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The paradox of smart cities: technological advancements and the disconnection from social participation

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ABSTRACT

As smart city initiatives proliferate globally, whether they genuinely foster inclusive and participatory governance remains unclear. This study examines the "smart governance paradox" by integrating macro-level evaluations of urban smartness with micro-level analyses of citizen perceptions across six large Chinese cities. At the macro level, we construct a Smart City Development Index using factor analysis and a neural network optimized by genetic algorithms. Results reveal significant regional disparities: some cities (Beijing and Shanghai) lead in smart economy, infrastructure, and innovation, while others lag in mobility and connectivity, highlighting uneven implementation capacities. At the micro level, we analyze 2021 Chinese Social Survey data using ordered logit models to examine associations between smart city development and public perceptions. Smart city development is positively associated with perceived trust, fairness, and protection, but negatively associated with civic participation—especially among younger demographics. This disconnect suggests that technological development may accompany favorable service-related perceptions while correlating with lower community engagement, potentially reflecting digital substitution and governance centralization. We propose reframing "smartness" as a socio-political construct emphasizing inclusion, responsiveness, and equity, and offer policy recommendations bridging digital efficiency with democratic engagement.

1. Introduction

According to the World Cities Report 2022, urban populations accounted for 56% of the global population in 2021, projected to rise to 68% by 2050(United Nations Human Settlements Programme, 2022). This highlights the importance of managing urban resources and ensuring inclusive, sustainable development. As urbanization progresses, cities face challenges including population expansion and infrastructure pressures, while information technology advances provide tools to enhance urban management (Loo and Wang, 2017).

Smart cities utilize digital technologies to enhance urban management and services, integrating information technology to improve efficiency and optimize resource utilization. Following the Smart Growth concept (2000) and IBM's Smart City concept (2008), this paradigm emphasizes comprehensive, intelligent, and sustainable urban operations (Sajhau, 2017; Cao and Zhen, 2015). Pioneer countries include the United States (National Strategic Plan), United Kingdom (Digital Britain initiative), and Japan (i-Japan Strategy). As of 2023, over 1,000 smart city projects launched globally, with China initiating more than 500 projects (Newswire, 2024). The

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global smart city market was valued at $748.7 billion in 2023, projected to reach $3.7283 trillion by 2030 (CAGR: 25.8%) (Grand View Research, 2023).

China has actively integrated smart city initiatives into its development strategy, though regional disparities exist. National central cities were designated in phases: Beijing, Shanghai, Tianjin, Guangzhou, and Chongqing (2010); Chengdu, Wuhan, and Zhengzhou (2016); and Xiamen (2017), with expansion to emerging cities like Xiong'an New Area (Meiling et al., 2014). However, challenges remain in securing financial investment and innovating governance models (Clark, 2020; Green, 2019). Whether these initiatives effectively enhance governance capabilities and ensure stability remains urgent for research and implementation (Cao et al., 2023).

Despite rapid expansion, evidence questions whether technological investment alone delivers governance improvements. Five key concerns emerge:

First, technocentric thinking marginalizes humanistic considerations. Smart city research emphasizes technology-driven visions while neglecting cities' complexity as social, political, and human systems (Mu et al., 2022; Mora et al., 2017; Myeong et al., 2020; Cardullo and Kitchin, 2019; Schuler, 2016). Chinese smart city construction focuses on urban performance while limiting attention to community empowerment (Tarachucky et al., 2021), struggling to meet diverse, localized governance needs (Rochet and Belemlih, 2021).

Second, the digital divide exacerbates social exclusion. Smart city development may intensify socioeconomic inequalities by excluding digitally disadvantaged groups from participatory governance (Cardullo and Kitchin, 2019; de Wijs et al., 2016; Almulhim and Yigitcanlar, 2025). Research on platforms like SeeClickFix shows wealthier communities receive prompt responses while lower-income neighborhoods are neglected (Lee et al., 2025; Ziosi et al., 2024; Eubanks, 2018). Limited ICT infrastructure in developing regions like China poses significant e-participation barriers (He et al., 2022; He et al., 2017), as seen in India's smart city projects (Basu and Kalra, 2022; Prasad et al., 2024; Praharaj et al., 2018; Datta, 2018).

Third, top-down governance models inhibit citizen participation. Many initiatives position citizens as passive recipients rather than co-creators (Datta, 2018; Deng and Fei, 2023; Granier and Kudo, 2016). India's Smart Cities Mission featured largely symbolic participation through online portals with minimal consultation (Basu and Kalra, 2022; Datta, 2018). South Korea's u-City project, despite technological sophistication, failed to consider citizen acceptance due to technocratic approaches (Jang and Gim, 2022; Kim, 2010).

Fourth, institutional constraints weaken technology-enabled governance effectiveness. Projects face bureaucratic rigidity, poor coordination, and weak political will (Vadiati, 2022; Pansera et al., 2023; Schmidt and Groeneveld, 2021). In China, legal frameworks lag behind technological innovation, while institutional fragmentation restricts long-term viability (He et al., 2022; He et al., 2017; Yigitcanlar et al., 2022; Underdal, 2010).

Finally, ethical and privacy concerns challenge sustainability. Smart technologies collect personal data without informed consent, raising privacy and cybersecurity concerns (Cohen et al., 2014; Money and Cohen, 2015; Angelidou, 2014). Data-driven governance may evolve into "panoptic surveillance," reducing citizens to data points and undermining democratic engagement (Sadowski, 2019; Ranchod, 2020; Johnson et al., 2020; Amoore, 2018).

These patterns suggest potential mismatches between technological advancement and governance outcomes. Digital divides create unequal participation—high-income communities engage more actively with platforms while marginalized groups face institutional exclusion (Lee et al., 2025; Schiff, 2025; Greenfield, 2013; Perrin and Atske, 2021; Desouza and Bhagwatwar, 2012; Magro, 2012). South Korea's Songdo u-City project exemplifies this, prioritizing technical deployment over citizen needs (Jang and Gim, 2022; Kim, 2010).

Smart city development reflects tension between technocentrism and human-centered approaches, often neglecting citizen empowerment, social justice, and cultural sensitivity (Hollands, 2020; Kitchin, 2016; Coletta et al., 2019; Hovik and Giannoumis, 2022). This reinforces technological determinism and challenges citizen-centered urban futures (Goodman et al., 2020; Almeida et al., 2018).

Citizen participation increasingly features transactional rather than transformative engagement—reduced to app clicks and data generation rather than meaningful collaboration (Cardullo and Kitchin, 2019; Johnson et al., 2020; Kleinhans et al., 2015; Welch et al., 2005; Lynch, 2020; Broccardo et al., 2019). This alienation weakens governance connections and may erode political trust and civic identity.

While smart cities promise enhanced public service delivery, social trust, and urban resilience, whether these ambitions are realized from citizens' lived experiences remains unclear. Do smart city investments translate into stronger social trust, fairness, political participation, and perceived protection? Or does the reality on the ground reflect a more fragmented or uneven transformation? This study adopts a dual-level analytical strategy: constructing a Smart City Development Index to map heterogeneous development patterns across Chinese cities (macro level), and analyzing residents' subjective perceptions using Chinese Social Survey data to evaluate trust, fairness, participation, and protection outcomes (micro level).

This integrated approach uncovers potential mismatches between infrastructural advancement and social governance outcomes—a phenomenon increasingly discussed but rarely quantified in a single empirical framework. The research questions stem from sustained reflection on gaps between idealized visions and real-world challenges, as smart cities promise efficiency, inclusiveness, and equity (Mora et al., 2017; Hajduk, 2018) while empirical research reveals systemic implementation challenges (Mora et al., 2017; Schindler and Silver, 2019). This study's two central research questions are designed to critically engage with these challenges, drawing on evidence from both China and global experiences.

- Political Participation: From "Technological Empowerment" to Tokenism and digital exclusion

Information and communication technologies (ICTs) are widely promoted as tools for enhancing civic engagement (O'Brien, 2018; Kopackova et al., 2022). However, in practice, technological empowerment often translates into tokenistic participation—symbolic involvement without substantive influence. For instance, studies on India's smart city initiatives reveal that citizen engagement is frequently passive and procedural, with key decisions predetermined by governments and private actors (Basu and Kalra, 2022; Prasad et al., 2024; Vaishampayan et al., 2020), aligning with the lower rungs of Arnstein's (1969) "ladder of citizen participation" (Arnstein, 1969).

At the same time, the digital divide further constrains broad-based participation. Empirical studies show that citizens' willingness and ability to engage online are significantly shaped by education, income, age, and ICT self-efficacy (Deng and Fei, 2023; Obringer and Nateghi, 2021; Glasmeier and Christopherson, 2015; Hollands, 2015). In the Chinese context, digitally disadvantaged groups—such as the elderly and low-income residents—often lack access to adequate devices or digital training (Shin et al., 2021; Chang and Lo, 2016), leading to a situation in which "smart participation" may actually reinforce or even deepen existing inequalities (Chib et al., 2022; Jung et al., 2001). This raises a critical question for this study: Do smart city investments truly foster inclusive and widespread political participation, or do they create a technologically advanced yet socially fragmented model of engagement?

- Fairness and Inclusiveness: Between technological Promises and elite capture

Smart cities promise fine-grained, data-driven governance that delivers equitable services to all (Bouzguenda et al., 2019; Goel and Vishnoi, 2022). Yet in practice, many projects disproportionately benefit specific groups or regions, exacerbating spatial and social inequalities (Shelton et al., 2015; Caragliu and Del Bo, 2019). The case of SeeClickFix is illustrative: studies have shown that communities with higher incomes and a greater proportion of white residents receive more attention and responses from municipal governments through the platform (Kopackova et al., 2022). Although such tools appear neutral, they often embed structural biases in their algorithms and response mechanisms.

In many Global South contexts, smart city development is shaped by elite capture. India's Smart Cities Mission, for example, has been criticized for prioritizing middle-class interests and fostering fragmentation between "smarter" and "less smart" urban zones (Waghmare, 2024). This reflects a broader trend of splintered urbanism, wherein smart infrastructures disproportionately benefit privileged segments. Meanwhile, vulnerable groups—including the elderly, persons with disabilities, and low-income residents—are often marginalized in their access to smart services such as transportation and healthcare (Jang and Gim, 2022; Scheerder et al., 2017; Zait, 2017). This study thus interrogates not only the success of technological deployment but also whether the underlying distributional logic of smart cities is genuinely inclusive.

- Social trust and citizen Protection: Balancing efficient governance and privacy risks

Smart governance frameworks emphasize open data, transparency, and coordination as pathways to enhancing citizen trust. However, when service quality falls short or privacy safeguards are weak, smart initiatives may instead generate a trust deficit. Previous studies highlight that citizen satisfaction is a key driver of both political trust and participation (Lebrument et al., 2021; Wong et al., 2011).

Yet the data-intensive nature of smart cities raises new ethical dilemmas. For example, a wearable device initiative in Calgary, Canada used moral economy rhetoric—such as community improvement and scientific progress—to solicit residents' health and activity data for planning purposes (Burns and Welker, 2022). While framed as civic engagement, such practices often lack robust consent mechanisms and pose risks to personal rights. Similarly, community platforms like Nextdoor, while fostering neighborhood connectivity, have been associated with false reporting and privacy violations (Payne, 2021).

Moreover, many smart city projects developed through public–private partnerships (PPPs) operate through opaque "black-box" systems. In Mexico City, the newly established ADIP (Digital Agency for Public Innovation), despite its aims to enhance efficiency and fight corruption, has faced public skepticism due to its top-down decision-making and lack of transparency (Pansera et al., 2023). Against this backdrop, this study critically asks: Can the logic of efficient governance truly sustain public trust, or does it inadvertently construct new forms of participatory exclusion?

By analyzing specific cases from China and other national contexts, this study seeks to unpack the complex and often contradictory effects of smart city investments on social trust, fairness, participation, and citizen protection—and to explore the mechanisms driving their fragmented and uneven transformation.

2. Literature review

This paper first explores the concept of smart cities and adopts both qualitative and quantitative research perspectives to analyze the relationship between smart cities and social governance. Through a comprehensive and systematic review of relevant literature, this study aims to provide a deeper understanding of the diversity and complexity of smart city development, offering theoretical guidance and practical support for smart city construction.

2.1. The concept of smart cities

In today's economic environment, cities enhance their competitiveness by fostering creativity, innovation, and the skills of their citizens. The core objective of this competition is to drive economic growth, optimize industrial structure, and improve overall urban development. As urban regions expand in number, their economic value and competitive advantage increasingly depend on these factors. To deliver more citizen-centered services, cities must adopt advanced information technologies, analytics, and systems thinking. To enhance the provision of public services both now and in the future, cities must make their core systems—such as public safety, transportation, government services, and healthcare—more “intelligent” (Dirks et al., 2010). As a result, smart cities have gained increasing attention from policymakers and urban studies scholars.

