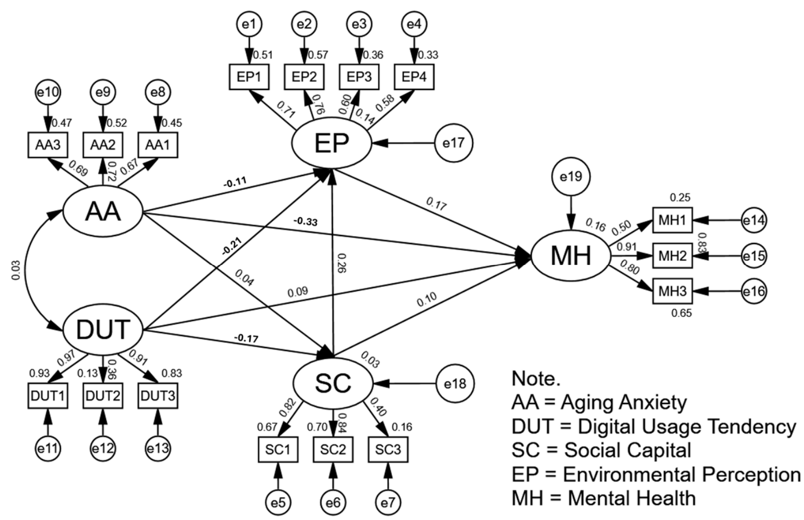


**Figure 3:** Structural equation model of environmental governance and mental health.

**Table 6:** Model fit indices of the structural equation model.

| Fit Index | CMIN/DF | RMSEA | SRMR | GFI | AGFI | IFI | TLI | CFI |
|---|---|---|---|---|---|---|---|---|
| Reference Standards | <3 | <0.08 | <0.08 | >0.9 | >0.9 | >0.9 | >0.9 | >0.9 |
| Test Results | 1.534 | 0.038 | 0.050 | 0.954 | 0.933 | 0.974 | 0.966 | 0.974 |

Note: CMIN/DF = Normed Chi-Square; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; GFI = Goodness-of-Fit Index; AGFI = Adjusted Goodness-of-Fit Index; IFI = Incremental Fit Index; TLI = Tucker–Lewis Index; CFI = Comparative Fit Index.

Among the nine hypothesized paths, five were statistically significant. First, AA shows a significant negative association with MH ($\beta = -0.328$, $p < 0.001$), suggesting that anxiety about aging directly undermines psychological well-being. Its paths to EP or SC were non-significant, indicating that AA operates mainly as a direct psychological stressor rather than through community-level variables.

Second, DUT exerted significant negative effects on both EP ($\beta = -0.212$, $p < 0.001$) and SC ($\beta = -0.173$, $p < 0.01$), implying that heavier reliance on digital media is associated with weaker engagement with the physical environment and interpersonal networks, and thus with lower perceived environmental quality and weaker social connection. However, DUT did not directly affect MH, suggesting that its impact is transmitted indirectly via EP and SC.

Third, SC was positively associated with EP ($\beta = 0.260$, $p < 0.001$), indicating that stronger community ties enhance perceptions of the natural environment and implying a potential indirect pathway from SC to MH. The direct path from SC to MH was not significant, suggesting that the effects of SC on MH are primarily mediated.

Finally, EP had a direct and significant positive effect on MH ($\beta = 0.170$, $p < 0.05$), indicating that favorable environmental perceptions promote emotional well-being and help mitigate psychological distress. EP thus functions as a pivotal node in the structural model. It is shaped by both social factors and digital behavior and, in turn, directly contributes to mental health, serving as a key mediating pathway. Full path estimates are reported in Table 7.

**Table 7:** Structural path estimates and hypothesis testing results.

| Label | Path | Std. Coeff. | S.E. | C.R. | $p$ | Result |
|---|---|---|---|---|---|---|
| H1 | SC → EP | 0.260 | 0.175 | 3.587 | <0.001*** | Yes |
| H2 | EP → MH | 0.170 | 0.051 | 2.410 | 0.016* | Yes |
| H3 | SC → MH | 0.096 | 0.117 | 1.451 | 0.147 | No |
| H5 | AA → EP | −0.107 | 0.057 | −1.592 | 0.111 | No |
| H6 | AA → SC | 0.039 | 0.023 | 0.572 | 0.567 | No |
| H7 | DUT → EP | −0.212 | 0.027 | −3.482 | <0.001*** | Yes |
| H8 | DUT → SC | −0.173 | 0.012 | −2.667 | 0.008** | Yes |
| H9 | AA → MH | −0.328 | 0.046 | −4.393 | <0.001*** | Yes |
| H10 | DUT → MH | 0.091 | 0.019 | 1.511 | 0.131 | No |

Note: Std. Coeff. = standardized coefficient; S.E. = standard error; C.R. = critical ratio (z). Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ (two-tailed).

### *4.4 Mediation Effect Test*

To further explore how community environmental governance influences MH through indirect channels, mediation effects were tested using 5000 bootstrap resamples. Bias-corrected and percentile-based confidence intervals were computed for seven hypothesized mediation paths. An indirect effect was regarded as significant when the 95% confidence interval did not include zero and $p < 0.05$.

As shown in Table 8, three mediation paths achieved statistical significance. The negative indirect effects for DUT → EP → MH (H14) with an effect size of −0.036 ($p = 0.011$), and DUT → SC → EP → MH (H15) with an effect size of −0.008 ($p = 0.009$). These results suggest that DUT undermines MH by weakening EP and SC. As the direct path from DUT to MH was non-significant, both indirect effects qualify as full mediation.

Another significant pathway was SC → EP → MH (H4), with a positive indirect effect of 0.044 ($p = 0.012$). This indicates that greater social capital enhances environmental perception, which in turn improves mental health. As the direct effect from SC to MH was also non-significant, this too represents full mediation.

The remaining four mediation paths (H11, H12, H13, H16) did not reach statistical significance, suggesting no confirmed mediation effects for AA or DUT through those specific routes.

