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A Thesis Submitted in Partial Fulfillment of Requirements for
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Multi-subject Participation in Urban Community Governance in Guang xi: A Comprehensive SEM analysis

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ABSTRACT

Urban community governance plays a crucial role in China's modernization, particularly in multi-ethnic regions like Guangxi. With the rapid urbanization of China, the complexity of urban community governance has significantly increased. This research explores the multi-subject participation in urban community governance in Guangxi, analyzing key influencing factors and the effectiveness of governance models. By integrating Structural Equation Modeling(SEM) with Artificial Neural Network(ANN) and machine learning techniques such as Random Forest, XGBoost, and LightGBM, this study provides a comprehensive and data-driven evaluation of urban community governance mechanisms.

The study begins by establishing a theoretical framework, reviewing existing literature on urban community governance, governance participation models, and statistical methodologies. A key focus is placed on the role of government leadership, community collaboration, and resident engagement in shaping governance effectiveness. The research employs a mixed-method approach, incorporating quantitative analysis through SEM and ANN alongside qualitative assessments from case studies and policy reviews.

The primary objectives of this study are threefold: (1) to identify the key factors influencing multi-subject participation in urban community governance, (2) to develop and validate a structural model explaining the relationships among these factors, and (3) to evaluate the impact of these variables using ANN and other advanced machine learning models. The study draws on a large-scale survey dataset from urban communities in Guangxi, measuring governance participation through indicators such as party and government leadership, community resource allocation, social collaboration and resident satisfaction.

Through exploratory factor analysis (EFA) and principal component analysis (PCA), the study identifies key dimensions of governance participation. The SEM results confirm the significance of party leadership, social organizations, and

resident self-governance in enhancing governance outcomes. Moreover, ANN analysis provides further validation by ranking the relative importance of these factors, demonstrating the nonlinear relationships that SEM alone cannot capture. The integration of machine learning models refines the predictive accuracy of governance performance, highlighting the interplay of various social and administrative elements.

Findings reveal that the effectiveness of urban community governance in Guangxi is highly dependent on multi-subject participation, with strong government leadership serving as a crucial foundation. However, the results also underscore the necessity of enhancing digital service platforms, strengthening community organizations, and increasing resident involvement to optimize governance performance. The study suggests policy interventions aimed at improving governance transparency, fostering cross-sector collaboration and leveraging technology-driven governance solutions.

This research makes significant contributions to both theoretical and practical aspects of urban governance. Theoretically, it expands the understanding of multi-subject participation and governance efficiency by integrating statistical modeling with machine learning. Practically, it provides policymakers and community stakeholders with actionable insights to improve governance strategies in rapidly urbanizing regions. The findings are particularly relevant for addressing governance challenges in multi-ethnic areas like Guangxi, where cultural diversity and social dynamics shape governance effectiveness.

Future research could further explore longitudinal trends in governance participation and investigate the impact of emerging technologies such as smart governance systems and AI-driven community management. By continuously refining governance models and incorporating advanced analytical techniques, urban communities in China can achieve more effective and sustainable governance outcomes.

Keyword : Urban community governance, Guangxi, multi-subject participation, machine learning, Structural Equation Modeliing, Artificial Neural Network

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Finally, with a Lanna-style "ไหว้" (wai), I honor all mentors who illuminated my path. May this dissertation become a jasmine garland, humbly offered beneath the Bodhi tree of Sino-Thai academic exchange.

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Introduction

This chapter introduces the research by first outlining its background and significance. It then presents the research objectives and methods, which include a literature review and various other methodological approaches. Additionally, the chapter highlights the key innovations of the study.

1.1 Research background

The community is a crucial foundational unit of governance in urban society. At the end of the last century, China implemented the "community system" to enhance the effectiveness of grassroots governance in cities and to address the challenges of urban management. As the "last mile" of social governance, the community plays a pivotal role in enhancing the effectiveness of urban governance in China and serves as a crucial breakthrough in the modernization of national governance. Community governance, as a fundamental component of the national governance system, is essential for realizing social democracy at the grassroots level, maintaining social stability, and fostering harmonious social development.