In Western urban studies, there has been growing discourse on smart cities as a “city label phenomenon.” However, there is no universally accepted definition of a smart city (Albino et al., 2015; Bakıcı et al., 2013; Meijer and Bolívar, 2016), and scholars continue to debate its precise meaning (Tranos and Gertner, 2012; Zanella et al., 2014). Furthermore, the term “smart city” is not used uniformly across the literature. Instead, it is often applied to various urban aspects and multiple characteristics (Lombardi et al., 2012). Some scholars conceptualize smart cities through three key dimensions: technology, people, and institutions. They define smart cities in three distinct ways:

(1) As a process that integrates and delivers services through infrastructure and technological mediation,
(2) As a mechanism that enables people to learn and adapt to infrastructure use through continuous practice and experience,
(3) As a system for managing and controlling urban operations (Nam and Pardo, 2011).

Beyond these classifications, smart cities can also be defined from other perspectives. For example, some scholars identify six key domains of smart cities: smart economy, smart citizens, smart governance, smart mobility, smart environment, and smart living. Within this framework, they define a smart city as “a forward-thinking urban area that excels in these six dimensions, built on the foundation of ‘intelligence,’ and shaped by the autonomous, independent, and conscious actions of its citizens” (Giffinger et al., 2007).

The dominant academic discourse on smart cities, largely shaped by Western contexts, is embedded within specific governance traditions that influence its analytical frameworks. Western literature often critiques neoliberal urbanism, emphasizing the disproportionate influence of global tech firms like IBM and Cisco in urban governance (Anthopoulos et al., 2016; McNeill, 2015), and the resulting corporatized, market-driven urban models (Hollands, 2020; Mavelli, 2022). Within this discourse, citizen participation—though rhetorically emphasized—is frequently dismissed as superficial or tokenistic (Cardullo and Kitchin, 2019; Arnstein, 1969), casting citizens as data producers or service consumers rather than co-governors (Ranchod, 2020; Johnson et al., 2020). These debates highlight tensions between top-down (state or corporate-led) and bottom-up (civil society–driven) models, and have inspired alternative visions such as technological sovereignty, as seen in Barcelona’s efforts to reclaim digital infrastructure for the public (Barandiaran et al., 2017; Galdon, 2017).

In contrast, China’s smart city discourse reflects distinct governance logics rooted in a centralized, state-led model. Rather than being market-driven, Chinese smart city development is directed through top-down national planning, led by the central government (Guo et al., 2016; Fang and Shan, 2022). Since 2012, a series of national policies has launched extensive pilot programs (Zhang et al., 2022; Guo and Zhou, 2025), with the state acting as initiator, funder, and designer of development goals, performance metrics, and implementation strategies (Song et al., 2022; Crumpton et al., 2021; Cohen, 2014; Wang and Zheng, 2013). These initiatives are widely framed as tools to enhance national governance capacity and deliver both people-centered services and precision governance (Yue et al., 2024).

This governance model fundamentally shapes how citizen participation is structured. In China, participation is typically facilitated via official channels—e-government apps, IoT systems, and grievance platforms (Gao, 2018; Henman, 2019)—reflecting a collaborative state-citizen relationship, rather than the oversight-driven approaches common in Western contexts (Garcia Alonso and Lippez-De Castro, 2015; Scholl and Scholl, 2014). While this model enables rapid deployment, it also faces challenges, particularly around digital inclusion. Socioeconomic, age, and education-based disparities limit individuals’ capacity to engage with digital governance (Jang and Gim, 2022). Accordingly, enhancing digital literacy and ICT self-efficacy is essential to inclusive participation under China’s state-led framework (Deng and Fei, 2023).

Given the central role of the government in shaping both smart city strategies and participation modalities, this study defines smart cities as “government-led, human-centered initiatives that promote social innovation through the intelligent application of information technology to meet stakeholder needs.” This definition explicitly recognizes the influence of China’s strong, centralized governance model, contrasting it with the more pluralistic, market-oriented models prevalent in Western discourse (Basu and Kalra, 2022; Crumpton et al., 2021; Joshi and Houtzager, 2012). Inspired by these definitions and considering the unique characteristics of smart city development in China, this paper further defines a smart city as a government-led, people-centered initiative that fosters social innovation and creativity through the sustainable and intelligent management of information technologies, aimed at meeting the needs of urban stakeholders.

2.2. Qualitative perspectives on the theoretical framework of smart city development

As smart city initiatives continue to evolve, their impact on economic and social development is becoming increasingly evident, thereby refining the theoretical framework and strategic architecture of smart city development (Anttiroiko et al., 2014). Through the integration of technologies such as the Internet of Things (IoT) and cloud computing, cities are forming intelligent and interconnected subsystems across different domains (Giffinger et al., 2010). These systems enable cities to perceive and process information comprehensively through advanced digital intelligence techniques.

Tracing back to Schumpeter’s economic development theory, the growth of smart cities is driven by two fundamental forces: technological push and demand pull (Schumpeter, 2013). This theory has been extended to China’s multi-stakeholder coordination model, which reflects the country's unique approach to smart city development. Under this model, technological advancements serve as the foundation, while the government formulates corresponding policies to encourage the participation of businesses and citizens. This interaction further enhances demand-driven development, ultimately leading to comprehensive upgrades across six key areas: smart economy, citizen well-being, governance systems, transportation networks, environmental protection, and quality of life (Vanolo, 2014).

The conceptual framework shown in Fig. 1 synthesizes insights from three major strands of smart city literature, forming a structured model that links technological foundations, governance structures, and developmental outcomes.

First, drawing on Schumpeter's theory of economic development and subsequent studies on digital innovation, the left-hand section of the framework (Intelligent Processing Technology) reflects the logic of technology push (Schumpeter, 2013). It emphasizes the layered construction of smart infrastructure—from IoT sensing to cloud-based platforms and integrated public service

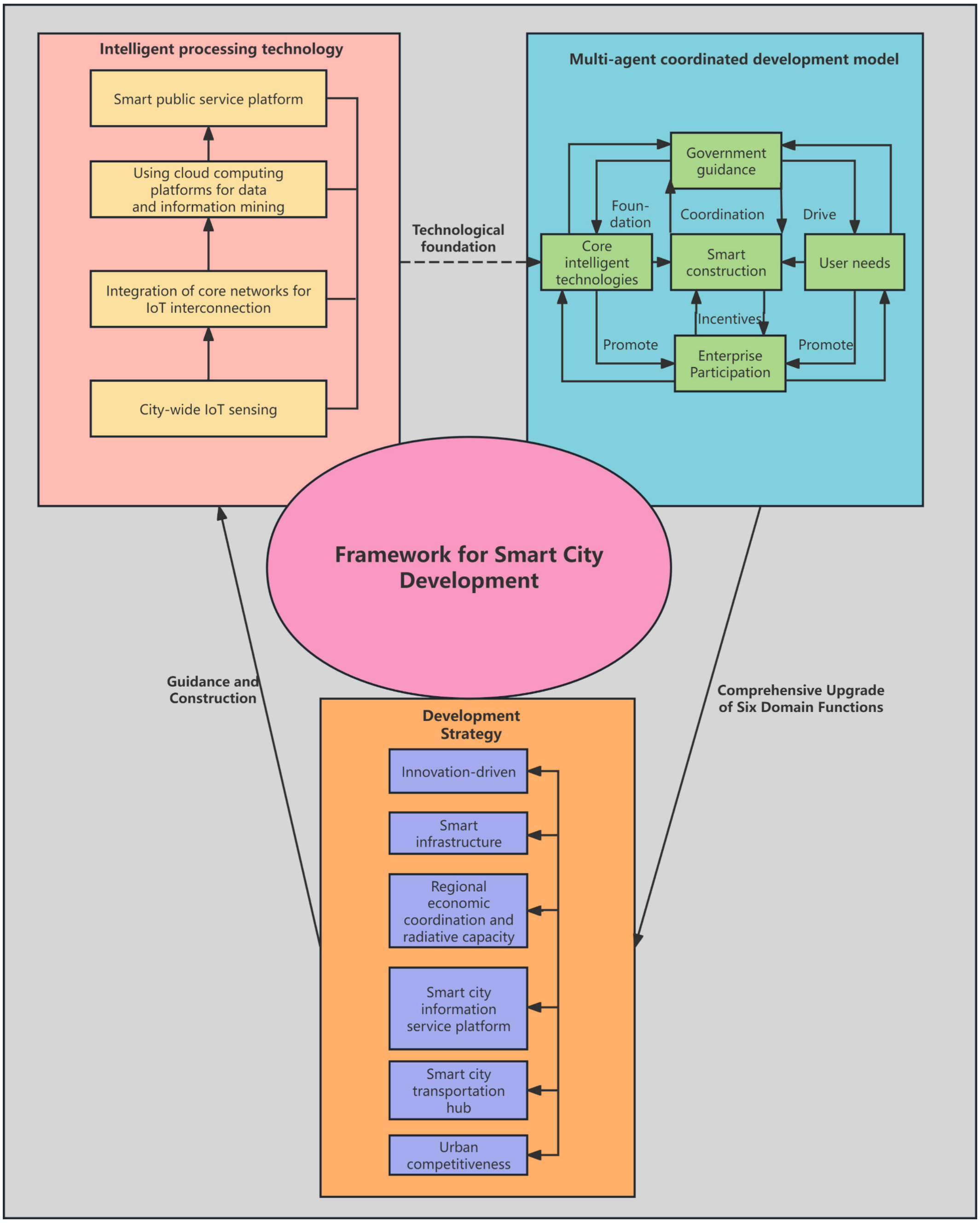

Fig. 1. Theoretical Framework of Smart City Development.

delivery—as essential technical foundations for smart urban transformation (Giffinger et al., 2010).

Second, the upper-right quadrant (Multi-agent Coordinated Development) is grounded in the governance literature on multi-stakeholder coordination and participatory urban planning (Vanolo, 2014). In the Chinese context, government-led smart city initiatives increasingly rely on coordinated participation among state, enterprise, and citizen actors. This model echoes theories of state-society synergy, where top-down strategic planning is dynamically influenced by bottom-up demands, forming a feedback-driven, co-evolutionary development model.

Third, the bottom section (Development Strategy) integrates the functionalist approach to smart city typologies, identifying six domain outcomes that characterize modern smart cities: infrastructure, digital services, governance capacity, mobility, economic competitiveness, and quality of life (Cao and Zhen, 2015; Anttiroiko et al., 2014). These outcomes are used both as policy targets and as evaluation dimensions for smart city performance.

This framework contributes to the literature by moving beyond siloed views of smart cities—those focused solely on technology, infrastructure, or governance—toward a more integrated theoretical model that captures the interactive dynamics among technological inputs, institutional structures, and strategic development goals. It serves as the theoretical basis for our empirical analysis that links macro-level developmental configurations with micro-level citizen governance perceptions.

2.3. Quantitative approaches to evaluating smart city development models

In the field of quantitative evaluation of smart cities, scholars have employed a variety of methods to assess the efficiency and progress of urban development. These methods include traditional statistical analyses as well as a range of decision-support techniques and evaluation models.

First, fuzzy logic has been applied in smart city evaluation models, focusing on empirical analysis from the perspectives of environment and energy. This method effectively handles uncertainty and vagueness, allowing for a more precise interpretation of the complex characteristics of smart cities (Lazaroiu and Roscia, 2012). Additionally, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method has been used to analyze the importance of six key dimensions: smart environment, smart economy, smart governance, smart citizens, smart living, and smart mobility. This technique emphasizes interactions and influences among factors, offering a systematic perspective to evaluate the diverse characteristics of smart cities (Koca et al., 2021).

Moreover, a combination of entropy weighting and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) has been employed to assess cities' performance in smart infrastructure, smart economy, smart living, smart governance, and smart environment. By quantifying the importance and performance of various indicators, this method helps determine the overall level of urban intelligence (Zhang et al., 2022).

In terms of methodological innovation, a difference-in-differences (DID) model has been applied to evaluate the impact of smart city development on urban innovation performance. This model leverages time-series data to identify performance differences before and after smart city investments and policy changes (Guo and Zhong, 2022). The DEA: AR-CCR model has also been utilized to assess the relative efficiency of sustainable development indicators in smart cities under specific input and output standards. This model highlights the importance of input considerations in resource allocation and policymaking to achieve efficient and sustainable outcomes (Anand et al., 2017).

Finally, a study based on Maslow's hierarchy of needs theory developed an evaluation system for urban citizens' demand for personalized innovation in smart city development. Through field research and surveys, a fuzzy analytic hierarchy process (FAHP) model was constructed, and K-Means clustering analysis was applied to generate indicator weights and evaluation results (Zhang et al., 2019).

While each of these research methods has distinct strengths, smart city development is a dynamic and regionally specific process. Current universal evaluation models and replicable construction approaches face limitations in addressing localized challenges. The methodologies applied often exhibit strong subjectivity (e.g., analytic hierarchy process) and are result-oriented, emphasizing indicator universality across all regions while neglecting the impact of regional economic disparities and differences in innovation capacity.