**Table 8:** Standardized bootstrap mediation effects.

| Path | Estimate | Standard Error | Bias-Corrected 95% CI | | | Percentile 95% CI | | | Result |
|---|---|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | *p* | Lower | Upper | *p* | |
| **H4** | **0.044** | **0.023** | **0.009** | **0.103** | **0.012** | **0.006** | **0.097** | **0.020** | **Yes** |
| H11 | −0.018 | 0.014 | −0.056 | 0.001 | 0.062 | −0.049 | 0.004 | 0.125 | No |
| H12 | 0.002 | 0.004 | −0.004 | 0.013 | 0.445 | −0.005 | 0.011 | 0.644 | No |
| H13 | 0.004 | 0.010 | −0.008 | 0.036 | 0.404 | −0.013 | 0.028 | 0.686 | No |
| **H14** | **−0.036** | **0.019** | **−0.087** | **−0.007** | **0.011** | **−0.078** | **−0.004** | **0.024** | **Yes** |
| **H15** | **−0.008** | **0.005** | **−0.023** | **−0.001** | **0.009** | **−0.020** | **−0.001** | **0.023** | **Yes** |
| H16 | −0.017 | 0.014 | −0.054 | 0.004 | 0.111 | −0.049 | 0.008 | 0.176 | No |

Note: H4 = SC → EP → MH; H11 = AA → EP → MH; H12 = AA → SC → EP → MH; H13 = AA → SC → MH; H14 = DUT → EP → MH; H15 = DUT → SC → EP → MH; H16 = DUT → SC → MH. Significant indirect effects ($p < 0.05$) are highlighted in bold. AA = Aging Anxiety; DUT = Digital Usage Tendency; EP = Environmental Perception; SC = Social Capital; MH = Mental Health; CI = Confidence Interval.

### *4.5 Refined Structural Path Analysis*

Drawing on the model fit results and path analysis, a refined structural model was developed (Fig. 4), retaining five empirically supported and theoretically grounded paths. This framework offers greater clarity and a more focused representation of the key relationships.

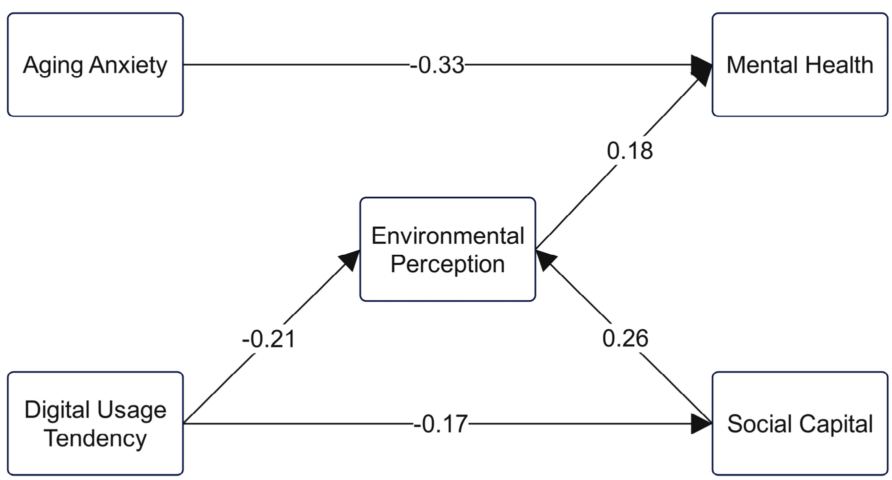


**Figure 4:** Refined structural equation model.

First, the influence of DUT on MH is mediated by two significant pathways. One operates through diminished EP (DUT → EP → MH), while the other involves a sequential effect where reduced SC further weakens EP, which then impacts MH (DUT → SC → EP → MH). Across both indirect chains, negative associations in the early segments outweigh the later positive link to MH, resulting in a net negative indirect effect. These findings suggest that unhealthy digital behavior may gradually erode engagement with physical and social environments, thereby compromising psychological well-being. Second, AA continues to exert a direct and significant negative impact on MH ($\beta = -0.33$), underscoring its role as an internal psychological stressor that affects mental health independently of external or social mediators.

Most notably, the refined model reinforces the importance of the chain mediation SC → EP → MH. In this pathway, SC significantly enhances EP, which in turn positively influences MH. The removal of the direct SC → MH path further confirms that EP fully mediates the effect of social capital on mental health. EP thus emerges as a core bridge linking external governance conditions to internal psychological outcomes and provides theoretical support for environment-based mental health interventions.

Taken together, the refined model emphasizes the negative psychological pathways stemming from DUT and AA while elevating EP—along with SC—as central mediators. This optimized structure improves both the explanatory power and theoretical coherence of the model.

### *4.6 Robustness Check*

The PLS-SEM results were largely consistent with the CB-SEM estimates (Fig. 5 and Table 9), with all paths showing the same direction and significance levels except for H3 (SC → MH). While this path remained non-significant in the CB-SEM model, it reached significance at the 0.05 level in the PLS-SEM estimates. Given the similar coefficient signs and magnitudes, and the small effect size, the evidence is still insufficient to support H3. As CB-SEM is the primary estimation approach, this path continues to be treated as unsupported. Overall, the high consistency across both methods confirms the robustness and reliability of the structural model.