Statistics show that China's urbanization rate increased from 36% in 2000 to over 50% for the first time in 2011. This marked a significant shift, with the urban population surpassing the rural population, signaling that urban governance would face numerous challenges due to the rapid population growth. Over the past decade, the urbanization rate rose from 53.1% in 2012 to 65.2% in 2022 (NBS, 2022), an increase of 12.1 percentage points. Globally, China's urbanization rate of over 60% has surpassed the world average of 56.2% (Ahk, 2023). By 2024, the urbanization rate further climbed to 67%, indicating a steady upward trend in China's urban development. According to United Nations estimates, China's urbanization rate is projected to reach 71.2% by 2050, highlighting the vast potential for growth in urbanization. With this advancement, a large influx of unincorporated populations into cities is expected, leading to the continuous expansion of urban communities and significantly increasing the burden on urban governance.

With the deepening urbanization process, the complexity and challenges of community governance have been increasing. The 19th CPC National Congress in 2017 explicitly called for shifting the focus of social governance downward, emphasizing the need to concentrate more resources, services, and management at the grassroots community level (Xi, 2017).

In the same year, the Central Committee of the Communist Party of China and the State Council issued their opinions on strengthening and improving governance in urban and rural communities. These guidelines emphasized the principles of adhering to a people-centered approach, focusing on the fundamental role of grassroots mass self-governance organizations, and reinforcing party leadership. The goal was to promote the establishment of a governance system in urban and rural communities that is led by grassroots party organizations, with the grassroots government playing a central role, and characterized by the participation of various parties in joint governance.

In February 2020, the Central Committee of the CPC issued the Proposal on the Formulation of the Fourteenth Five-Year Plan for National Economic and Social Development and the Social Development Plan for the Fourteenth Five-Year Plan, along with the visionary goals for the Twenty-third Five-Year Plan. The proposal emphasized the need for a comprehensive, coordinated, and efficient urban community governance system. It called for the implementation of Party leadership, strengthened collaboration between the government, social organizations, and residents, and other corresponding principles and expected goals. This further reaffirmed the shift of the core of social governance to the grassroots level.

Additionally, the proposal emphasizes promoting residents' self-governance, strengthening the development of community residents' self-governance organizations, and enhancing residents' self-governance capabilities. The aim is to achieve the organic integration of residents' self-governance and government governance. In 2021, the Central Committee of the CPC and the State Council issued further opinions on strengthening the modernization of the grassroots governance system and governance capabilities. These opinions reaffirmed that governance in urban and rural communities "is a fundamental project for realizing the modernization of the country's governance system and governance capabilities."

In 2022, the "14th Five-Year Plan" for the construction of urban and rural community service systems further clarified the need to adhere to the concept of innovative development. It emphasized the full mobilization of social forces, including group organizations, social organizations, social workers, volunteers, and charitable resources, as well as the guidance of market forces. The plan also highlighted the importance of maximizing the role of the government and constructing a participatory governance model involving multiple stakeholders. The introduction of these policy documents has provided crucial policy support and directional guidance for community governance both in Guangxi and across China.

The 20th National Congress of the CPC, held in October 2022, emphasized the importance of adhering to the principle that "people's cities are built by people, and people's cities are for people." It called for improving the level of urban planning, construction, and governance, as well as implementing urban renewal initiatives, strengthening urban infrastructure, and creating livable, resilient, and smart cities. The Congress also proposed perfecting the system of social governance through shared governance, aiming to build a social governance community in which everyone has responsibility, contributes to the community, and benefits from it. Additionally, it stressed the need to "accelerate the modernization of social governance in urban areas."

The 20th CPC Central Committee's Third Plenary Session in 2024 emphasized strengthening grassroots governance by shifting focus and resources downward to local communities. It called for improving community management, enhancing grid-based governance, and reinforcing Party leadership. Additionally, the session highlighted the need for a governance system that combines autonomy, the rule of law, and moral governance, while promoting a collaborative, shared responsibility model in community governance. These proposals aim to enhance grassroots governance capabilities.

Guangxi, located in the southwest of China, has been home to various ethnic minorities since ancient times. People from different ethnic groups in Guangxi have lived together, supported one another, and integrated through centuries of migration, forming a multi-ethnic landscape characterized by large mixed communities and smaller settlements. Since the founding of the People's Republic of China, twelve hereditary ethnic groups have been officially recognized in Guangxi through ethnic identification efforts. Today, the region's ethnic composition includes twelve hereditary groups and forty-four other ethnic minority components.