To address these limitations, this study builds upon the theoretical framework of smart city development and employs a multi-model combined analysis approach. Specifically, it integrates factor analysis and a Radial Basis Function (RBF) neural network optimized by a genetic algorithm to overcome the shortcomings of single-method evaluations. This approach enables horizontal and vertical comparative analysis of representative cities with comparable characteristics, providing a more robust and adaptable assessment framework.

2.4. Smart city construction and social governance concepts

As a key trajectory of contemporary urban development, smart cities have received growing global attention in recent years. With the rapid advancement of information technologies and the acceleration of urbanization, smart cities have demonstrated significant potential not only in enhancing urban management, optimizing public service delivery, and improving resource efficiency, but also in playing an increasingly crucial role in multiple dimensions of social governance. From a governance perspective, smart city construction is often regarded as a catalyst for modernizing governance through improved efficiency, transparency, and civic engagement (Lewandowska and Chodkowska-Miszczuk, 2022; Qiu et al., 2023). More specifically, smart city development influences social governance in four core areas: public participation, social protection, social trust, and social justice.

2.4.1. Public participation

Public participation is widely recognized as a cornerstone of smart governance. Its essence lies in transforming citizens from passive recipients of services into active co-creators of urban development (Johnson et al., 2020; Cao and Kang, 2024). The widespread use of information and communication technologies (ICTs) has provided unprecedented tools and channels for citizen engagement (Chatigny-Vincter, 2020; Aderibigbe and Gumbo, 2024). E-participation platforms—including online forums, e-voting systems, mobile applications, and service crowdsourcing tools—have become mainstream mechanisms for interaction between governments and the public (Chatigny-Vincter, 2020; Aderibigbe and Gumbo, 2024; Zolotov et al., 2018). Examples include Barcelona's Decidim platform, Indonesia's LAPOR! app, and widely used tools such as SeeClickFix and FixMyStreet in the U.S. and U.K., all of which aim to empower citizens to report community issues, propose policy suggestions, and participate in budgeting decisions, thereby promoting broader democratic practices (Lee et al., 2025; Johnson et al., 2020; Febriani et al., 2024).

However, despite the opportunities brought by technology, achieving genuinely inclusive and effective participation remains a major challenge. The digital divide is a pervasive issue: disparities in socioeconomic status, age, education level, and digital skills significantly affect citizens' ability to access and utilize digital platforms (Deng and Fei, 2023; Jang and Gim, 2022; Lorenzo and Joia, 2024). This may result in unequal participation opportunities, where the voices of tech-savvy elites and wealthier populations are amplified, while the elderly, low-income groups, and informationally disadvantaged populations are further marginalized (Lee et al., 2025; Deng and Fei, 2023; Jang and Gim, 2022).

Moreover, many civic engagement practices in smart cities are criticized for being tokenistic or symbolic (Chantry, 2023; Cardullo et al., 2018). According to Arnstein's "Ladder of Citizen Participation," much of what is labeled as participation—particularly in online consultation or information disclosure—often reflects the lower rungs of participation, lacking real influence on decision-making (Arnstein, 1969). Cardullo and Kitchin's "smart city participation framework" further reveals that citizens are frequently positioned as data providers or service consumers, rather than co-governors—reflecting a civic paternalism embedded in neoliberal rationality (Cardullo and Kitchin, 2019; Cardullo and Kitchin, 2019). Thus, the success of smart governance hinges not only on the availability of participatory channels but also on the institutional mechanisms that can effectively translate civic input into policy action (Viale Pereira et al., 2017).

2.4.2. Social protection

Social protection, a core function of governance, aims to ensure that all citizens—particularly vulnerable groups—can equally access basic services and social security. Smart city technologies offer new potential to enhance social protection by improving resource allocation and service efficiency (Song et al., 2022). For example, smart healthcare systems provide remote diagnosis and electronic health records to deliver accessible services to elderly and disabled individuals (Qiu et al., 2023; Bricout et al., 2021); smart transportation systems assist in planning barrier-free travel routes (Bricout et al., 2021); and big data analytics help governments identify populations in need more precisely, enabling targeted social assistance (Goel and Vishnoi, 2022).

Nonetheless, technology-driven social protection systems may also introduce new risks of exclusion. Service accessibility becomes a critical concern. For informationally disadvantaged groups—those unable to operate smart devices or lacking internet access—digital services may not only fail to provide convenience but could become additional barriers, leading to the formation of a digital poorhouse (Eubanks, 2018; Jang and Gim, 2022). Research emphasizes that improving accessibility—by offering multichannel services, reducing usage costs, and providing tailored support programs for marginalized groups—is key to encouraging their participation in smart city development (Jang and Gim, 2022).

In addition, algorithmic bias may exacerbate social inequality. Algorithms used for distributing public resources, when trained on biased data, risk reproducing or amplifying real-world discrimination, leading to unfair resource allocation across communities (Lee et al., 2025; Ziosi et al., 2024). Therefore, ensuring that smart social protection systems follow the principles of inclusive design and universal design is vital for removing environmental and technological barriers, thereby ensuring that all citizens—including those with disabilities—benefit from smart technologies (Bricout et al., 2021).

2.4.3. Social trust

Social trust—referring to citizens' trust in government, society, and one another—is a key lubricant of effective governance (Johnson et al., 2020; Paskaleva and Cooper, 2018). Smart city initiatives can strengthen trust in multiple ways. Open government data and transparent decision-making processes enhance governmental accountability and credibility (Ranchod, 2020; Burns and Welker, 2022; Aderibigbe and Gumbo, 2024). When citizens are able to monitor government responses to community issues via online platforms like SeeClickFix, the visibility of state responsiveness can help restore and build public trust (Lee et al., 2025; Viale Pereira et al., 2017). Moreover, collaborative governance models, such as public–private partnerships (PPPs) and cooperation with academia and civil society, pool diverse resources and expertise to address complex urban challenges, fostering trust between stakeholders through joint action (Ranchod, 2020; Lorenzo and Joia, 2024; Viale Pereira et al., 2017).

Yet the hyper-digitization of smart cities also poses potential threats to trust. Data privacy and security rank among citizens' top concerns (Crumpton et al., 2021; Kuang et al., 2024). The mass collection of personal data—particularly in public surveillance—has provoked critiques of surveillance capitalism, with citizens fearing misuse or leakage of personal information, thereby questioning the motivations of both governments and corporations (Pansera et al., 2023; Burns and Welker, 2022). The opaque nature of algorithmic decision-making—the so-called "black box" problem—further weakens transparency and accountability. When citizens do not understand how decisions are made, trust in their fairness diminishes (Eubanks, 2018).

In some contexts, entrenched clientelism and patronage networks may infiltrate digital platforms, distorting participatory processes and turning them into tools for narrow interest groups, thereby undermining broader social trust (Pansera et al., 2023). Thus, building robust data governance frameworks—ensuring ethical data use, procedural transparency, and citizen control over their personal information—is essential to sustaining trust in the era of smart governance (Aderibigbe and Gumbo, 2024; Bou Nassar et al., 2025).

2.4.4. *Social justice*

Social justice concerns the fair distribution of urban resources, rights, and opportunities, and serves as a fundamental benchmark for assessing governance outcomes (Crumpton et al., 2021). Smart city advocates often claim that technology can help foster more equitable urban development. For instance, optimized public transport systems can improve accessibility for peripheral neighborhoods, while online learning platforms can provide quality educational resources to underserved students (Deng and Fei, 2023; Goel

Table 1
Smart City Development Indicator System.

Primary Indicators	Secondary Indicators	Tertiary Indicators
Smart Economy – Comprehensive Economic Development A_1	Economic Development Vitality B_1	Per Capita GDP (CNY) X_1 Average Annual GDP Growth Rate (%) X_2 Per Capita Disposable Income in Urban Areas (CNY) X_3
	Innovative Economic Development B_2	Total Output Value of High-Tech Industries (Billion Yuan) X_4 Average Growth Rate of High-Tech Production Value (%) X_5 Internal R&D Expenditure (Billion Yuan) X_6
Smart Environment – Intelligent Infrastructure A_2	Communication Network Applications B_3	Mobile Phone Users per 100 people (%) X_7 Broadband Connections per 100 Households (%) X_8 Internet Penetration Rate (%) X_9 Total Telecommunications Revenue (Billion Yuan) X_{10}
	Public Infrastructure Investment B_4	Total Urban Infrastructure Investment (Billion Yuan) X_{11} Proportion of infrastructure investment on smart facilities(Billion Yuan) X_{12}
Smart Living – Smart Public Information Services A_3	High-Quality Medical Services B_5	Number of Tertiary Hospitals (Units) X_{13}
	Development of Information Services Industry B_6	Information Technology Industry Value (Billion Yuan) X_{14} Employment in the Information Technology Transmission Services Industry (Ten Thousand People) X_{15} Information Technology Industry Growth Rate (%) X_{16} E-commerce Transaction Volume (Billion Yuan) X_{17}
	Information Technology Service Development B_7	Growth Rate of Enterprises in High-Tech Industrial Development Zones (%) X_{18} Number of Scientific Researchers (Individuals) X_{19}
	Smart City Management B_8	Sewage Treatment Rate (%) X_{20} Wastewater Centralized Treatment Rate (%) X_{21} Green Coverage Rate in Urbanized Areas (%) X_{22} Per Capita Park Green Space Area (m^2) X_{23}
	Citizen Participation in Smart Living B_9	Rate of Government Information Disclosure Response to Public Requests (%) X_{24}
Smart Mobility – Intelligent Transportation Hubs A_4	Urban Transportation Accessibility B_{10}	Internet + Transportation Index (%) X_{25} Urban Traffic Congestion Index X_{26}
	Urban Transportation System B_{11}	Urban Road Length (Kilometers) X_{27} Total Urban Road Area (Ten Thousand Square Meters) X_{28} Urban Rail Transit Length (Kilometers) X_{29} Taxis with GPS / smart payment coverage (%) X_{30}
Smart Networks – Global Cooperation and International Competitiveness A_5	Development of Import and Export Business B_{12}	Total Import and Export Trade Volume (Billion US Dollars) X_{31} Exports of High-Tech Products (Billion US Dollars) X_{32} Cargo Throughput (Billion Tons) X_{33}
	Cross-Border Investment B_{13}	Actual Utilization Value of Foreign Investment Contracts (Billion US Dollars) X_{34}
	Global Transportation Network Development B_{14}	Airport Aircraft Takeoff and Landing Movements (Ten Thousand Movements) X_{35} Real-time Monitoring-enabled Passenger Volume (Billions of People) X_{36}
Smart Citizens – Innovative Development Capacity A_6	Innovation and Creativity Capability B_{15}	Number of Patents Granted in the Current Year (Ten Thousand Cases) X_{37} Number of Registered Scientific and Technological Achievements (Units) X_{38} Number of Patents Granted per Ten Thousand People (Pieces) X_{39}
	Innovation Resources B_{16}	Equivalent R&D Personnel Number to Last Year (Ten Thousand Person-Years) X_{40} Average Income per Capita for Scientific Researchers (Yuan) X_{41}
	Innovation and Creative Value B_{17}	Technology Transaction Amount (Billions of Yuan) X_{42}

and Vishnoi, 2022). In theory, data-driven decisions can reduce human bias and enhance fairness in resource allocation.

However, critical studies argue that many current smart city projects may actually exacerbate spatial and social inequalities (Lee et al., 2025; Waghmare, 2024). Influenced by neoliberal urbanism, these projects often prioritize investment attraction and the interests of the "creative class," with benefits concentrated in central or affluent districts—creating smart enclaves that exclude poorer areas and informal economies (Obringer and Nateghi, 2021; Hollands, 2015). The controversial Quayside project in Toronto illustrates how smart city developments led by large tech firms often prioritize commercial logic over citizens' real needs and rights (Chantry, 2023).

In response, scholars and activists have proposed alternative paradigms for justice-oriented smart cities, centered on the idea of a digital right to the city (Suter et al., 2024). Building on Lefebvre's notion of the "right to the city," this concept asserts that all citizens should have the right to shape both the digital and physical environments in which they live (Purcell, 2002). The technological sovereignty agenda advanced by Barcelona offers a prominent example of this approach—treating technology and data as urban commons, ensuring they serve the public good rather than private profit (Galdon, 2017; Suter et al., 2024). This vision calls for governance models that transcend market logic, adopt community-centered and public value–oriented paths, and ensure that the benefits of smart cities are shared equitably by all residents.

3. Construction of the smart city development evaluation index system

3.1. Design of the evaluation index system

To establish a more scientific and rational evaluation index system, this study reviews and synthesizes relevant literature from both domestic and international sources. The literature includes studies on sustainable development in areas such as economics and energy, as well as research on government-enterprise collaborative smart city projects (Calvillo et al., 2016; Tokoro, 2015). Additionally, references are drawn from literature on strategic smart city evaluations (Letaifa, 2015; Raparthi, 2015) and cutting-edge studies on big data, cloud computing, and data mining in smart city development (Hashem et al., 2016).