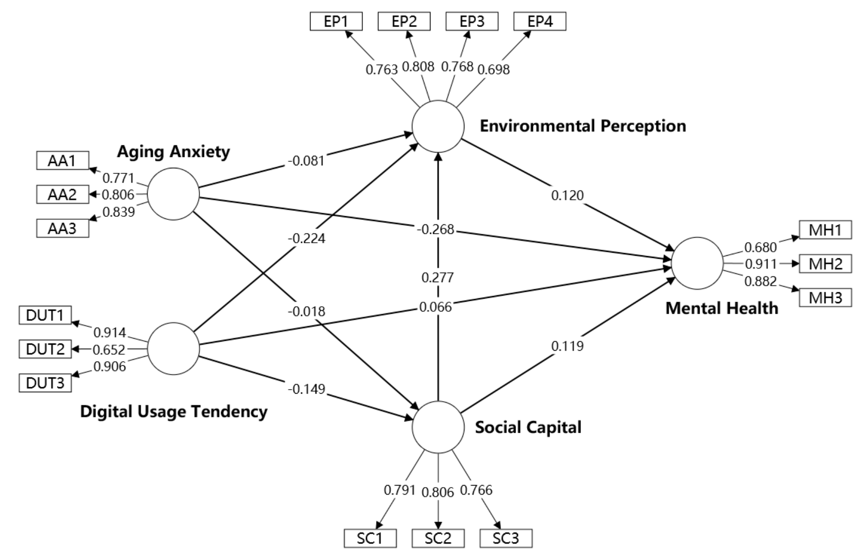


**Figure 5:** Results of the PLS-SEM structural model.

**Table 9:** PLS-SEM path estimates and their consistency with CB-SEM results.

| Label | Path | PLS-SEM β | STDEV | T | *p* | Result | Consistency with CB-SEM |
|---|---|---|---|---|---|---|---|
| H1 | SC → EP | 0.277 | 0.046 | 6.003 | <0.001*** | Yes | Consistent |
| H2 | EP → MH | 0.119 | 0.058 | 2.062 | 0.039* | Yes | Consistent |
| H3 | SC → MH | 0.120 | 0.055 | 2.154 | 0.031* | No | Different |
| H5 | AA → EP | −0.081 | 0.047 | 1.724 | 0.085 | No | Consistent |
| H6 | AA → SC | −0.018 | 0.060 | 0.301 | 0.763 | No | Consistent |
| H7 | DUT → EP | −0.224 | 0.052 | 4.277 | <0.001*** | Yes | Consistent |
| H8 | DUT → SC | −0.149 | 0.050 | 2.970 | 0.003** | Yes | Consistent |
| H9 | AA → MH | −0.268 | 0.047 | 5.671 | <0.001*** | Yes | Consistent |
| H10 | DUT → MH | 0.066 | 0.052 | 1.268 | 0.205 | No | Consistent |

Note: CB-SEM = covariance-based structural equation modeling (AMOS); PLS-SEM = partial least squares structural equation modeling (SmartPLS). Significance: ****p* < 0.001, ***p* < 0.01, **p* < 0.05 (two-tailed). "Consistency" indicates whether the PLS-SEM result aligns with the CB-SEM result reported in Table 7.

## 5 Discussion and Suggestions

### *5.1 Key Findings and Interpretations*

This study employed SEM to examine how community environmental governance influences urban residents' mental health (MH), and how socio-psychological factors shape psychological states through community natural and social environments. The results indicate that environmental perception (EP) and social capital (SC) occupy central positions within the overall path structure: both exert direct effects on MH and serve as bridges transmitting the influence of digital usage tendency (DUT) to MH. This extends existing theories of the relationship between community environmental factors and MH, highlighting its social–ecological nature, characterized by multilayered interactions among social background, environmental conditions, and individual psychological states. Accordingly, MH should not be viewed merely as an individual attribute but as embedded in a dynamic system in which community governance and the technological milieu are intertwined.

First, the analysis confirms a significant positive effect of EP on MH ($\beta = 0.170$, $p = 0.016$), aligning with prior findings [6]. Urban residents' subjective perception of the natural environment directly influences feelings of safety, comfort, and life satisfaction, which are integral to emotional regulation and stress recovery. These perceptions do more than register external conditions; they are cognitively processed and transformed into emotional experiences, thereby acting as an intermediary between external environments and psychological states. For community governance, this implies that improving environmental quality and optimizing residents' subjective environmental experiences may serve as effective levers for preventing mental disorders and enhancing psychological resilience.

From a broader international perspective, multiple European cohort studies consistently report robust associations between green-space exposure and mental health, including reductions in depressive symptoms and improvements in self-rated health [107–109]. While our findings align with this literature, they also reveal contextual differences: in Chinese communities, the psychological benefits of perceived natural environments depend more strongly on the frequency of social interactions and on local governance contexts, highlighting the relationally embedded nature of community governance.

In contrast, SC does not exert a significant direct effect on MH but positively predicts EP, forming a fully mediated pathway (SC $\rightarrow$ EP $\rightarrow$ MH). This indicates that social capital indirectly influences psychological well-being by fostering more favorable environmental perceptions. This finding goes beyond the conventional view of social capital as merely a psychological buffer [69,70,73], and reveals its perception-enhancing function, whereby social context shapes how residents experience and interpret their physical surroundings. Overall, sound community environmental governance integrates social capital and environmental perception to foster positive environmental experiences and improve MH, thereby responding to RQ1.

Second, in response to RQ2, the analysis focuses on how aging anxiety (AA) and DUT influence SC and EP. The results show that AA does not significantly affect individuals' subjective evaluations of either the social or natural environment, reflecting a form of cognitive detachment in the structural pathways. In practice, worries about future physical decline, decision-making difficulties, and economic uncertainty do not necessarily translate into negative assessments of current community environment. This may be because such individuals concentrate their attention on personal survival capacity and security, with limited awareness of external social relationships or the ecological environment. This suggests that simply improving community governance conditions is unlikely to address the deep-seated sources of AA. It should instead be regarded as a risk factor with an independent psychological structure, more appropriately addressed through targeted psychological support and resilience-building measures.

By comparison, DUT demonstrates significant pathway connections in the model. DUT negatively affects both SC and EP, suggesting that digital usage, as a daily behavioral pattern, may subtly reshape how individuals interact with and perceive the real world. In the YRD, residents' growing dependence on digital platforms has reduced casual face-to-face contact, weakening neighborhood trust and emotional bonds, a pattern consistent with Xi et al.'s findings that digital consumption and on-demand delivery, while convenient, erode weak-tie interactions and community embeddedness [110]. At the same time, domestic studies also reveal heterogeneity for some groups and contexts, with online interactions complementing offline cohesion, particularly in intergenerational communication and interest-based communities [111,112]. Thus, digital dynamics are not inherently negative; they are co-shaped by group structures and institutional contexts. Community governance should therefore attend to residents' communication habits and interaction modes to ensure that technology strengthens—rather than erodes—social ties and environmental perception, thereby safeguarding the supportive foundations of psychological well-being.

Finally, addressing RQ3, the structural model reveals two distinct pathways of influence associated with AA and DUT. For AA, the results show a consistent and significant negative direct effect on MH, indicating that concerns about aging may be internalized as a persistent psychological burden that gradually erodes mental well-being. At the same time, AA exerts no significant influence on either EP or SC, suggesting that this endogenous negative emotion does not shape individuals' engagement with their community. In public life, those experiencing AA are unlikely to exhibit marked differences in participation or interaction. This implies that conventional community governance measures are insufficient to address such internalized psychological distress. Urban communities need to develop targeted psychological support systems and public service mechanisms grounded in a clear understanding of the living conditions of this group. The findings also underscore a lag in current psychosocial intervention mechanisms. AA not only reflects the negative emotions of middle-aged and older adults about their present circumstances but also captures anticipatory anxiety among younger populations regarding their future. In practice, however, interventions targeting aging anxiety often remain focused on the functional care and welfare provision for specific age groups, while largely overlooking anticipatory anxiety at the population level. This gap should be a priority in future community-based public mental health initiatives.