Guangxi's urbanization process has led to a unique pattern where large mixed dwellings coexist with small settlements. This pattern has evolved as urbanization progresses, gradually shifting towards a model characterized by large-scale multi-ethnic mobility and integrated residential areas. As of 2024, Guangxi's urbanization rate stands at 57.39%, which is lower than the national average of 67%. To accelerate urbanization, the Guangxi Zhuang Autonomous Region has outlined specific measures in the 2018 implementing opinions on strengthening and improving urban and rural community governance. These measures emphasize the enhancement of grassroots party organizations, the improvement of residents' self-governance mechanisms, and the development of community social organizations, all aimed at raising the overall governance level of urban and rural communities.

The implementation of these measures has played a significant role in promoting the development of community governance in Guangxi. In 2021, Guangxi introduced the Guangxi New Urbanization Plan (2021-2035), which set a target for the urbanization rate of the resident population to reach approximately 68% by 2035, during the Fourteenth Five-Year Plan period.

In 2022, the Department of Civil Affairs of the Guangxi Zhuang Autonomous Region, in collaboration with the Guangxi Zhuang Autonomous Region Development and Reform Commission, proposed the "Guangxi Urban and Rural Community Service System Construction" 14th Five-Year Plan. This plan called for accelerating the leadership of grassroots party organizations in building urban and rural community service systems, emphasizing the role of government leadership, and actively developing the professional services of social organizations. It also encouraged the participation of market entities and social forces in community service. These initiatives aim to stimulate residents' enthusiasm and initiative for participation in urban and rural community services, enhance self-help and mutual assistance capabilities, and establish a collaborative, multi-party participation model for urban and rural community services.

In 2024, Guangxi continued to advance urban and rural community governance through the introduction of various policies and measures. The Department of Housing and Urban-Rural Development of the Guangxi Zhuang Autonomous Region issued the "Guidelines for the Work of Property Management Committees," outlining the responsibilities of property management committees and promoting the establishment and standardized operation of owners' associations and committees. These initiatives aim to strengthen grassroots party organizations, enhance community governance, and foster the integrated development of urban and rural areas.

However, there are several challenges in the current urban community governance in Guangxi, including outdated digital service platforms, underdeveloped community organizations, low resident participation, and an imbalanced service system. These issues not only affect the quality of life for community residents but also hinder the sustainable development of urbanization. Against this policy backdrop, this paper conducts an in-depth study of the key factors influencing urban community governance in Guangxi. It explores how multiple stakeholders can effectively play their roles, achieve synergy, and enhance governance effectiveness. The findings aim to provide valuable insights for community governance in Guangxi and across the country, offering significant theoretical and practical contributions to advancing the overall development of community governance in China.

1.2 Research objectives and significance

1.2.1 Research objectives

As a crucial component of the national governance system, urban community governance plays a vital role in advancing China’s modernization. As a key province in southwest China, urban community governance in Guangxi not only has a significant impact on local development but also exerts a profound influence on the country’s overall modernization. Furthermore, machine learning methods such as Random Forest, XGBoost, and LightGBM, combined with Artificial Neural Network (ANN) analysis, are employed to assess the relative importance of various factors influencing community governance outcomes. These advanced analytical techniques offer an additional layer of insight to the SEM results, providing a more detailed and precise understanding of the factors shaping governance performance. By integrating SEM with machine learning methods, this study presents a comprehensive and robust analysis of the mechanisms driving urban community governance, offering actionable strategies for improving governance performance in Guangxi.

(1) Identify the key factors influencing multi-subject participation in urban community governance in Guangxi

Through exploratory factor analysis (EFA) and principal component analysis (PCA), this study aims to identify the key variables and underlying structures that influence multi-subject participation in urban community governance in Guangxi. This process will help establish an initial theoretical framework, providing a solid foundation for subsequent analyses and deeper exploration of the factors shaping governance dynamics.