Building upon these theoretical foundations, this study also incorporates policy documents issued by the Chinese government to design evaluation indicators tailored to the unique characteristics of Chinese cities. Since 2014, the National Development and Reform Commission (NDRC) and eight other ministries have jointly issued the Guiding Opinions on Promoting the Healthy Development of Smart Cities, aiming to foster smart city development. Subsequently, in 2016, the Inter-Ministerial Coordination Working Group for New-Type Smart City Construction emphasized the importance of smart city development and provided a guiding framework along with a specific index system for evaluation and development (Cyberspace Administration of China, 2014). This choice is grounded in the institutional logic of China's smart city development, which is characterized by state-led governance, top-down planning, and performance-oriented assessment. The adoption of a policy-oriented indicator system ensures alignment with national development priorities, enhances data availability, and facilitates horizontal comparability across cities.

The evaluation system in this study consists of six primary indicators:

(1) Smart Economy – Comprehensive economic development.
(2) Smart Environment – Intelligent infrastructure.
(3) Smart Living – Smart public information services and management.
(4) Smart Mobility – Intelligent transportation hubs.
(5) Smart Network – Global cooperation networks and international competitiveness.
(6) Smart Citizens – Innovation capacity.

These six indicators are used to compare and analyze the development models of six comparable cities. The detailed evaluation criteria are presented in Table 1.

Although the current framework does not explicitly designate a separate "social governance" dimension, core elements of social governance are embedded across multiple dimensions through a set of proxy variables, thus forming what may be termed a "structural mapping" logic.

Specifically, under the dimension of Smart Living, indicators such as the number of tertiary hospitals (X13) and per capita green park area (X23) directly reflect the provision of essential public services and environmental equity. The government information disclosure response rate (X24) captures administrative transparency and responsiveness, indirectly reflecting institutional trust and the robustness of feedback mechanisms.

In the Smart Environment dimension, broadband penetration (X8) and internet access rate (X9) serve as structural indicators of digital accessibility, forming the infrastructural basis for evaluating digital inclusion. While they do not directly measure the capabilities of marginalized groups, they provide indirect evidence of progress in narrowing the digital divide.

In the Smart Mobility dimension, indicators such as urban rail transit length (X29) and total road area (X28) capture the spatial accessibility and freedom of movement for residents, which are closely associated with spatial justice and transportation equity.

Under Smart Citizens, indicators such as the number of patents granted per 10,000 people (X39) and average income for scientific researchers (X41) reflect citizens' capacity to engage in innovation and receive economic returns, thereby indicating empowered civic participation. In addition, employment in the information transmission industry (X15) serves as a proxy for the degree to which citizens are integrated into the digital economy.

It should be noted, however, that while these variables structurally embed certain aspects of social governance, they fall short of capturing softer dimensions such as the quality of participation, civic trust, digital literacy, perceived safety, and subjective satisfaction. Due to limitations in the availability and standardization of perceptual data, such as surveys and trust indices, this study has not incorporated subjective indicators like those from the Chinese Social Survey (CSS) into the cross-city comparative framework. Nevertheless, future research should aim to integrate large-scale perceptual datasets, digital literacy assessments, and social capital indicators to construct a multi-layered and expandable "extended social governance dimension", thereby enhancing the system's capacity to reflect the people-centered values of smart governance.

3.1.1. Smart economy – comprehensive economic development

The smart economy refers to an economic development model that leverages information technology, the Internet, and big data, alongside modern digital infrastructures and GDP-based economic conditions, to enhance economic efficiency, optimize resource allocation, promote industrial upgrading, and foster innovation-driven growth. In this model, various economic entities achieve highly efficient coordination through information sharing and interconnectivity, thereby driving digitalization and intelligent transformation within the economic system (Caragliu et al., 2011).

3.1.2. Smart environment – intelligent infrastructure

The smart environment is closely related to intelligent infrastructure, utilizing advanced information technologies, communication networks, and the Internet of Things (IoT) for real-time environmental monitoring, data collection, and precision management. The core of a smart environment lies in intelligent infrastructure, including smart transportation systems, smart energy networks, smart waste management systems, and smart water supply systems. These infrastructures enable real-time data collection, analysis, and application, ensuring efficient resource utilization and optimized environmental management, while also contributing to fixed-asset investments (Chang and Sheppard, 2013).

3.1.3. Smart living – smart public information services and management

Smart public information services and management represent a crucial component of smart living, encompassing the digitalization, intelligence, and personalization of various urban public services. For instance, smart healthcare leverages big data analytics and telemedicine technologies to optimize medical resource allocation and enhance healthcare service quality. Similarly, smart governance services utilize online platforms to improve administrative efficiency and public service quality. These information services and technological advancements further enhance the standard of smart living (Caragliu et al., 2011).

3.1.4. Smart mobility – intelligent transportation hubs

The intelligent transportation hub is a critical element of smart mobility, serving as a key node that integrates various modes of urban transportation, including buses, subways, taxis, and private vehicles. By employing advanced information technologies and smart devices, intelligent transportation hubs enable real-time traffic monitoring, management, and regulation, offering real-time traffic information and travel recommendations to enhance transportation efficiency and convenience (Meneguette et al., 2018). These hubs typically include urban transportation systems, such as road networks, subway systems, and other key transportation infrastructures.

3.1.5. Smart network – global cooperation networks and international competitiveness

The smart network is one of the core objectives of smart city development, emphasizing international cooperation and collaboration between cities. By fostering global city networks, different countries and cities can share best practices and innovative achievements in smart city development, jointly addressing challenges and obstacles to advance global smart city initiatives (Hollands, 2020). Strengthening smart cooperation networks also enhances a city's international competitiveness, attracting foreign investments and businesses, driving industrial upgrades, boosting innovation capacity, and ultimately enhancing economic strength and global influence.

3.1.6. Smart citizens – innovation capacity

Smart citizens are the core and essential components of smart city development. Through intelligent technologies and digital tools, urban residents actively engage in innovation-driven development. Smart citizens possess strong innovation capabilities, enabling them not only to effectively utilize information technologies for daily problem-solving but also to actively participate in urban governance and community-building, thereby contributing to the city's overall innovation-driven growth (Yigitcanlar and Kamruzzaman, 2018).

3.2. Data sources

In line with the 2010 National Urban System Planning Outline, we examine five national central cities (Beijing, Shanghai, Tianjin, Guangzhou, and Chongqing) and additionally include Xiamen, which was added in 2017 as an emerging-city expansion case. These cities were prioritized due to their strategic roles in national urban development, early adoption of smart city policies, and consistent data availability.

The analysis uses panel data from 2015 to 2022, corresponding to the period following China's first national smart city evaluation initiative in 2016. Data were primarily collected from municipal statistical yearbooks, city statistical bulletins, and official databases maintained by city-level statistics bureaus. Supplementary data on traffic congestion and mobility indicators were obtained from

Gaode Map (Amap), which provides standardized real-time urban transport indices.

To ensure comparability, all data were normalized and cross-checked for consistency. In cases of missing values (less than 5% of total), mean imputation was applied within the same indicator and city. This allowed for a robust and coherent construction of the Smart City Development Index across all cities and years.

4. Research methods: establishing the evaluation model using factor analysis, RBF neural network, and genetic algorithm optimization

This study addresses a key limitation of existing smart city evaluation frameworks: their reliance on static, additive indicators that fail to reflect the multidimensional, regionally diverse, and nonlinear nature of urban transformation—particularly in China's complex administrative context.

To overcome this, we develop a Smart City Development Index that combines factor analysis to extract latent dimensions and a Radial Basis Function (RBF) neural network to model nonlinear development patterns. This approach captures variations that traditional linear models often overlook. The detailed analytical methods and specific mathematical procedures are presented in the Appendix.

To assess whether structural development aligns with citizens' lived experiences, we use Chinese Social Survey (CSS) data on five outcomes: overall social evaluation, political participation, perceived protection, interpersonal trust, and fairness. Ordered logit regression links macro-level smart development to micro-level governance perceptions.

By bridging structural inputs and individual perceptions, this study advances debates on urban inequality and smart governance, offering an evidence-based perspective on where and for whom smart cities deliver meaningful outcomes.

4.1. Justification for method selection

To evaluate the multi-dimensional, high-variance, and nonlinearly correlated indicators of smart city development, this study adopts a two-stage hybrid modeling strategy combining Exploratory Factor Analysis (EFA) and a Radial Basis Function (RBF) Neural Network optimized by genetic algorithms. This integrated approach is chosen for both theoretical and empirical considerations, as detailed in Appendix.

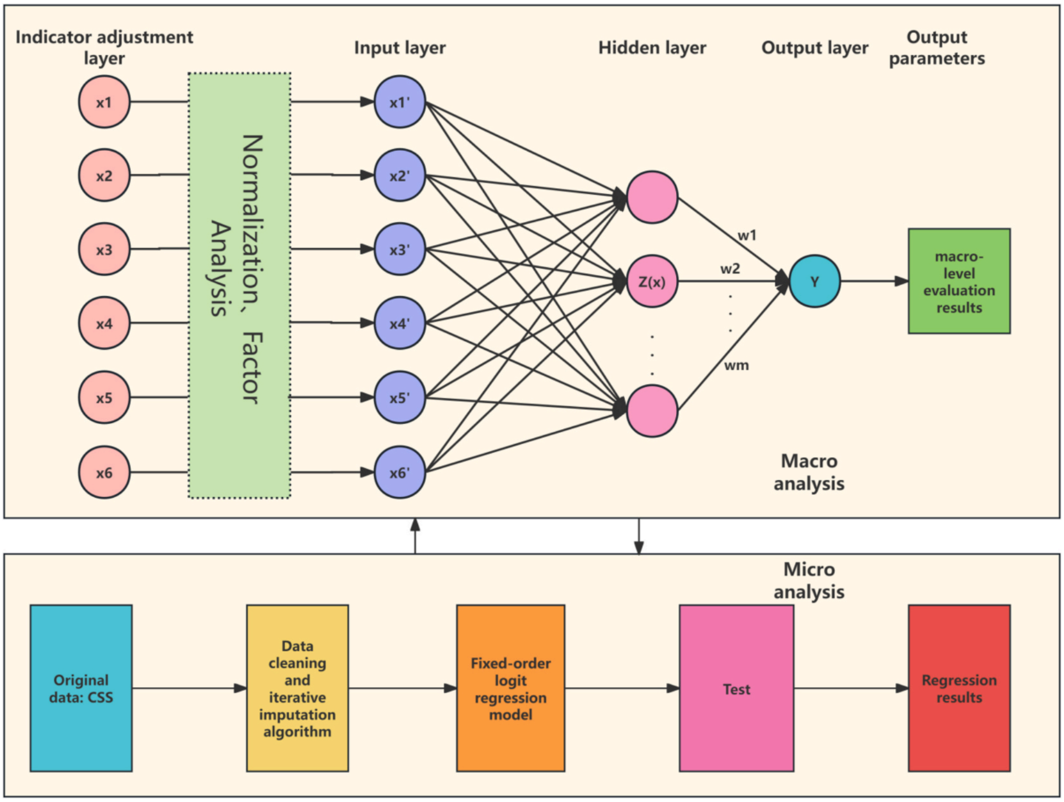

Fig. 2. RBF Neural Network Evaluation Model.

4.2. Factor analysis: data simplification and interpretation

Factor analysis reduces high-dimensional data by identifying underlying common factors that explain correlations among observed variables. This dimensionality reduction condenses redundant information into a smaller set of interpretable factors that reflect the core structure of smart city characteristics. Key variables are first selected from multi-source data, followed by factor extraction and interpretation, with scoring coefficients computed to quantify each factor's contribution.

4.3. RBF neural network: prediction and classification

The Radial Basis Function (RBF) neural network, with its three-layer structure (input, hidden, output), enables fast and effective classification and regression. In this study, factor scores serve as inputs to the RBF network, which is trained on historical data to recognize urban smartness patterns and predict development trends. Parameters like learning rate and kernel width are optimized to minimize prediction error, and performance is validated on an independent test set. The combined evaluation model structure of factor analysis RBF neural network is illustrated in Fig. 2:

4.4. Genetic algorithm: parameter optimization

Genetic algorithms optimize the weights and biases of the RBF neural network by simulating natural evolution through selection, crossover, and mutation. Starting from a randomly generated population of parameters, the algorithm evaluates fitness based on prediction error and iteratively evolves toward the optimal configuration.

By combining factor analysis for dimensionality reduction, the RBF network for pattern recognition, and genetic algorithms for parameter tuning, the model effectively identifies key drivers of smart city development and forecasts future trends. This integrated method enhances both accuracy and practical applicability.