Conversely, DUT affects MH exclusively through two significant negative indirect pathways. One pathway operates via EP, where unregulated digital media use appears to weaken individuals' capacity to perceive and engage with the natural environment, disrupt their ability to acquire and interpret information about the physical world, and consequently limit the emotional recovery space and cognitive support systems essential for psychological well-being. The other pathway runs through the combined mediation of SC and EP, showing that excessive digital reliance can diminish the need for in-person interaction, erode trust-based social networks, and intensify withdrawal into enclosed residential spaces, further distancing individuals from nature. Together, these two adverse pathways highlight perceptual dulling caused by digital dependence as a psychological risk factor that must be carefully addressed during digital transformation. To mitigate this risk, communities should incorporate residents' technology use and digital literacy into mental health monitoring and governance frameworks and strengthen interventions that focus on the digital cognitive ecology, thereby fostering a more resilient system of information exposure and interaction support.

### *5.2 Policy Recommendations*

Drawing on the findings, this study proposes four sets of policy recommendations to advance community governance for mental health promotion. The aim is to build a multidimensional, community-based system that integrates social policy with psychological intervention. These recommendations target governments, communities, and social organizations and highlight the importance of coordinated, multi-level action to enhance residents' psychological well-being.

First, communities should cultivate subjective environmental experiences that support mental well-being. This involves more than physical infrastructure; it is an essential pathway to mental health. Communities should continuously strengthen ecological protection and public infrastructure—air quality, water management, green-space layout, lighting, recreational facilities, and accessibility—to create stable, comfortable living spaces that reduce stress and ease anxiety. Governance actors should also prioritize residents' subjective experiences by strengthening feedback mechanisms through surveys, immersive assessment tools, and real-time online platforms. These tools can form a "perception–action–improvement" feedback loop. Given the mediating role of environmental perception, communities should enhance collaboration among governments, enterprises, social organizations, and residents. Clear responsibilities and effective communication can improve policy implementation and strengthen perceptual and emotional bonds between residents and their surroundings, reinforcing psychological identification with the community.

Second, communities should cultivate social capital to enhance residents' psychological resilience. Stable social relationships and support networks buffer stress, build resilience, and improve well-being. Therefore, social capital should be incorporated into community mental health promotion. Communities can strengthen neighborly interaction and interpersonal networks through communication platforms, interest groups, collaborative networks, and volunteer programs that increase civic participation while reducing loneliness and isolation. Institutional support should also be improved through collaboration between community organizations and social service agencies to create complementary social and psychological support systems. To counter rising social alienation, communities can also use spatial design to create symbolic shared spaces and collective memory scenes that enhance belonging and identification. Initiatives such as Shanghai's "micro-renewal" projects, which co-create neighborhood gardens and shared spaces, have improved neighborly interaction and cohesion, demonstrating the synergy between social capital and environmental improvement [113].

Third, communities should build an integrated psychological support system to address aging anxiety. As an endogenous psychological stressor, aging anxiety directly harms mental health and increasingly affects not only the elderly but also middle-aged and younger groups. Community interventions can proceed in three complementary directions. One approach is to promote positive communication about aging through public media campaigns, exhibitions, and community education programs. These initiatives can gradually dispel residents' fear of aging, reduce feelings of psychological deprivation, and foster a more optimistic and proactive attitude toward later life. Another priority is to strengthen elder care institutions by offering preparation courses and planning guidance for aging, establishing elder-care centers, and forming mutual-aid groups, thereby creating a comprehensive support system combining facilities and services. A third direction involves developing preventive psychological risk-management mechanisms by establishing counseling rooms, promoting resilience training and preventive mental-health education, and enhancing data sharing with primary healthcare systems. By leveraging health data platforms, communities can build screening models for early identification and timely intervention. Intergenerational support mechanisms can also facilitate emotional relief. Facilitating communication across generations can help anxious individuals construct a more secure, connected, and positive vision of aging. These initiatives offer valuable policy references for the development of community-level mental health promotion that integrates prevention, support, and emotional resilience.

Finally, communities should guide digital engagement back to real-life settings to restore the community's role as a psychosocial support space. This requires integrating media literacy education, spatial design, and digital platform optimization to prevent social isolation and environmental desensitization caused by digital dependence. Workshops, lectures, and community-sharing events can help residents recognize algorithm-driven cognitive biases, while digital literacy education can also encourage greater engagement with local issues. Communities should also enhance the appeal of offline activities by organizing festivals, family-oriented salons, and recreational sports events that foster enjoyment and real-world interaction. This does not mean resisting the digital era; rather, it calls for leveraging digital media to improve information delivery and service coordination within community affairs. Developing dedicated community apps, social media accounts, and interactive age-friendly governance platforms can integrate online and offline participation and support digitally inclusive communities. Within the broader context of Digital Government reform [114,115], cities such as Hangzhou and Suzhou can take the lead in piloting integrated "community environment–mental health" monitoring systems. Quarterly assessments of environmental satisfaction and psychological well-being can establish a regional, data-driven governance model that aligns technological innovation with psychological care.

## 6 Conclusions

This study employed an SEM to examine how community environmental governance influences MH of urban residents in the YRD. The results show that well-functioning community environmental governance can exert a positive impact on MH, whereas AA and DUT undermine MH through different pathways. The analysis further elucidates the structural relationships among these factors, offering both a theoretical explanation and a fresh perspective for understanding the interplay between community governance and mental health. Building on these findings, the study proposes a set of policy recommendations aimed at providing actionable insights for policymakers and practitioners engaged in community governance.

### *6.1 Limitations*

Despite its contributions, this study is subject to several limitations. First, the study adopts a cross-sectional design, which allows for the identification of associations rather than causal relationships among variables. Therefore, the findings should be interpreted as correlational rather than causal. Second, the survey data were collected from the CGSS 2021 wave, which coincided with the COVID-19 pandemic. The pandemic may have affected respondents' mental health, digital usage, and social interactions, potentially introducing confounding influences that could not be fully controlled in the current model. Third, the measurement of mental health relies on self-reported items from a general social survey rather than clinical diagnostic indicators. Although standardized procedures and bias tests were applied, potential response bias and subjective distortions may still exist. Finally, the sample focuses on urban residents in the YRD, where economic development and community governance are relatively advanced. Hence, the conclusions primarily apply to this highly urbanized context and may not be generalizable to all Chinese cities. Nevertheless, considering that the YRD represents a leading region in China's urbanization process, its experience may serve as a useful reference for other developing urban areas.