(2) Develop and validate a structural model of influencing factors

Using Structural Equation Modeling (SEM), this research constructs a path model to examine the relationships between multi-subject participation and its key influencing factors. By analyzing model fit, direct effects, indirect effects, and total effects, the study aims to uncover the mechanisms driving multi- subject participation in urban community governance, providing a comprehensive understanding of how various factors interact and influence governance outcomes.

(3) Evaluate the importance of key variables and optimize governance strategies

By integrating Artificial Neural Network (ANN) analysis with advanced machine learning methods such as Random Forest, XGBoost, and LightGBM, this study conducts a thorough evaluation of the key variables identified in the SEM model to assess their relative importance in community governance performance. Through precise quantification of these variables' impacts, the research aims to propose actionable strategies for optimizing urban community governance in Guangxi. The findings provide scientific evidence and practical guidance for government bodies, community organizations, and residents, contributing to the enhancement of governance efficiency and community well-being.

1.2.2 Research significance

In urban communities, the relationship between multiple subjects has been a popular topic of much attention in the theoretical community. By systematically sorting out the composition of multiple subjects, this paper has successfully sorted out the relationship and interaction mechanism between these subjects. This research not only enhances the understanding of urban community governance but also makes remarkable progress in theory. Therefore, this article provides valuable theoretical results for academic research in terms of clarifying the way power is constituted and the mode of interaction in urban communities.

(1) Theoretical significance

In the field of urban community governance in China, with the continuous emergence of all kinds of problems, the theoretical value of studying urban community governance has gradually come to the fore and occupies an important position in the academic world of administration in China. In recent years, the theoretical study of urban governance in China has been increasing, and various theoretical trends have emerged. Although in the early 21st century, we have gradually enriched and perfected our urban community governance theories based on Western community governance frameworks, there are still dilemmas. These theories have not yet been able to solve the problems faced by urban community governance in China, failing to realize the full autonomy of the masses, while the dominant position of the government in urban community management still exists.

This study will focus on the specifics of the participation of multiple subjects in China's urban community management, with particular attention to one of the biggest dilemmas in China's urban community management, the unclear division of subject responsibilities. Currently, several issues plague China's urban social management, including excessively administrative community management, challenges in the survival of community organizations, and low participation of community residents. These problems are influenced by the current situation and historical conditions of China's socio-economic development. The central objective of this study is to analyze and explore in-depth how to enhance urban community governance in China under the backdrop of multiple subject participation. This research held significant importance in providing robust support for the enrichment and refinement of related theories.

(2) Realistic significance

Multiple subjects in urban community governance are both decision makers and implementers, as well as beneficiaries of governance outcomes, and their participation directly involves the actual interests of all parties, which has a far-reaching impact on the harmony and stability of society. This study originates from practical work and adopts data and methods obtained from actual cases and interviews with various parties. Because of this practical foundation, the countermeasures proposed in the study are more operational and targeted, making them highly applicable in real-world situations.

Under China's current social and economic environment, the traditional government-led social governance model, relying on the synergy of other social organizations, no longer appears to meet the overall development needs of society. Although China's new urban community governance policy has begun to emerge, there are still a series of problems, including the insufficient participation of multiple actors in urban community governance. This research aims to provide strong support for improving the mechanisms and related measures of urban community governance in China, further optimizing the macroscopic decision-making of the public administration, and shaping a harmonious and stable new socialist pattern in China.

The research results are of practical and important significance for the formation of a harmonious and stable new situation of Chinese socialism. By upgrading the urban community governance mechanism and making up for the shortcomings of the existing policies, the research contributes to the improvement of the city's image and China's position in the international arena. This has the practical significance of positively promoting the enhancement of the government's grassroots social management capacity, deepening China's urban community governance, and realizing social harmony and stability. Therefore, this study not only focuses on the optimization of domestic social governance but also provides substantial support for China's important position on the global stage.

1.3 Research ideas and methods

1.3.1 Research ideas

This paper selects Guangxi urban community in southwest China as the research object. Taking the participation of multiple subjects in urban communities as the entry point, the study adopts the research ideas of theoretical analysis, mechanism exploration and practical summary, and constructs an analytical model of influencing factors by systematically analyzing the current situation of the participation of multiple subjects in the governance of urban communities in Guangxi, combined with field research.