5. Empirical analysis of smart city development model

5.1. Empirical data results

For the six primary indicators in the established evaluation system—Smart Economy (comprehensive economic development), Smart Environment (intelligent infrastructure), Smart Living (smart public information services), Smart Mobility (intelligent transportation hubs), Smart Network (global cooperation network and international competitiveness), and Smart Citizens (innovation capability)—a factor analysis was conducted to screen corresponding tertiary indicators.

First, the appropriateness of the factor analysis method was tested using the Kaiser-Meyer-Olkin (KMO) measure. The KMO values for the six dimensions were 0.661, 0.724, 0.503, 0.611, 0.530, and 0.529, respectively, with an overall KMO value above 0.6, and the Bartlett's test of sphericity showing $P < 0.001$, confirming the method's suitability. The cumulative variance explained rates were 89.314%, 78.681%, 98.307%, 83.190%, 84.365%, and 92.745%, indicating that the extracted principal components sufficiently replaced the original variables, covering almost all the information from the original variables.

After screening the tertiary indicators through factor analysis, 14 new virtual secondary indicator variables were generated, which can be used as the input layer for the RBF neural network in the next step of simulation calculations. The secondary virtual intermediary indicators were defined as follows: A_{11} and A_{12} for Smart Economy (comprehensive economic development), A_{21} for Smart Environment (intelligent infrastructure), A_{31}, A_{32}, A_{33}, A_{34}, and A_{35} for Smart Living (smart public information services), A_{41} and A_{42}

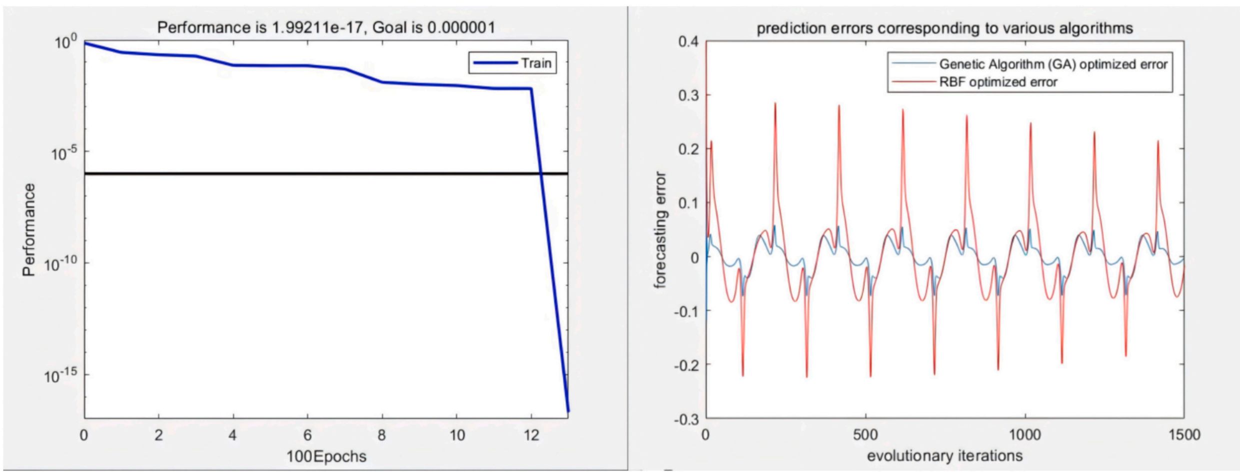

Fig. 3. Simulation Results.

for Smart Mobility (intelligent transportation hubs), A_{51} and A_{52} for Smart Network (global cooperation network and international competitiveness), and A_{61} and A_{62} for Smart Citizens (innovation capability). The specific factor score coefficients from the factor analysis results are shown in Appendix Table 2.

To eliminate differences in indicator attributes, all data were normalized to form a positive definite matrix. Using MATLAB R2021a, the sample data for the six primary indicators were subjected to RBF neural network training and simulation. During the training process, multiple parameter adjustments were made, with the total maximum number of training iterations set to 1,000.

After 120 iterations, the training and test sample values gradually converged, achieving the best training performance at the 100th iteration. Additionally, the genetic algorithm (GA) was used to optimize the error. The final training results and optimized error are shown in Fig. 3.

Using the same methods of factor analysis, RBF neural network, and genetic algorithm optimization, we conducted an empirical evaluation of the smart development models for Xiamen and five other cities. This evaluation covered a comparison of six sub-indicators, as shown in Fig. 4.

To generate the results illustrated in Fig. 4 and Appendix Table 9, this study applied a two-stage modeling strategy that translates high-dimensional raw indicators into standardized, comparable scores for each city. In the first stage, all tertiary indicators listed in

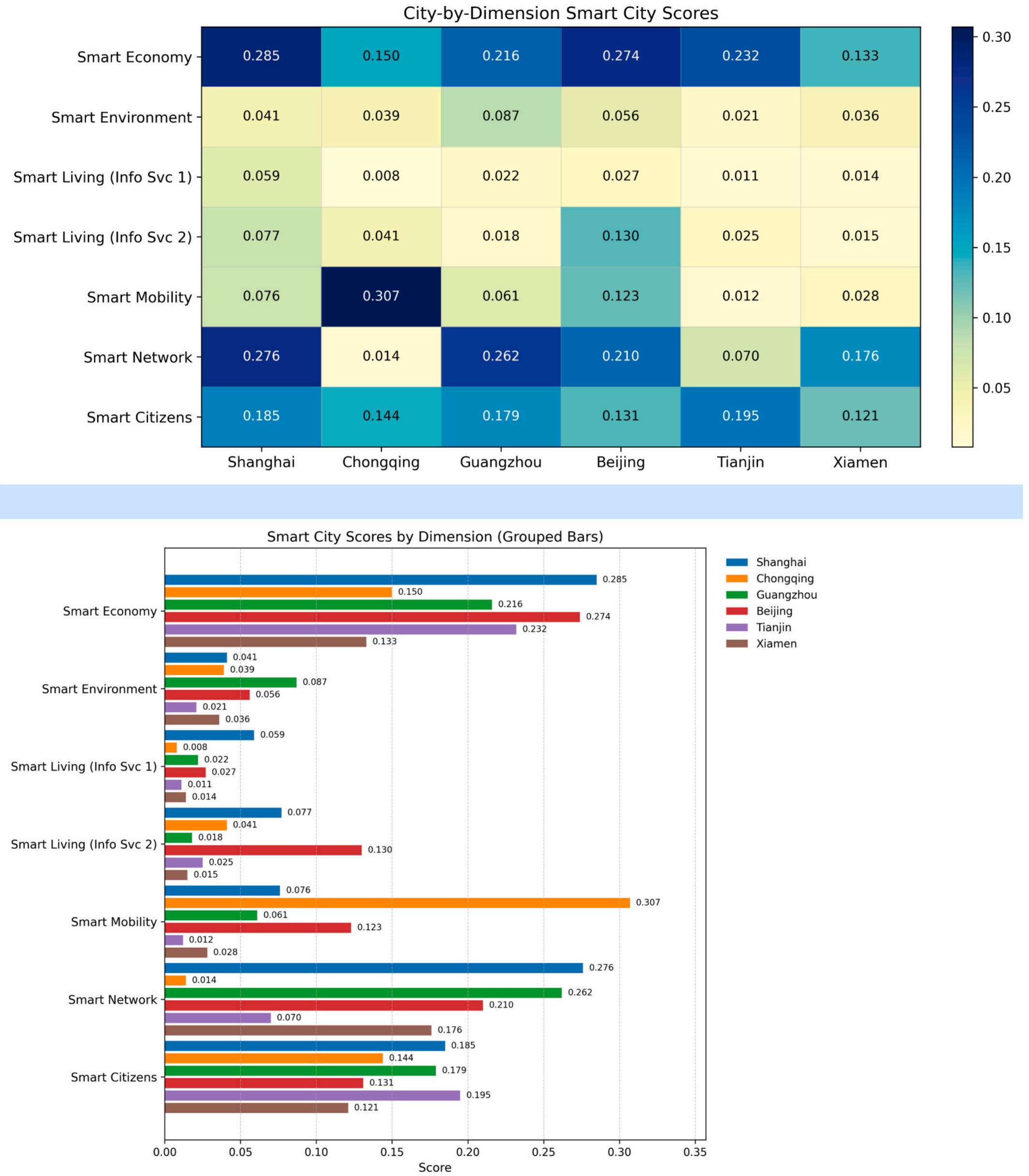

Fig. 4. City-by-Dimension Smart City Scores.

Table 1 were grouped under their respective primary dimensions and subjected to Exploratory Factor Analysis (EFA). For each dimension, one or more latent factors were extracted based on the Kaiser criterion (eigenvalues > 1), cumulative variance explained, and loading coherence. For instance, the Smart Living dimension, due to its heterogeneity, yielded five latent factors capturing distinct aspects such as healthcare infrastructure, digital services, environmental quality, and administrative responsiveness.

The extracted factors—e.g., A11, A12 for Smart Economy, A31–A35 for Smart Living—were calculated using regression-based scoring coefficients derived from the rotated component matrix (see Table 2). These factor scores were then normalized to a (United Nations Human Settlements Programme, 2022) scale to ensure cross-dimensional and cross-city comparability. As such, the scores for each dimension represent relative performance rather than absolute values, which allows for meaningful horizontal comparison among cities.

In the second stage, the normalized factor scores were used as inputs into an RBF neural network, which was trained to capture the nonlinear dependencies across dimensions and to compute an integrated development score for each city. The final values for each city's dimension in Fig. 4 were obtained from the output neuron activations corresponding to each factor group. The weights were optimized through a genetic algorithm to ensure convergence and minimize prediction error, improving the model's generalizability.

Therefore, each bar segment in Fig. 4 reflects the composite score of a smart city dimension, derived from underlying factor structures and learned neural weights. This approach goes beyond simple averaging or additive scoring, enabling a multidimensional and interaction-aware representation of smart city development across the six benchmarked cities.

5.2. Refined analysis of empirical findings: moving beyond descriptive comparison

This section synthesizes the empirical results derived from the factor analysis, Radial Basis Function (RBF) neural network, and genetic optimization algorithm, applied to five national central cities (Beijing, Shanghai, Tianjin, Guangzhou, and Chongqing) and additionally include Xiamen. While initial findings suggest heterogeneous performance across cities, a more critical reading reveals deeper structural dynamics that challenge dominant assumptions in smart city literature.

5.2.1. Smart economy: a divided landscape of innovation capacity

Shanghai (28.5%) and Beijing (27.4%) dominate the Smart Economy dimension, not merely due to their GDP size, but because of their advanced innovation ecosystems—characterized by strong high-tech industries, research infrastructure, and human capital investment. In contrast, cities like Xiamen (13.3%) and Chongqing (15%) show fragmented industrial upgrading, highlighting a developmental divide between national megacities and regional centers. This spatial imbalance questions the assumption of "smart city catch-up" in late-developing regions and suggests that economic modernization may not be uniformly attainable through smart infrastructure alone.

5.2.2. Smart infrastructure: centralization and resource asymmetry

While Beijing, Shanghai, and Guangzhou benefit from coordinated technological integration, the low scores of Tianjin and Chongqing reflect both fiscal constraints and institutional fragmentation in infrastructure planning. The uneven distribution of infrastructure capacity challenges conventional smart city evaluation models that assume uniform platform adoption. These findings point to a governance asymmetry in smart city development—where infrastructure is less a function of need, and more a product of elite-driven urban investment patterns.

5.2.3. Smart information services: functional expansion without systemic coupling

Despite relatively stable scores across cities, the internal fragmentation between public service digitalization (Smart Living 1) and urban management platforms (Smart Living 2) suggests limited synergy between technological application and service delivery. For example, Guangzhou scores moderately in information services but exhibits weak performance in citizen engagement metrics. This divergence questions the assumption that digital platforms inherently enhance governance responsiveness. The lack of cross-sectoral integration highlights a systemic bottleneck in achieving inclusive and participatory smart governance.

5.2.4. Smart transportation and network infrastructure: a structural paradox

Chongqing performs exceptionally in Smart Mobility (30.7%), yet scores the lowest in Smart Network (1.4%), reflecting a paradox: physical infrastructure may advance rapidly while digital and global connectivity lags behind. Conversely, Guangzhou and Shanghai exhibit high international cooperation scores (26.2%, 27.6%) but average transportation performance. These asymmetries suggest that smart city development is not a linear progression across sectors but is shaped by city-specific economic roles, spatial layout, and governance priorities. This observation invites a rethinking of "integrated smartness" as an overly idealized concept.

5.2.5. Smart citizens: toward convergence with diverging foundations

While overall gaps in Smart Citizens indicators are narrowing (ranging from 12.1% to 19.5%), the underlying composition varies widely. Tianjin's high score is driven by patent output and R&D investment, whereas Shanghai's is more balanced across innovation, education, and participation. This points to different models of citizen smartness: top-down innovation versus participatory engagement. These variations challenge the assumption that "smart citizen" development follows a universal path and underscore the need for more nuanced, context-specific assessments.