### *6.2 Future Research Directions*

Future research can extend and deepen the current work in several meaningful ways. One possible direction is to employ longitudinal tracking or quasi-experimental designs to verify temporal dynamics and strengthen causal inferences regarding the pathways linking community governance and mental health. Another promising avenue involves integrating objective environmental indicators and psychological or physiological measures—such as clinical assessments of mental health or community-level ecological data—to enhance measurement robustness and enable multi-dimensional validation.

Future studies could also benefit from conducting comparative analyses across regions and demographic groups, which may reveal both shared mechanisms and contextual variations, thereby deepening understanding of how community governance influences mental health under diverse social and cultural conditions. Moreover, combining digital behavior data with indicators of community participation would enable future research to capture more accurately the evolving roles of digitalization and civic engagement in shaping residents' well-being. Advancing these directions will provide a stronger empirical foundation and more actionable insights for promoting urban mental health in China and beyond.

**Acknowledgement:** The manuscript benefited from the use of an AI-based language tool for language refinement, which helped enhance its linguistic clarity and readability.

**Funding Statement:** This research was funded by the National Social Science Fund Major Program, "Research on the Theoretical Connotations, Practical Pathways, and Safeguarding Mechanisms for Transforming Urban Development Models" (No. 24ZDA051), the National Social Science Fund Key Program, "Research on the Modernization of Governance Systems and Governance Capabilities in Megacities" (No. 22AZD141), and the Shenzhen Philosophy and Social Sciences Planning Project (2024), "Research on Governance Innovation for Shenzhen as a Global Benchmark City" (No. SZ2024B029).

**Author Contributions:** The authors confirm their contributions to the paper as follows: Conceptualization, Zhengliang Zhang and Haowen Wu; methodology, Zhengliang Zhang; software, Zhengliang Zhang; validation, Zhengliang Zhang; formal analysis, Haowen Wu; investigation, Zhengliang Zhang and Xinna Tang; resources, Haowen Wu; data curation, Zhengliang Zhang and Shijian Wu; writing—original draft preparation, Zhengliang Zhang and Haowen Wu; writing—review and editing, Zhengliang Zhang, Shijian Wu and Haowen Wu; visualization, Zhengliang Zhang; supervision, Haowen Wu; project administration, Haowen Wu. All authors reviewed the results and approved the final version of the manuscript.

**Availability of Data and Materials:** The data that support the findings of this study are openly available from the 2021 wave of the Chinese General Social Survey (CGSS) at http://cgss.ruc.edu.cn/English/Home.htm (accessed on 25 March 2025).

**Ethics Approval:** Not applicable.

**Conflicts of Interest:** The authors declare no conflicts of interest to report regarding the present study.

**Supplementary Materials:** The supplementary material is available online at https://www.techscience.com/doi/10.32604/ijmhp.2025.071999/s1.

## References

1. Okkels N, Kristiansen CB, Munk-Jørgensen P, Sartorius N. Urban mental health: challenges and perspectives. Curr Opin Psychiatry. 2018;31(3):258–64. [CrossRef].
2. Chen CW. From smart cities to a happy and sustainable society: urban happiness as a critical pathway toward sustainability transitions. Local Environ. 2022;27(12):1536–45. [CrossRef].

3. Fu Q. Bringing urban governance back in: neighborhood conflicts and depression. Soc Sci Med. 2018;196:1–9. [CrossRef].
4. Mao W, Agyapong VIO. The role of social determinants in mental health and resilience after disasters: implications for public health policy and practice. Front Public Health. 2021;9:658528. [CrossRef].
5. Qiu YZ, Chen HS, Li ZG, Wang RY, Liu Y, Qin XF. Exploring neighborhood environmental effects on mental health: a case study in Guangzhou, China. Prog Geogr. 2019;38(2):283–95. (In Chinese).
6. Lei K, Yang J, Ke X. The impact of neighborhood environment on the mental health: evidence from China. Front Public Health. 2025;12:1452744. [CrossRef].
7. He J, Chen H, Cai Y, Li Z, Ye J. From urban village housing to tenant mental health: the crucial role of community attachment in Chinese megacities. Front Public Health. 2025;13:1490105. [CrossRef].
8. Lu N, Wu B. Perceived neighborhood environment, social capital and life satisfaction among older adults in Shanghai, China. Sci Rep. 2022;12(1):6686. [CrossRef].
9. Mao S, Lu N, Xiao C. Perceived neighborhood environment and depressive symptoms among older adults living in urban China: the mediator role of social capital. Health Soc Care Community. 2022;30(5):e1977–90. [CrossRef].
10. Si W, Jiang C, Meng L. The relationship between environmental awareness, habitat quality, and community residents' pro-environmental behavior—mediated effects model analysis based on social capital. Int J Environ Res Public Health. 2022;19(20):13253. [CrossRef].
11. Zhen F, Liu M, Yang R. Deriving the impact mechanism of urban green space environment on community social capital based on multi-source data integration: a case study of Nanjing city, China. Comput Urban Sci. 2025;5(1):5. [CrossRef].
12. Chen W, Li X. Digital inequalities in American disadvantaged urban communities: access, skills, and expectations for digital inclusion programs. Inf Commun Soc. 2022;25(13):1916–33. [CrossRef].
13. Xiang H, Heng X, Zhai B, Yang L. Digital and culture: towards more resilient urban community governance. Land. 2024;13(6):758. [CrossRef].
14. Hunter MG, Soro A, Brown RA, Harman J, Yigitcanlar T. Augmenting community engagement in city 4.0: considerations for digital agency in urban public space. Sustainability. 2022;14(16):9803. [CrossRef].
15. Bronfenbrenner U. Toward an experimental ecology of human development. Am Psychol. 1977;32(7):513–31. [CrossRef].
16. McLeroy KR, Bibeau D, Steckler A, Glanz K. An ecological perspective on health promotion programs. Health Educ Q. 1988;15(4):351–77. [CrossRef].
17. Stokols D. Establishing and maintaining healthy environments. Toward a social ecology of health promotion. Am Psychol. 1992;47(1):6–22. [CrossRef].
18. Logan AC, Jacka FN. Nutritional psychiatry research: an emerging discipline and its intersection with global urbanization, environmental challenges and the evolutionary mismatch. J Physiol Anthropol. 2014;33(1):22. [CrossRef].
19. Srivastava K. Urbanization and mental health. Ind Psychiatry J. 2009;18(2):75. [CrossRef].
20. Collins PY, Sinha M, Concepcion T, Patton G, Way T, McCay L, et al. Making cities mental health friendly for adolescents and young adults. Nature. 2024;627(8002):137–48. [CrossRef].
21. Hoare E, Jacka F, Berk M. The impact of urbanization on mood disorders: an update of recent evidence. Curr Opin Psychiatry. 2019;32(3):198–203. [CrossRef].
22. Murphy LE, Jack HE, Concepcion TL, Collins PY. Integrating urban adolescent mental health into urban sustainability collective action: an application of Shiffman & Smith's framework for global health prioritization. Front Psychiatry. 2020;11:44. [CrossRef].
23. Evans BE, Tuvblad C, Larsson H. Urban living and mental health. Nat Med. 2023;29(6):1322–3. [CrossRef].
24. Altwaijri YA, Al-Subaie AS, Al-Habeeb A, Galea S, Akkad M, Naseem MT, et al. Urbanization and mental health: a perspective from Riyadh City, Kingdom of Saudi Arabia. Int J Soc Psychiatry. 2023;69(5):1121–33. [CrossRef].
25. Buttazzoni A, Doherty S, Minaker L. How do urban environments affect young people's mental health? a novel conceptual framework to bridge public health, planning, and neurourbanism. Public Health Rep. 2022;137(1):48–61. [CrossRef].