In the research process, this paper uses SPSS and R software to conduct hypothesis testing using Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) to verify the feasibility and validity of the model. Additionally, Random Forest (RF), XGBoost, and LightGBM were employed to enhance the robustness of the analysis and to capture complex nonlinear relationships between variables. Through these diverse research methods, a scientific and comprehensive assessment of the key influencing factors of the participation of multiple subjects in urban community governance was conducted. This integrative approach ensures a deeper understanding of the interplay among variables and the validity of the proposed model.

Building on the identification of the issues in current practices, this research proposes specific and targeted realization paths in combination with the law of community governance and the requirements of Chinese-style modernization. These paths aim to make up for the deficiencies in the participation of multiple subjects in the current community governance and to promote more effective, coordinated and sustainable urban community governance. By integrating theoretical analysis and empirical research, this study aims to provide actionable recommendations for improving Guangxi's urban community governance model while contributing to the advancement of the community governance system and urban modernization in southwestern China.

1.3.2 Research method

1.3.2.1 Literature research method

We conducted a systematic literature search in the CNKI full-text database, thesis database, Web of Science, Elsevier SDOC, Google Scholar, and other Chinese and English databases using the keywords 'party building leadership,' 'community governance,' and 'multiple subjects.' The advantages and limitations of domestic and international literature were analyzed to provide theoretical support for this study.

1.3.2.2 Qualitative and quantitative research methods

This study will focus on a city in Guangxi as the research site, conducting in-depth investigations at the frontline of urban communities. Through questionnaires, structured interviews, and other research methods, data will be collected from government departments, subdistrict offices, community staff, social organization representatives, and residents. The study aims to ensure a systematic and comprehensive investigation with clear objectives, precise analysis, and standardized research procedures.

The research methodology consists of data collection, preprocessing, and quantitative analysis. First, a questionnaire survey was conducted to examine the participation of various stakeholders in urban community governance in Guangxi, identifying key variables. The collected data were then cleaned and processed, addressing missing values, outliers, and data types, followed by descriptive statistical analysis. Subsequently, a series of quantitative methods, including the Mann-Whitney test, Kruskal-Wallis test, factor analysis, Principal Component Analysis (PCA), Structural Equation Modeling (SEM), Artificial Neural Network (ANN), Random Forest (RF), XGBoost, and LightGBM, were applied to explore variable relationships and influencing factors. The integration of advanced machine learning techniques further enhances the robustness of the analysis by capturing complex nonlinear relationships and identifying key contributors, offering a more comprehensive understanding of multi-subject participation in urban community governance in Guangxi.

1.4 Research content

Chapter 1 is the introduction. This chapter provides an overview of the research background, objectives, and significance. It outlines the research methodology and approach, presents the study's main content and framework, and highlights its innovative aspects.

Chapter 2 is a literature review. This chapter reviews domestic and international research on the definition of community, urban community governance, and the factors influencing governance. It establishes a theoretical foundation for the targeted selection and modeling of multi-actor participation in urban community governance.

Chapter 3 introduces the methodology of urban community governance. This chapter introduces the methodology for analyzing urban community governance. It provides an overview of the Mann-Whitney test, Kruskal-Wallis test, factor analysis, Principal Component Analysis (PCA), Structural Equation Modeling (SEM), Artificial Neural Network (ANN), Random Forest (RF), XGBoost, and LightGBM.

Chapter 4 is to presents the results. This chapter presents the findings from the constructed model of key factors influencing multi-stakeholder participation in urban community governance. First, the Mann-Whitney and Kruskal-Wallis tests are used to examine differences in overall satisfaction with community governance across demographic characteristics such as gender, age, education level, and political identity. Next, the empirical analysis framework is established using PCA, SEM, and ANN. Additionally, RF, XGBoost, and LightGBM are applied to refine the analysis and validate the results. Through this comprehensive approach, the key factors affecting multi-actor participation in urban community governance in collar cities are systematically identified.

Chapter 5 is conclusion and discussion. This chapter synthesizes findings from the empirical analysis and current research, summarizing the challenges of multi-actor participation in urban community governance in Guangxi. It proposes recommendations to enhance participation and offers insights into future research directions on the influencing factors of urban community governance in Guangxi.