5.2.6. Conclusion of empirical analysis

Rather than simply ranking cities by aggregate performance, the findings expose a "composite paradox" in Chinese smart city development: high technology adoption does not guarantee institutional synergy or citizen empowerment. Traditional evaluation frameworks that rely on linear, additive metrics fail to capture these structural contradictions. Therefore, this study advocates for a more relational and interaction-based model, where performance is understood through cross-domain coupling, governance alignment, and social inclusivity.

While the above macro-level analysis reveals meaningful heterogeneity in smart city development across economic, infrastructural, and technological domains, it also underscores a structural paradox: technological progress does not uniformly guarantee corresponding improvements in governance quality or civic experience. This raises a pivotal question: Do smart city investments and structural transformations effectively translate into enhanced perceptions of governance, fairness, and participation among citizens?

To address this, the study now turns to a micro-level analysis, grounded in residents' subjective evaluations. After all, the ultimate legitimacy of smart cities lies not in infrastructure alone, but in their capacity to improve citizens' lived experience, promote inclusive governance, and reinforce social trust. This shift enables us to assess whether the macro-level "smartness" perceived in urban systems has yielded tangible benefits in the social domain—especially in the areas of public participation, social protection, trust in institutions, and perceived fairness.

6. Empirical analysis of micro smart cities and social governance

Building on the macro-level insights discussed above, this section investigates the lived experience of smart city residents by examining whether technological and infrastructural advances are associated with improved perceptions of governance effectiveness.

6.1. Bridging macro-level structures and micro-level perceptions

However, the preceding macro-level modeling across six key dimensions reveals that although smart cities have achieved significant progress in areas such as economic development, infrastructure, and innovation capacity, improvements in governance outcomes remain uneven across domains. Persistent disparities among cities, structural bottlenecks, and limitations in citizen empowerment continue to pose critical challenges (Cardullo et al., 2018; Bou Nassar et al., 2025). This raises a fundamental question: To what extent is the "structural development" of smart cities actually perceived by citizens, and does it translate into improved "social governance performance"? (Deng and Fei, 2023; Paskaleva and Cooper, 2018).

To more comprehensively assess whether smart city development has fulfilled its core governance objective of being "people-centered" (Bouzguenda et al., 2019); this section incorporates micro-level data from the Chinese Social Survey (CSS). It investigates whether the level of smart city development has a positive impact on citizens' subjective perceptions of social trust, fairness, participation, and protection (Goel and Vishnoi, 2022). This section should not be seen as analytically disconnected from the macro-level analysis; rather, it aims to construct a feedback loop that links structural input with perceptual output (Bouzguenda et al., 2019), thereby examining the presence of a significant structural–perceptual mismatch (Lebrument et al., 2021) and revealing potential challenges in the social responsiveness of smart governance.

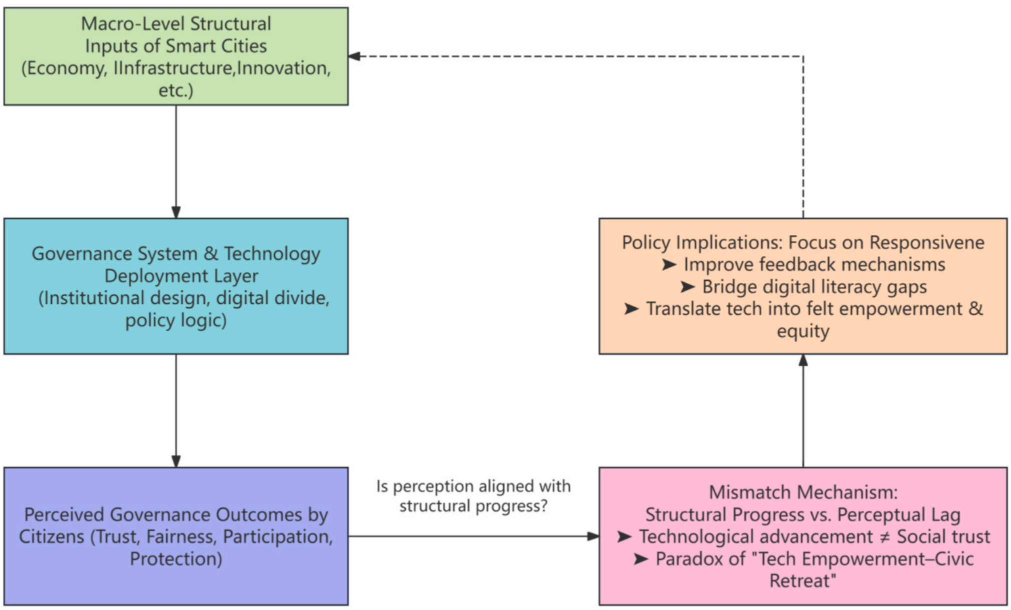

Fig. 5. The linking framework diagram.

Although previous studies have devoted considerable attention to infrastructure deployment, technological adoption, and institutional design in smart city construction (Deng and Fei, 2023; Crumpton et al., 2021; Kołakowska et al., 2013), the question of whether urban "smartness" truly enhances residents' perceived quality of governance remains an unresolved empirical issue. In response to this structural–perceptual mismatch, this study draws on microdata from the CSS and employs an ordered logit regression model to systematically analyze the relationship between smart city development and citizens' perceived governance performance from a bottom-up perspective.

The primary objective of this section is not to introduce an entirely new empirical domain, but rather to validate and extend the macro-level structural evaluation by capturing its social resonance. It emphasizes the need to assess whether "technological governance" is accompanied by "social responsiveness," thereby deepening our understanding of the governance outcomes of smart cities. The specific mathematical modeling process is presented in the appendix.

The specific framework is shown in the Fig. 5 below.

6.2. Data sources

This study employs microdata from the 2021 Chinese Social Survey (CSS), a nationwide, large-scale household survey conducted by the Institute of Sociology, Chinese Academy of Social Sciences (CASS), to analyze the impact of smart city development on social governance outcomes. Given that certain variables in the dataset contain missing values, Multiple Imputation (MI) is applied to estimate the 3,053 missing values for the variable b4e: skill level using an Iterative Imputation algorithm.

The imputation process builds a predictive model using fully observed variables to estimate missing values as dependent variables. Through 10 iterative refinements, it captures the relationships among observed data to generate consistent, structure-based estimates—rather than simple statistical fills—thus minimizing bias. This approach enhances the robustness of the empirical analysis and supports a more accurate assessment of smart cities' social governance effects.

6.3. Variable selection

Based on the literature review, this study evaluates the impact of smart city development on social governance from five dimensions: overall social evaluation, public participation, social protection, social trust, and social justice.

6.3.1. Dependent variables

(1) Overall Social Evaluation: G6. On a scale of 1 to 10, how would you rate the current overall social situation?
(2) Public Participation: H2a. In the past two years, have you participated in any of the following activities? Specific coding rules are provided in the Appendix.
(3) Social Protection: E5_6. On a scale of 1 to 10, how would you rate the overall level of social protection services provided by the government?
(4) Social Trust: F1b. On a scale of 1 to 10, how would you rate the current level of interpersonal trust?
(5) Social Justice: F3b. On a scale of 1 to 10, how would you rate the overall fairness and justice of society?

6.3.2. Independent variable: smart city development

Based on the macro-level indicator design and the available survey questions, the following indicators are selected:

(1) Information Resource Utilization: D4b1. How frequently do you engage in the following online activities? Specific coding rules are provided in the Appendix.
(2) Cybersecurity and Government Governance Evaluation:

G5a. How would you rate the security level of the following aspects in today's society? (e.g., personal information and privacy protection).

G3a. How well do you think the government performs in the following areas?

1. Government transparency and information disclosure.
2. Public service awareness and responsiveness to citizens' demands.

(3) Innovation Capacity:

B4e. In your non-agricultural work, do you hold a professional title or technical certification? Specific coding rules are provided in the Appendix.

A1d1. Level of education.

These variables are subjected to factor analysis with varimax rotation to derive a comprehensive smart city index score. The Kaiser-Meyer-Olkin (KMO) value of 0.77 exceeds the 0.6 threshold, and the Bartlett's test of sphericity ($p < 0.001$) confirms the adequacy of factor analysis for this dataset.

6.3.3. Control variables

This study incorporates the following control variables to account for potential confounding effects:Age; Gender; Marital Status (1. Single, 2. First marriage with spouse, 3. Remarried with spouse, 4. Divorced, 5. Widowed, 6. Cohabiting); Political Affiliation (1. Communist Party Member, 2. Communist Youth League Member, 3. Member of a Democratic Party, 4. General Public); Household Registration Type (1. Agricultural Hukou, 2. Non-agricultural Hukou, 3. Resident Hukou); Employment Status (1. Employed, 2. Employed but currently on leave, in training, or temporarily out of work, 3. Unemployed, 4. Student).

These variables are controlled to mitigate potential biases and ensure the robustness of the empirical analysis. Detailed descriptive statistics are shown in Appendix Table 3.

6.4. Empirical model

Since the dependent variable is an ordered categorical variable, this study employs a standard ordered logit regression with robust standard errors for empirical analysis. The model is specified as follows:

$$\ln\left(\frac{P(Y_i \leq j)}{P(Y_i > j)}\right) = \alpha_j - \sum(\beta_n \times X_{ni} + \mu \times \text{Controls}_i + \varepsilon_i)$$

Y represents the public evaluation of governance performance, including assessments of overall social evaluation, public participation, social protection, social trust, and social justice.X represents the independent variable, which is smart city development. Controls denote the control variables, while ε represents the error term.

To examine whether the regression model is correctly specified, this study employs the Link Test. The linktest adds the predicted value (_hat) and its squared value (_hatsq) as new variables in the regression model and tests the significance of_hatsq to determine the model's validity. If the_hatsq variable is not significant, it indicates that the model does not suffer from omitted variables or specification errors, suggesting that the model is reasonably well-specified. The test results are presented in Appendix Table 4.

_hat is significant ($p < 0.05$), while_hatsq is not significant ($p > 0.05$), indicating that the model is correctly specified and does not suffer from serious omitted variable bias or nonlinear specification errors.

The regression results are presented in Appendix Table 5.

6.5. Regression analysis results

This study examines the association between smart city development and multiple dimensions of social governance using ordered Logit regression models, focusing on general social evaluation (g6), social participation (h2a_sum), social protection (e5_6), social trust (f1b), and social equity (f3b). The regression results indicate that the smart city index (smart_city_sum) is significantly associated with all dimensions of social governance: it shows a significant positive association with social evaluation, social protection, social trust, and social equity, while exhibiting a significant negative association with social participation.

The negative association between smart city development and social participation may reflect several factors. One possible explanation is the digital divide effect: the expansion of smart city technologies may be associated with lower participation among the elderly and individuals with lower educational attainment, which can reduce overall levels of social participation (Li and Woolrych, 2021; Shin et al., 2021). This pattern may be further linked to differences in digital skills and internet usage that limit the capacity of lower-skilled groups to engage in policy discussions and community governance (Smith et al., 2009). In addition, the observed relationship is also consistent with a transfer of participation forms, whereby online participation partially substitutes for offline participation. Prior studies suggest that although smart technologies facilitate online engagement, such engagement may take the form of "clicktivism" and lack the depth and continuity typical of offline activities (Galais and Anduiza, 2016; Chen et al., 2022). Moreover, smart-city-related changes in social structure and identity may be associated with weakened community interactions, potentially reducing social capital and group cohesion (Hampton et al., 2011). Finally, smart city practices may shift citizen engagement toward service feedback and problem-solving rather than policy co-creation and social collaboration (Singh et al., 2021), which may be related to a decline in the breadth and depth of traditional participation.

Regarding control variables, age (a1c1) is positively associated with social appraisal, indicating that older individuals tend to report higher evaluations of social governance, although age does not show significant associations with social participation or other dimensions. Gender (a1b1) indicates that males report higher levels of social participation but lower ratings of social trust. Marital status (a1e1) is negatively associated with social trust and social protection, suggesting that married or divorced individuals tend to report less favorable views of these aspects of governance. Political affiliation (a3) is significantly associated across all models, consistent with differences in governance evaluations by political identity. Hukou type (a4a) shows a significant positive association only for social protection, with urban residents reporting higher evaluations than rural residents. Finally, employment status (b1) is negatively associated with most dimensions, indicating that unemployed individuals tend to report lower evaluations of social governance.

6.6. Robustness analysis

In the empirical analysis, this study further conducted robustness tests to ensure the reliability of the research results. The robustness analysis was carried out from two perspectives: grouped regression analysis and alternative model estimation.

(1) Grouped regression test

To examine whether the association between smart city development and social governance effectiveness varies by age, this study used 40 years old as the cutoff, based on the sample's average age, to divide the sample into two subgroups: individuals aged below 40 and individuals aged 40 and above. Ordered logit regression analyses were then conducted separately for each subgroup. See Appendix Tables 6 and 7 for the ordered logit regression results by age group (over and under 40).