26. Gruebner O, Rapp MA, Adli M, Kluge U, Galea S, Heinz A. Cities and mental health. Dtsch Ärzteblatt Int. 2017;114(8):121–7. [CrossRef]
27. Ventriglio A, Torales J, Castaldelli-Maia JM, De Berardis D, Bhugra D. Urbanization and emerging mental health issues. CNS Spectr. 2021;26(1):43–50. [CrossRef].
28. Frey VN, Langthaler PB, Huf MJ, Gruber G, Prinz T, Kedenko L, et al. Stress and the city: mental health in urbanized vs. rural areas in Salzburg, Austria. Int J Environ Res Public Health. 2024;21(11):1459. [CrossRef].
29. Morozov PV. Mental health and urbanization: a Russian perspective. Curr Opin Psychiatry. 2018;31(3):272–5. [CrossRef].
30. Shahjahan M, Islam MM, Islam M, Das KP, Al Sabbir A. Urban insights into mental health: a study of depression and anxiety factors among urban adults of Bangladesh in the COVID-19 pandemic. J Hum Behav Soc Environ. 2025;35(2):131–42. [CrossRef].
31. Trivedi JK, Sareen H, Dhyani M. Rapid urbanization—its impact on mental health: a South Asian perspective. Indian J Psychiatry. 2008;50(3):161–5. [CrossRef].
32. Hepat A, Khode D, Chakole S. A narrative review of urbanization and mental health: an Indian perspective. Cureus. 2024;16(3):e55381. [CrossRef].
33. Chen J, Chen S, Landry PF. Urbanization and mental health in China: linking the 2010 population census with a cross-sectional survey. Int J Environ Res Public Health. 2015;12(8):9012–24. [CrossRef].
34. Ochnik D, Buława B, Nagel P, Gachowski M, Budziński M. Urbanization, loneliness and mental health model—a cross-sectional network analysis with a representative sample. Sci Rep. 2024;14:24974. [CrossRef].
35. Wang R, Xue D, Liu Y, Chen H, Qiu Y. The relationship between urbanization and depression in China: the mediating role of neighborhood social capital. Int J Equity Health. 2018;17(1):105. [CrossRef].
36. Li D, Ruan Y, Kang Q, Rong C. Association of urbanization with psychological well-being in Chinese adults aged 50 years and older: a population-based study. Braz J Psychiatry. 2023;45(3):249–57. [CrossRef].
37. Pan D, Yan N, Pu L, He X, Wang H, Zhang X, et al. The association between urbanization and adolescent depression in China. PeerJ. 2024;12:e16888. [CrossRef].
38. Li J, Rose N. Urban social exclusion and mental health of China's rural-urban migrants—a review and call for research. Health Place. 2017;48:20–30. [CrossRef].
39. He X, Zhang F, Zhao H, Li J. How migration in later life shapes their quality of life: a qualitative investigation of the well-being of the "drifting elderly" in China. Soc Indic Res. 2022;160(2):909–33. [CrossRef].
40. Chandra PS, Shiva L, Nanjundaswamy MH. The impact of urbanization on mental health in India. Curr Opin Psychiatry. 2018;31(3):276–81. [CrossRef].
41. Lecic-Tosevski D. Is urban living good for mental health? Curr Opin Psychiatry. 2019;32(3):204–9. [CrossRef].
42. Firdaus G. Mental well-being of migrants in urban center of India: analyzing the role of social environment. Indian J Psychiatry. 2017;59(2):164. [CrossRef].
43. Xie B, Wang X, Wu L. Exploring the effect of urban greenspace on residents' mental health using a quasi-natural experiment: taking Wuhan East Lake Greenway as an example. Prog Geogr. 2021;40(7):1141–53. [CrossRef].
44. Chen K, Zhang T, Liu F, Zhang Y, Song Y. How does urban green space impact residents' mental health: a literature review of mediators. Int J Environ Res Public Health. 2021;18(22):11746. [CrossRef].
45. Chen C, Luo W, Li H, Zhang D, Kang N, Yang X, et al. Impact of perception of green space for health promotion on willingness to use parks and actual use among young urban residents. Int J Environ Res Public Health. 2020;17(15):5560. [CrossRef].
46. Li S, Chen T, Chen F, Mi F. How does the urban forest environment affect the psychological restoration of residents? A natural experiment in environmental perception from Beijing. Forests. 2023;14(10):1986. [CrossRef].
47. Zhu W, Wang J, Qin B. Quantity or quality? Exploring the association between public open space and mental health in urban China. Landsc Urban Plan. 2021;213:104128. [CrossRef].
48. Wu R, Pan ZL, Liu Y, Li ZG. The effect of streetscape greenery on residents' mental health: a case study of Guangzhou. Geogr Res. 2021;40(8):2272–91. (In Chinese).
49. Lee HJ, Lee DK. Do sociodemographic factors and urban green space affect mental health outcomes among the urban elderly population? Int J Environ Res Public Health. 2019;16(5):789. [CrossRef].