1.5 Innovation points

(1) This research innovatively adopts a comprehensive approach by simultaneously analyzing party and government leadership, community workforce, residents' self-governance, community force synergy, resource inputs, integration satisfaction, and resident satisfaction. Instead of examining these factors in isolation, the study explores their interconnections to provide a holistic and nuanced perspective on community governance.

(2) Employing advanced modeling techniques, this research quantitatively assesses the impact of various factors on community governance. Beyond traditional statistical methods, the integration of data-driven approaches enhances analytical rigor, enabling a more precise identification of key influencing factors.

Chapter 2
Literature Review

Significant differences exist between China and Western countries in terms of political systems, party structures, and social governance models. China has developed a distinctive "party-government-society" relationship model based on its national conditions. The Communist Party of China (CPC) holds a central and dominant role in social governance, contributing not only to national stability and development but also to social harmony and progress. In contrast, Western countries primarily adopt a dualistic "state-society" model, which shapes the direction of social governance research in Western academia, focusing predominantly on governance theory and community governance frameworks.

2.1 Definition of community

Foreign scholars have conducted extensive research on the concept and connotation of community. The earliest exploration of this topic can be traced back to 1887, when the German sociologist Ferdinand Tönnies introduced it in his seminal work *Community and Society: The Basic Concepts of Pure Sociology*. Tönnies provided a profound analysis of community (*Gemeinschaft*) and society (*Gesellschaft*), distinguishing them as two fundamental forms of human association. He defined a community as "a social group bound by kinship and blood ties" and identified three key characteristics: a specific geographic space, a network of social relationships, and a shared collective identity. Additionally, in his pioneering typology of communities, he classified them into three categories: kinship-based communities, geographically defined communities, and spiritually connected communities.

The Chicago School of Sociology in the United States conducted empirical research on the human geography of Chicago, its neighborhoods, and related urban issues, further enriching foreign studies on the concept and connotation of community. Among these contributions, the field of human ecology emphasized the impact of spatial positioning on human organization and behavior, viewing the community as a form of ecological spatial order. It highlighted the existence of a symbiotic relationship within communities, characterized by both interdependence and competition, as part of the natural environment essential for human survival. One of the leading figures of this school, Robert Park (1987), succinctly defined a community as "a collection of people occupying a more or less clearly defined territory." This definition encompassed both the gathering of individuals and the institutional structures that bind them, contributing to the understanding of the essential nature of community.

In the mid-1950s, American sociologist George A. Hillery further explored the concept of community in his article Definition of Community: A Field of Consensus. He conducted a comparative analysis of the 94 definitions of community available at the time, categorizing them into two main perspectives: one emphasizing territorial and local foundations, and the other focusing on social networks and relationships. Synthesizing key elements from these definitions, Hillery identified three core characteristics inherent in the concept of community: a specific geographic area, social interaction, and shared relationships. He ultimately defined a community as "encompassing groups of people who share one or more elements of commonality and maintain social contacts within the same area."

Since the introduction of the concept of "community" into China, domestic scholars have conducted extensive research and engaged in considerable debate on its definition. Early academic discussions largely emphasized the regional characteristics of communities. Fei (2008), in *Native China*, described a community as the spatial and temporal context of people's lives. In *Introduction to Sociology*, he further defined it as a collection of social groups or organizations concentrated within a geographic area, forming a large, interconnected community of life. Similarly, He (1991) viewed communities as microcosms of the larger society, defining them as regional and particularized social units.

Over time, scholars have expanded the definition of community beyond geography, incorporating perspectives of interaction and culture. Zheng (1997) and Xu (2000) highlighted both the territorial nature of communities and the importance of internal interactions and cultural cohesion. Additionally, some scholars have approached the concept from a political science perspective, emphasizing its administrative and governance functions. Yang (2006) argued that, in China’s post-unit society during the transition period, the community functioned as a political-social space constructed by the state to address urban social integration and governance challenges.

In China, communities encompass both urban and rural areas. Compared to rural communities, where activities are primarily agricultural, urban communities are characterized by non-agricultural commercial and industrial engagements in daily life. Urban communities also tend to be more densely populated and culturally diverse. While the values of community members may vary, social interaction remains relatively high. In 2000, the Ministry of Civil Affairs issued the *Circular on Opinions Regarding the Promotion of Urban Community Construction Nationwide*, which defined a community as "a social living unit formed by people residing within a specific geographic area."