The smart city index (smart_city_sum) exhibits a consistent direction across all dimensions and is statistically significant in most cases, though the magnitude of its estimated association varies slightly, indicating that the regression results are relatively robust. Among the 40 and above age group, the smart city index is significantly positively associated with social governance evaluation, social protection, social trust, and social fairness, which may suggest that older individuals are more reliant on government-provided smart governance services and may report a stronger perception of their effectiveness in improving social governance. However, in the under-40 age group, the association of smart city development with social trust is not significant, whereas the negative association with social participation is larger in magnitude. This pattern is consistent with the possibility that younger individuals are more inclined towards online interaction, and smart city initiatives may be associated with weaker offline social connections, which could be related to a lower depth of social interaction (Van Deursen and Van Dijk, 2014).

Overall, the results suggest structural differences across generations in terms of the estimated associations. Older individuals report stronger positive associations with public service optimization and social protection, whereas younger individuals may experience a substitution of participation modes (Putnam, 2000). Therefore, policymakers should pay attention to different patterns of social participation when advancing smart city initiatives, ensuring that digital governance does not entirely replace offline interactions. Instead, integrating online and offline engagement mechanisms may help improve social governance outcomes while avoiding potential reductions in public social connections and trust.

(2) Ordered probit regression test

This study further employed ordered probit regression as an alternative model estimation to examine whether the regression results remained consistent across different model specifications. The results indicate that regardless of whether ordered probit or ordered logit was used, the core explanatory variable smart_city_sum maintained a consistent direction and statistical significance in its regression coefficients, supporting the robustness of the conclusions. See Appendix Table 8 for the ordered probit regression results.

7. Discussion and conclusion: reconciling the smart governance paradox

This study set out to explore a core paradox in the global smart city agenda: While smart city initiatives promise enhanced governance capacity, efficiency, and equity, do they in practice correspond to more inclusive and participatory governance—or do they risk reinforcing existing structural inequalities and civic disconnection under a new digital guise?

By integrating macro-level structural evaluations (Section 5) with micro-level citizen perception analysis (Section 6), this study constructs an analytical feedback loop from "structural input" to "perceptual output," thereby highlighting a potential "structural–perceptual mismatch" in the development of smart cities within the Chinese context. While cities have made considerable technological investments and achieved improvements in governance across multiple dimensions, these structural advancements do not necessarily correspond to enhanced public recognition, trust, or willingness to participate. In some cases, a paradoxical trajectory is observed—technological progress is accompanied by a decline in civic engagement.

This mismatch underscores a critical implication for future smart city governance: performance should not be evaluated solely based on technological coverage or investment volume. Instead, greater attention must be paid to how citizens perceive these technological reforms and whether they are associated with genuine empowerment, social equity, and trust-building.

7.1. *Interpreting the structural paradox: technological progress vs. participatory regression*

At the macro level, our findings show that China's flagship smart cities—Beijing, Shanghai, Guangzhou—have made significant strides in areas such as infrastructure, intelligent services, and economic innovation. Yet these gains were asymmetric: certain domains such as smart mobility and digital industry were comparatively stronger, while others such as citizen empowerment and interdepartmental coordination remained underdeveloped. Cities like Xiamen and Chongqing demonstrated uneven growth patterns, where technological rollout appeared to outpace the institutional capacity for integrated governance. This structural imbalance reveals that "smartness" has outpaced "responsiveness"—a condition that may coincide with governance inefficiencies, redundancies, or public disillusionment.

At the micro level, our analysis using CSS data indicated a more complex narrative. Smart city development was significantly and positively associated with residents' perceptions of overall social governance effectiveness, fairness, protection, and trust. This pattern is consistent with the possibility that technological improvements may be linked to more favorable perceptions of institutional performance. However, these gains are counterbalanced by a statistically significant decrease in social participation, especially among younger and digitally active groups. This suggests that, in this context, technologically advanced governance may be associated with lower participation, particularly where participation is already constrained by institutional design.

We discuss four mechanisms that may help interpret this paradox:

(1) Digital substitution: Online participation may replace—but not replicate—the deliberative depth of offline civic engagement.
(2) Algorithmic alienation: Data-driven decision-making, while efficient, may be perceived as lacking procedural transparency, which could be related to disengagement.
(3) Selective empowerment: Those with digital capital may benefit more from smart services, while marginalized groups may face new barriers to participation.
(4) Governance centralization: Smart governance in China is often top-down and techno-bureaucratic, which may reinforce administrative control rather than pluralism.

7.2. Revisiting the "smart" in smart cities

These findings motivate us to critically revisit what is meant by a "smart city." If technological innovation does not translate into inclusive civic life, empowered public deliberation, and equal access to governance, then smartness risks becoming an empty signifier—one that privileges control and consumption over community and collaboration.

Our study thus conceptualizes "smart" governance not as a function of infrastructure or algorithmic capacity alone, but as a system's ability to integrate technology with social legitimacy, distributive justice, and participatory responsiveness.

7.3. Contributions and policy implications

This study makes several contributions:

(1) Conceptual: It introduces the notion of "smart governance paradox" to describe the tension between infrastructural capability and participatory governance.
(2) Methodological: It bridges machine learning evaluation (RBF neural networks, factor analysis) with large-scale social survey modeling (ordered logit), offering a hybrid toolkit for interdisciplinary research.
(3) Empirical: It documents multi-level divergences between digital governance outputs and citizen experiences in the Chinese smart city context.

From a policy perspective, the findings suggest three policy implications:

(1) Re-center participation in smart city governance through hybrid online-offline mechanisms, citizen deliberation platforms, and participatory budgeting tools, which may help strengthen participatory linkages;
(2) Address the digital divide proactively by designing inclusive digital literacy programs, especially for older and rural populations, which may reduce participation barriers;
(3) Tailor smart city design to local political cultures, avoiding one-size-fits-all technological templates that ignore institutional or civic capacity differences, which may improve policy fit and legitimacy.

Given the cross-sectional nature of the survey evidence, these implications should be interpreted as suggestive directions for policy design rather than as claims about causal effects.

7.4. Future research and limitations

Future research should consider three important extensions. First, conduct longitudinal studies to assess the dynamic effects of smart city development on trust and participation over time. Second, integrate qualitative or ethnographic data to capture how citizens interpret and navigate smart governance systems in practice. Third, conduct comparative analyses across regime types to assess whether this paradox holds in democratic or hybrid contexts.

It is important to acknowledge a key limitation of this study: the CSS data are cross-sectional, and therefore the empirical findings should be interpreted as associations rather than causal effects. In particular, reverse causality cannot be ruled out—for example, baseline levels of civic participation or institutional trust, as well as unobserved local governance characteristics, may influence both smart city development and residents' reported perceptions. Future research using longitudinal or quasi-experimental designs would help strengthen causal inference and clarify the directionality of these relationships.

Ultimately, our study argues that smart cities must be reimagined not only as technological infrastructures but as socio-political systems. The true measure of "smartness" lies not in how much data a city collects or how efficient its services become, but in how deeply it listens, includes, and empowers its people.

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CRediT authorship contribution statement

Beizhen Tang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Daniel P. Aldrich:** Writing – review & editing, Supervision, Conceptualization, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Dependent variables

1. Public Participation: H2a. In the past two years, have you participated in any of the following activities?

(1) Discussing political issues with others or online communities.
(2) Reporting social issues to newspapers, radio, or online forums.
(3) Providing feedback to government agencies (via phone, email, etc.).
(4) Utilizing professional knowledge to participate in public policy and public affairs discussions.
(5) Expressing personal opinions on government policies through various channels.
(6) Attending public hearings on policies organized by government departments.
(7) Petitioning government departments.
(8) Participating in major decision-making discussions within one's village, community, or workplace.
(9) Engaging in community or voluntary social welfare activities (e.g., blood donation, environmental cleanup, assisting the elderly, disabled, or sick).
(10) Attending religious activities.
(11) Participating in online/offline collective rights protection actions.

Independent variable: smart city development

(1) Information Resource Utilization: D4b1. How frequently do you engage in the following online activities?

1. Browsing current affairs and political news.
2. Entertainment and leisure.
3. Social networking and chatting.
4. Business or work-related activities.
5. Learning and education.
6. Online shopping and lifestyle services.
7. Investment and financial management.

(2) Innovation Capacity: B4e. In your non-agricultural work, do you hold a professional title or technical certification?

1. Professional title (e.g., senior, intermediate, or junior professional titles).
2. Technical certification (e.g., senior, intermediate, or junior technician levels).
3. No current certification, but potential future evaluation.
4. No professional title or technical certification.

Table 2
Factor analysis results.

Indicator	A_{11}	A_{12}	A_{21}	A_{31}	A_{32}	A_{33}	A_{34}	A_{35}
1	0.208	−0.258	0.207	0.284	−0.024	0.057	0.303	0.042
2	0.231	−0.036	0.205	0.109	0.304	0.202	−0.042	0.352
3	0.235	0.017	0.096	0.379	−0.273	−0.09	0.157	0.242
4	0.172	0.352	0.197	−0.314	−0.005	0.17	−0.471	0.410
5	0.006	0.828	0.208	−0.16	0.811	−0.112	−0.136	0.396
6	0.236	0.055	−0.189	−0.095	−0.086	0.911	−0.307	−0.069

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Table 2 (*continued*)

Indicator	A_{11}	A_{12}	A_{21}	A_{31}	A_{32}	A_{33}	A_{34}	A_{35}
Indicator	A_{41}	A_{42}	A_{51}	A_{52}	A_{61}	A_{62}		
1	0.135	−0.534	0.003	0.451	0.218	0.137		
2	0.297	−0.208	0.321	−0.019	0.129	0.899		
3	0.228	−0.047	−0.079	−0.45	0.213	−0.036		
4	0.085	0.491	0.317	0.154	0.206	−0.083		
5	0.248	0.203	0.327	−0.001	0.187	−0.164		
6	−0.278	−0.001	−0.175	0.201	0.261	0.243		

Table 3
Descriptive Statistical Analysis.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Gender (a1b1)	6055	0.46	0.50	0	1
Age (a1c1)	6055	40.72	13.69	18	70
Marital Status (a1e1)	6055	2.00	0.83	1	6
Political Affiliation (a3)	6055	3.37	1.11	1	4
Household Registration (Hukou Status) (a4a)	6055	1.62	0.80	1	4
Employment Status (b1)	6055	2.08	1.10	1	4
Overall Social Evaluation (g6)	6055	7.79	1.51	1	10
Social Protection (e5_6)	6055	7.20	2.20	1	10
Social Trust (f1b)	6055	6.71	1.98	1	10
Social Fairness (f3b)	6055	7.06	1.89	1	10
smart_city_sum	6055	6.55	1.02	2.7	9.7
Public Social and Political Participation (h2a_sum)	6055	0.69	1.10	0	11

Table 4
Link Test Results for Model Specification.

Variable	Test Variable	P-Value
Overall Social Evaluation (g6)	_hat	0.025
	_hatsq	0.618
Public Social and Political Participation (h2a_sum)	_hat	0.001
	_hatsq	0.131
Social Protection (e5_6)	_hat	0.000
	_hatsq	0.802
Social Trust (f1b)	_hat	0.000
	_hatsq	0.163
Social Fairness (f3b)	_hat	0.002
	_hatsq	0.298

Table 5
Ordered Logit Regression Results.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	Overall Social Evaluation (g6)	Public Social and Political Participation (h2a_sum)	Social Protection (e5_6)	Social Trust (f1b)	Social Fairness (f3b)
smart_city_sum	0.259***	−0.365***	0.138***	0.0881***	0.196***
	(0.0249)	(0.0282)	(0.0244)	(0.0246)	(0.0246)
Age (a1c1)	0.00854***	0.00098	−0.00208	0.00112	−0.00103
	(0.00202)	(0.00230)	(0.00200)	(0.00201)	(0.00201)
Gender (a1b1)	0.219***	0.454***	0.0680	−0.0872*	0.00127
	(0.0472)	(0.0534)	(0.0467)	(0.0465)	(0.0466)
Marital Status (a1e1)	−0.0456	−0.0614*	−0.0815**	−0.108***	−0.0607*
	(0.0318)	(0.0371)	(0.0319)	(0.0319)	(0.0318)
Political Affiliation (a3)	−0.127***	−0.274***	−0.216***	−0.168***	−0.161***
	(0.0207)	(0.0230)	(0.0208)	(0.0206)	(0.0206)

(*continued on next page*)

Table 5 (*continued*)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	Overall Social Evaluation (g6)	Public Social and Political Participation (h2a_sum)	Social Protection (e5_6)	Social Trust (f1b)	Social Fairness (f3b)
Household Registration (Hukou Status) (a4a)	−0.0433	0.0119	0.165***	−0.0200	0.0351
	(0.0289)	(0.0327)	(0.0284)	(0.0284)	(0.0283)
Employment Status (b1)	−0.0659***	0.0308	−0.0462**	−0.0733***	−0.0999***
	(0.0217)	(0.0246)	(0.0214)	(0.0214)	(0.0214)