50. Liu Y, Li C, Li Y. Impact of leisure environmental supply on new urban pathology: a case study of Guangzhou and Zhuhai. Humanit Soc Sci Commun. 2021;8:297. [CrossRef].
51. Zhai WY, Cheng H, Gou FC, Wang ZL, Li ZG. A meta-analysis of the impact of urban blue spaces on residents' mental health. Landsc Arch Front. 2024;12(5):20. [CrossRef].
52. Yuan X, Li H, Zhao J. Impact of environmental pollution on health-evidence from cities in China. Soc Work Public Health. 2020;35(6):413–30. [CrossRef].
53. Wang R, Yuan Y, Liu Y, Zhang J, Liu P, Lu Y, et al. Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health. Health Place. 2019;59:102186. [CrossRef].
54. Chen J, Chen S. Mental health effects of perceived living environment and neighborhood safety in urbanizing China. Habitat Int. 2015;46:101–10. [CrossRef].
55. Feng Y, Nie C. The effect of housing price on health: new evidence from China. Appl Econ Lett. 2022;29(15):1439–46. [CrossRef].
56. Zhang Z, Shu H, Yi H, Wang X. Household multidimensional energy poverty and its impacts on physical and mental health. Energy Policy. 2021;156:112381. [CrossRef].
57. Zapata Moya ÁR, Navarro Yáñez CJ. Urban regeneration policies and mental health in a context of economic crisis in Andalusia (Spain). J Hous Built Environ. 2021;36(2):393–405. [CrossRef].
58. Wang S, Zhou P, Yang X, Wang N, Jie J, Li Y, et al. Can urban prosperity aid in recovery?: the relationship between healthcare workers' mental health status and the city level during the COVID-19 epidemic. Cities. 2021;118:103361. [CrossRef].
59. Song Y, Lin X. The effects of exercise and social interaction in different natural environments on the mental health of urban residents. Sustainability. 2022;14(21):14095. [CrossRef].
60. Dong Y, Li Z, Dong W. The influence of perceived living street environmental characteristics on mental health of residents: the empirical evidence from old district in Harbin. Chin Landsc Archit. 2021;37(11):45–50. (In Chinese). [CrossRef].
61. Liu Y, Wang R, Grekousis G, Liu Y, Yuan Y, Li Z. Neighbourhood greenness and mental wellbeing in Guangzhou, China: what are the pathways? Landsc Urban Plan. 2019;190:103602. [CrossRef].
62. Lee M, Park S, Yoon K. Does health promotion program affect local resident' emotions? Int J Environ Res Public Health. 2019;16(4):549. [CrossRef].
63. Nie W, Hu M, Ye X. Internet use and rural-urban mental health inequalities: evidence from China. Front Public Health. 2023;11:1107146. [CrossRef].
64. Wang Y, Li C. Mitigate or exacerbate? Assessing digital engagement's impact on mental health inequalities across gender and urban-rural divides. Digit Health. 2025;11:20552076251326673. [CrossRef].
65. Zheng Z, Sun N, Chen Y, Chen H. Social media use and mental health of urban residents during China's second COVID-19 outbreak. Front Public Health. 2022;10:1016849. [CrossRef].
66. Liu Y, Li J. Longitudinal associations between neighborhood characteristics and adults' mental health in China: do age and urbanicity moderate the associations? Cities. 2024;152:105160. [CrossRef].
67. Generaal E, Timmermans EJ, Dekkers JEC, Smit JH, Penninx BWJH. Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. Psychol Med. 2019;49(1):149–61. [CrossRef].
68. Xiao Y, Miao S, Sarkar C, Fan L, Li Z. Do neighborhood ties matter for residents' mental health in affordable housing: evidence from Guangzhou, China. Cities. 2020;100:102666. [CrossRef].
69. Deng X, Wei Z, Lu H, Tu C, Yang Y. Community social capital enhances the subjective well-being of urban residents: the mediating role of psychological flourishing and moderating effect of educational attainment. Soc Sci. 2024;13(4):214. [CrossRef].
70. Gu N. The effects of neighborhood social ties and networks on mental health and well-being: a qualitative case study of women residents in a middle-class Korean urban neighborhood. Soc Sci Med. 2020;265:113336. [CrossRef].
71. Desdiani D, Sutarto AP. Impact of the restrictions on community activities policy during the COVID-19 on psychological health in Indonesia's urban and rural residents: a cross-sectional study. Health Sci Rep. 2022;5(5):e725. [CrossRef].