Table 6
Ordered Logit Regression Results for Individuals Aged Over 40.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	Overall Social Evaluation (g6)	Public Social and Political Participation (h2a_sum)	Social Protection (e5_6)	Social Trust (f1b)	Social Fairness (f3b)
smart_city_sum	0.277***	−0.353***	0.140***	0.135***	0.209***
	(0.0343)	(0.0396)	(0.0337)	(0.0339)	(0.0340)
Age (a1c1)	0.0119**	−0.00323	0.00872*	−0.000604	0.00239
	(0.00466)	(0.00540)	(0.00457)	(0.00459)	(0.00459)
Gender (a1b1)	0.110	0.454***	0.00733	−0.153**	−0.0407
	(0.0672)	(0.0780)	(0.0666)	(0.0664)	(0.0664)
Marital Status (a1e1)	−0.0605	0.0384	−0.0919**	−0.163***	−0.108***
	(0.0414)	(0.0471)	(0.0411)	(0.0410)	(0.0408)
Political Affiliation (a3)	−0.161***	−0.242***	−0.211***	−0.180***	−0.202***
	(0.0290)	(0.0326)	(0.0293)	(0.0288)	(0.0289)
Household Registration (Hukou Status) (a4a)	−0.0450	−0.0410	0.163***	0.0451	0.0753*
	(0.0416)	(0.0487)	(0.0409)	(0.0410)	(0.0406)
Employment Status (b1)	−0.103***	−0.0225	−0.141***	−0.113***	−0.152***
	(0.0366)	(0.0425)	(0.0359)	(0.0360)	(0.0360)

Table 7
Ordered Logit Regression Results for Individuals Aged Under 40.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	Overall Social Evaluation (g6)	Public Social and Political Participation (h2a_sum)	Social Protection (e5_6)	Social Trust (f1b)	Social Fairness (f3b)
smart_city_sum	0.231***	−0.401***	0.112***	0.0309	0.177***
	(0.0371)	(0.0413)	(0.0364)	(0.0366)	(0.0366)
Age (a1c1)	0.00466	0.00330	−0.0203***	0.00184	−0.0133*
	(0.00718)	(0.00817)	(0.00718)	(0.00715)	(0.00716)
Gender (a1b1)	0.320***	0.440***	0.0799	0.00604	0.0216
	(0.0685)	(0.0755)	(0.0675)	(0.0672)	(0.0674)
Marital Status (a1e1)	−0.00548	−0.198***	−0.00154	−0.00956	0.0433
	(0.0519)	(0.0646)	(0.0532)	(0.0533)	(0.0530)
Political Affiliation (a3)	−0.0794**	−0.292***	−0.177***	−0.162***	−0.0854***
	(0.0325)	(0.0354)	(0.0323)	(0.0320)	(0.0321)
Household Registration (Hukou Status) (a4a)	−0.0421	0.0643	0.174***	−0.0738*	0.000421
	(0.0409)	(0.0449)	(0.0401)	(0.0401)	(0.0401)
Employment Status (b1)	−0.0420	0.0584	−0.0252	−0.0214	−0.0689**
	(0.0333)	(0.0369)	(0.0328)	(0.0328)	(0.0329)

Table 8
Ordered Probit Regression Results.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	Overall Social Evaluation (g6)	Public Social and Political Participation (h2a_sum)	Social Protection (e5_6)	Social Trust (f1b)	Social Fairness (f3b)

(*continued on next page*)

Table 8 (*continued*)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	Overall Social Evaluation (g6)	Public Social and Political Participation (h2a_sum)	Social Protection (e5_6)	Social Trust (f1b)	Social Fairness (f3b)
smart_city_sum	0.146***	−0.223***	0.0855***	0.0549***	0.117***
	(0.0143)	(0.0165)	(0.0142)	(0.0141)	(0.0142)
Age (a1c1)	0.00445***	0.00111	−0.00155	0.000945	−0.000742
	(0.00117)	(0.00134)	(0.00117)	(0.00116)	(0.00116)
Gender (a1b1)	0.118***	0.278***	0.0295	−0.0623**	−0.00279
	(0.0274)	(0.0312)	(0.0273)	(0.0271)	(0.0271)
Marital Status (a1e1)	−0.0238	−0.0331	−0.0519***	−0.0673***	−0.0349*
	(0.0183)	(0.0213)	(0.0183)	(0.0181)	(0.0181)
Political Affiliation (a3)	−0.0801***	−0.161***	−0.132***	−0.0980***	−0.0974***
	(0.0124)	(0.0134)	(0.0125)	(0.0123)	(0.0123)
Household Registration (Hukou Status) (a4a)	−0.0209	0.00614	0.101***	−0.0195	0.0183
	(0.0168)	(0.0192)	(0.0168)	(0.0166)	(0.0166)
Employment Status (b1)	−0.0377***	0.0152	−0.0282**	−0.0417***	−0.0581***
	(0.0127)	(0.0144)	(0.0127)	(0.0125)	(0.0126)

Table 9
City-by-dimension values.

Indicator	Shanghai	Chongqing	Guangzhou	Beijing	Tianjin	Xiamen
Smart Economy	0.285	0.15	0.216	0.274	0.232	0.133
Smart Environment	0.041	0.039	0.087	0.056	0.021	0.036
Smart Living (Info Svc 1)	0.059	0.008	0.022	0.027	0.011	0.014
Smart Living (Info Svc 2)	0.077	0.041	0.018	0.13	0.025	0.015
Smart Mobility	0.076	0.307	0.061	0.123	0.012	0.028
Smart Network	0.276	0.014	0.262	0.21	0.07	0.176
Smart Citizens	0.185	0.144	0.179	0.131	0.195	0.121

Research methods: establishing the evaluation model using factor analysis, RBF neural network, and genetic algorithm optimization

Factor analysis is based on the idea of dimensionality reduction, integrating information from multiple observed variables to explain the variability in the data by identifying common factors (i.e., factors). This process transforms the representation of the original data from a high-dimensional space to a low-dimensional space, thereby achieving the goal of reducing data dimensionality. These factors are interrelated, and some variables may contain similar information. By identifying these latent common factors, redundant information is reduced, data dimensionality is compressed, and the structure and characteristics of the data are more concisely described. For a set of a observable vectors Z, represented by $z_1, z_2, ..., z_a$ and b unobservable factors F as, the model is depicted in equation (1). The observed variable set Z is decomposed into a linear combination of common factors F and specific factors Θ. The mean vector of common factors F is zero, and the covariance matrix is the identity matrix. h represents specific factors, with a mean vector of zero. m_{rs} represents factor loadings, reflecting the contribution of the rth variable to the sth factor, thereby determining which indicators are more important in constructing the factors.

$$\begin{aligned} z_1 &= m_{11}f_1 + m_{21}f_2 + m_{31}f_3 ... + m_{r1}f_r + \Theta_1 \\ &...... \\ z_a &= m_{1s}f_1 + m_{2s}f_2 + m_{3s}f_3 ... + a_{rs}f_r + \Theta_m \end{aligned} \tag{1}$$

The Radial Basis Function (RBF) neural network is a type of three-layer feedforward network that excels in function approximation and pattern classification, especially when one or more adjustable parameters' weights have a significant impact on the output. The RBF neural network achieves faster and better convergence compared to other types of neural networks. The formula for the hidden neuron function is:

$$Z(x) = \Phi\left(\frac{\|x - c_i\|}{\sigma_i}\right) \tag{2}$$

Where x represents the input value,$Z(x)$ denotes the output value of the neural network,c_i stands for the center point of the kernel function,σ is the width parameter controlling the radial influence range of the function, and Φ represents the radial basis function. The specific formula is:

$$\Phi(r) = e^{-\frac{r^2}{2\sigma^2}} \tag{3}$$

The specific steps for evaluating the smart city development model using the combined model of factor analysis and RBF neural network are as follows:

Firstly, factor analysis is utilized to adjust the evaluation indicators of the smart city development model. This involves conducting factor analysis on the secondary and tertiary indicators under each dimension to determine their correlation and main factors. Subsequently, for each dimension, indicator selection and testing are performed to identify the most representative and interpretable indicators, which are then integrated into new secondary virtual indicator categories.

Secondly, the selected and tested indicator data are normalized to generate the normalized sample dataset X', as shown in Formula (4). This normalization process ensures that the data are on the same scale, facilitating the training and convergence of the neural network model. Next, the normalized sample dataset is divided into training and testing samples, which are transformed into vector representations for the intermediate hidden layer. These steps fully utilize the knowledge and technology of neural networks, establishing an effective training sample set for evaluating the smart city development model and laying the foundation for training and testing the neural network model.

$$X' = (x - x_{\min})/(x_{\max} - x_{\min}) \tag{4}$$

Thirdly, the entropy weight method is utilized to quantify and analyze the information content of the indicators to determine their weights. Information entropy measures the uncertainty of the information, where indicators with higher information entropy imply greater information content and have a larger impact on decision-making outcomes. Therefore, higher weights should be assigned to indicators with higher information entropy. The calculation of information entropy is shown in Formula (5).

$$E_m = -\ln(n)^{-1} \sum_{j=1}^{N} p_{jm} \ln p_{jm} \tag{5}$$

Here, $p_{jm} = x'_{jm}/\sum_{j=1}^{N} x'_{jm}, p_{jm}$ represents the weight of the m-th indicator for the j-th sample, and $E_m = [E_1, E_2 \ldots E_k]$ corresponds to the information entropy of each set of indicators. The calculation of weights is shown in Formula (6).

$$w_m = \frac{1 - E_m}{K - E_m} (m = 1, 2 \ldots k) \tag{6}$$

Fourthly, the newly obtained secondary indicator vectors from steps (1) and (2) are transmitted as input vectors to the data centers, which are determined by clustering algorithms. Then, by adjusting the width and weight parameters of the RBF neural network, the model is optimized to ensure that the output closely matches the expected output, thereby improving the model's generalization and accuracy. This process is carried out through multiple iterations until the best training effect with the minimum total network error is achieved. The calculation of data centers, width, and weight parameters is shown in the following formulas.

$$\Delta c_i = u_1 \frac{\omega_i}{\sigma_j^2} \sum_{j=1}^{N} e_i G(x_j)(x_j - c_i) \tag{7}$$

$$\Delta \sigma_i = \mu_2 \frac{\omega_i}{\sigma_j^3} \sum_{j=1}^{N} e_i G(x_j) \|x_j - c_j\|^2 \tag{8}$$

$$\Delta \omega_i = \mu_3 \sum_{j=1}^{N} e_i G(x_j) \tag{9}$$

Where G represents the Gaussian function, i and j are subscripts for the number of hidden nodes and the number of samples, respectively. μ denotes the learning rate for each, while e represents the residual between the network output value and the sample value. Subsequently, genetic algorithm optimization is employed, simulating natural selection and genetic mechanisms through iteration to optimize the parameters of the neural network. This method exhibits adaptability with global search and multiple optimization objectives. Finally, a comparison of errors between RBF neural network and genetic algorithm optimization is conducted, and the method with smaller error is selected.

Fifthly, calculate the scores obtained from the indicators.

$$\mathrm{Z}(x) = \sum_{m=1}^{k} w_m \Phi\left(\frac{\|x - c_i\|}{\sigma_i}\right) \tag{10}$$

Justification for method selection

To evaluate the multi-dimensional, high-variance, and nonlinearly correlated indicators of smart city development, this study adopts a two-stage hybrid modeling strategy combining Exploratory Factor Analysis (EFA) and a Radial Basis Function (RBF) Neural

Network optimized by genetic algorithms.

(1) Dimensionality Reduction via Factor Analysis.

Smart city development involves collinear and conceptually overlapping indicators—such as economic activity, infrastructure, innovation, environment, and governance. To reduce multicollinearity and extract latent dimensions, EFA is employed to identify underlying structural factors, improving robustness and interpretability while aligning with prior literature emphasizing the multi-dimensional nature of smart city systems.

(2) Nonlinear Modeling via RBF Neural Network.

Based on the extracted factor scores, an RBF neural network is used to classify cities by development level. RBF is chosen for its ability to approximate nonlinear relationships, capture regional heterogeneity, and adapt to complex urban systems more effectively than traditional parametric models.

(3) Synergy of Statistical and Computational Techniques.

EFA identifies latent structures, while the RBF model adds predictive power by capturing nonlinear and emergent patterns. Genetic algorithm optimization (e.g., for spread and center selection) further enhances model performance and generalizability.

(4) Methodological Fit for Research Objectives.

This approach supports the study's aim to construct a Smart City Development Index that reflects both the structural logic and nonlinear, region-specific dynamics of smart city growth in China.

In sum, the combination of EFA and RBF provides a theoretically grounded and computationally adaptive framework that moves beyond conventional additive indices, enabling a more nuanced evaluation of smart city trajectories.

Data availability

Data will be made available on request.

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