72. Settels J. Multiple vulnerabilities: the effects of neighborhood structural changes upon older residents' mental health and perceptions of the broader community. J Community Psychol. 2021;49(2):672–90. [CrossRef].
73. Wang X, Zhou P, Liu Z. Neighborhood social capital and self-rated mental health: disparities between migrants and native residents in Beijing. Front Public Health. 2022;10:1055712. [CrossRef].
74. Chen M, Shi L, Wang B, Sun H, Lin D, Chang Y, et al. Perceptions of improvements and mental health outcomes of micro-renewal in old Danwei community: a survey of residents in Hengyang, China. Front Public Health. 2024;12:1419267. [CrossRef].
75. Castillo EG, Ijadi-Maghsoodi R, Shadravan S, Moore E, Mensah MO, Docherty M, et al. Community interventions to promote mental health and social equity. Curr Psychiatry Rep. 2019;21(5):35. [CrossRef].
76. Cole HVS, Caputo S, Specht K, Giedych R, Kaemper RF, Cook P, et al. Advancing GReencare in Europe: a multi-scalar approach to improve mental health equity (the GreenME project). ISEE Conf Abstr. 2023;2023(1):359. [CrossRef].
77. Araya R, Dunstan F, Playle R, Thomas H, Palmer S, Lewis G. Perceptions of social capital and the built environment and mental health. Soc Sci Med. 2006;62(12):3072–83. [CrossRef].
78. Kang S, Lee JL, Koo JH. The buffering effect of social capital for daily mental stress in an unequal society: a lesson from Seoul. Int J Equity Health. 2023;22(1):64. [CrossRef].
79. Chen Z, Wu J, Zhang A. The characteristics of urban governance in China: evidence from best practices in the Yangtze River Delta Region. Growth Change. 2022;53(4):1834–53. [CrossRef].
80. Xu X, Zhao Y, Xia S, Zhang X. Investigation of multi-scale spatio-temporal pattern of oldest-old clusters in China on the basis of spatial scan statistics. PLoS One. 2019;14(7):e0219695. [CrossRef].
81. Wang Y, Zhang X, Lin F, Peng M. The role of digital governance on carbon emission performance: evidence from the cities in Yangtze River Delta, China. Environ Res Commun. 2023;5(8):085013. [CrossRef].
82. Ware JE Jr, Sherbourne CD. The MOS 36-item short-form health survey (SF-36): I. conceptual framework and item selection. Med Care. 1992;30(6):473–83. [CrossRef].
83. Kessler RC, Andrews G, Colpe LJ, Hiripi E, Mroczek DK, Normand SLT, et al. Short screening scales to monitor population prevalences and trends in non-specific psychological distress. Psychol Med. 2002;32(6):959–76. [CrossRef].
84. Shi P, Feng X, Lyu S. Can exercise regulate the relationship between noise pollution and the perception of physical and mental health among Chinese adults? An empirical study based on CGSS 2021. Front Public Health. 2025;13:1594917. [CrossRef].
85. Hu J, Zhang G, Wang M. A study of the impact of internet use on the mental health of rural older adults-empirical analysis based on China General Social Survey 2021 data. Front Public Health. 2024;12:1470965. [CrossRef].
86. van Kamp I, Leidelmeijer K, Marsman G, de Hollander A. Urban environmental quality and human well-being. Landsc Urban Plan. 2003;65(1–2):5–18. [CrossRef].
87. Bonaiuto M, Aiello A, Perugini M, Bonnes M, Ercolani AP. Multidimensional perception of residential environment quality and neighbourhood attachment in the urban environment. J Environ Psychol. 1999;19(4):331–52. [CrossRef].
88. Putnam RD. Bowling alone: the collapse and revival of American community. New York, NY, USA: Simon & Schuster; 2000. [CrossRef].
89. Harpham T, Grant E, Thomas E. Measuring social capital within health surveys: key issues. Health Policy Plan. 2002;17(1):106–11. [CrossRef].
90. Phongsavan P, Chey T, Bauman A, Brooks R, Silove D. Social capital, socio-economic status and psychological distress among Australian adults. Soc Sci Med. 2006;63(10):2546–61. [CrossRef].
91. Wang D, Li H, Liu P. The impact of neighborhood environment and social interaction on the health of Chinese residents: empirical analysis from CGSS 2021. Front Public Health. 2025;13:1547499. [CrossRef].
92. Lasher KP, Faulkender PJ. Measurement of aging anxiety: development of the anxiety about aging scale. Int J Aging Hum Dev. 1993;37(4):247–59. [CrossRef].
93. Ellison NB, Steinfield C, Lampe C. The benefits of facebook "friends:" social capital and college students' use of online social network sites. J Comput Mediat Commun. 2007;12(4):1143–68. [CrossRef].
94. Junco R. Too much face and not enough books: the relationship between multiple indices of Facebook use and academic performance. Comput Hum Behav. 2012;28(1):187–98. [CrossRef].

95. Yang S, Ge D. Why does aging anxiety emerge? A study on the influence of socioeconomic status. Front Psychol. 2025;16:1602284. [CrossRef].
96. Jin L, Zhang Z, Jing F. The impact of internet use in the digital age on the subjective well-being of older adults—an empirical study based on CGSS2021 data. Heliyon. 2023;9(11):e21528. [CrossRef].
97. Miao J, Kuang J, Yang L, Chen M, Tian X. Internet use and social trust: empirical analysis based on CGSS2021. Front Sociol. 2025;9:1422731. [CrossRef].
98. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J Appl Psychol. 2003;88(5):879–903. [CrossRef].
99. Zhou H, Long LR. Statistical remedies for common method biases. Adv Psychol Sci. 2004;12(6):942–50. (In Chinese).
100. Kline RB. Principles and practice of structural equation modeling. 2nd ed. New York, NY, USA: Guilford Press; 2005.
101. Nunnally JC, Bernstein IH. Psychometric theory. 3rd ed. New York, NY, USA: McGraw-Hill; 1994.
102. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis: a global perspective. 7th ed. Upper Saddle River, NJ, USA: Pearson Prentice Hall; 2010.
103. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39–50. [CrossRef].
104. Browne MW, Cudeck R. Alternative ways of assessing model fit. In: Bollen KA, Long JS, editors. Testing structural equation models. Newbury Park, CA, USA: Sage; 1993. p. 136–62.
105. Baumgartner H, Homburg C. Applications of structural equation modeling in marketing and consumer research: a review. Int J Res Mark. 1996;13(2):139–61. [CrossRef].
106. Bollen KA. Structural equations with latent variables. 1st ed. Hoboken, NJ, USA: John Wiley & Sons, Inc.; 1989. [CrossRef].
107. Noordzij JM, Beenackers MA, Oude Groeniger J, Timmermans E, Chaix B, Doiron D, et al. Green spaces, subjective health and depressed affect in middle-aged and older adults: a cross-country comparison of four European cohorts. J Epidemiol Community Health. 2021;75(5):470–6. [CrossRef].
108. Xie Y, Fan S, Luo Y, Li J, Zhang Y, Hu L, et al. Credibility of the evidence on green space and human health: an overview of meta-analyses using evidence grading approaches. eBioMedicine. 2024;106:105261. [CrossRef].
109. Deng B, Boden J, Ye N, Morgenroth J, Campbell M, Eggleton P, et al. Life in green: associations between greenspace availability and mental health over the lifecourse—a 40-year prospective birth cohort study. Environ Int. 2025;195:109223. [CrossRef].
110. Xi G, Cao X, Zhen F. How does same-day-delivery online shopping reshape social interactions among neighbors in Nanjing? Cities. 2021;114:103219. [CrossRef].
111. Chai Q, Yang Z, Luo Y, Deng Y, Qin L, Yang Z, et al. The impact of digital communication and offline social interactions on depressive symptoms in Chinese older people. Front Public Health. 2024;12:1387637. [CrossRef].
112. Li H, Li H, Zhou X, Kuang Y, Liu F. The impact of online social interaction on urban community cohesion and group differences: evidence from China. BMC Public Health. 2025;25(1):1484. [CrossRef].
113. Kou H, Zhang S, Liu Y. Community-engaged research for the promotion of healthy urban environments: a case study of community garden initiative in Shanghai, China. Int J Environ Res Public Health. 2019;16(21):4145. [CrossRef].
114. Xu X, Dai M. Evaluation of local government digital governance ability and sustainable development: a case study of Hunan Province. Sustainability. 2024;16(14):6084. [CrossRef].
115. Bu F. The effect of digital government construction on the enhancement of public governance capacity: an analysis based on financial information transparency. Int Rev Financ Anal. 2025;107:104648. [CrossRef].