As one of the fundamental types of communities, the definition and connotation of the "urban community" have been widely studied in domestic academic circles. Tang (2000) highlighted that the classification of urban communities is based on multiple interrelated and influential factors, including economic structure, population density, organizational characteristics, and cultural patterns. Liang (2020) described urban communities as human living spaces characterized by a predominantly non-agricultural population, high population density, specialized division of labor, high social mobility, and significant heterogeneity.

Other scholars have emphasized both the defining characteristics of urban communities and their geographical and administrative dimensions. The Subject Group on Urban Community Building in China (1997) proposed that urban communities are primarily based on secondary and tertiary industries, with large populations and complex social structures. It also noted that the core form of urban micro-communities is the residents' committee. Liu (2018), integrating both theoretical and empirical perspectives, defined the geographical scope of an urban community as the jurisdiction of a reformed and restructured residents' committee.

2.2 Urban community governance

Foreign scholars have long regarded community governance as a crucial component of social governance. The American sociologist Farrington, in his 1915 book *Community Development: Making Small Towns Better Places to Live and Do Business*, was among the first to conceptualize communities as regional entities within modern society, implicitly incorporating the idea of community governance. The term "governance crisis" was first introduced by the World Bank in 1989 in the context of African development, marking the beginning of widespread academic interest in governance. Since then, the concept has gained significant traction, becoming a focal point of scholarly discussion.

British scholar Rohde (1997) argued that governance represents a shift in the meaning of domination, introducing a new way of governing society. French political scientist Jean-Pierre also emphasized that governance is a modern concept that helps break traditional stereotypes and serves as a substitute for the decline of public interventionism. American political theorists Kooiman and Vliet (1993) proposed that governance operates through the interaction of multiple actors who influence one another. Western scholars generally view community governance as involving both state institutions and civil society. Cambridge University professor Mike (1999) described community governance as the "soul" of governance, highlighting its primary purpose of establishing connections and support between grassroots communities and the state to ensure their security and sustainable development.

According to Chinese scholars, community governance refers to the joint management of social and public affairs by the government, community organizations, and community residents. It is an interactive model where different actors collaborate based on their respective resources. Some scholars further emphasize that community governance not only involves the government's and non-governmental organizations' (NGOs) interventions in community development but also includes citizens' active participation in public affairs and welfare activities, such as community development plans and service projects. The focus is on the shared responsibilities and equitable distribution of development benefits among community members.

Zhang (2023) explored the application of machine learning technology in urban community governance, developing an Artificial Neural Network (ANN) intelligent decision support model optimized through genetic algorithms to enhance smart governance decision-making. Wu (2024) highlighted that urban community governance relies on the collaborative participation of multiple stakeholders to improve residents' well-being and overall satisfaction.

2.3 Analysis of factors influencing urban community governance

2.3.1 Party building to lead urban community governance in terms of impact

In Western political systems, communities under the leadership of political parties serve as vital platforms for advancing political interests and electoral campaigns. This not only provides an essential mechanism for political parties to secure ruling legitimacy but also plays a crucial role in mobilizing grassroots support. Theoretical and practical research on political party participation in community governance, as well as the construction of grassroots organizations in socialist countries, has been widely explored. As Lipsey (2011) pointed out in Consensus and Conflict, political parties achieve self-integration and broad social mobilization by aligning with the interests of communities and various social groups. Similarly, Samuel (2008) examined the relationship between party organizations and urban social governance from the perspective of "party organizations and environmental change." However, some scholars, such as Jonathan (1998), argue that "there are limits to community participation, and the failures of community governance in recent years suggest that strategic planning and a leading role for the state remain essential."

As times have changed, many countries have increasingly emphasized the role of political parties at the grassroots level. For instance, Japan’s Liberal Democratic Party (LDP) not only encourages public participation in election campaigns through grassroots party organizations but also strengthens connections between political parties and the public through direct engagement, political discussions, and communication with party members. Similarly, Singapore’s People's Action Party (PAP) follows a model of national corporatism, managing numerous grassroots organizations through the People’s Association. By leveraging its network of affiliated organizations, the PAP plays a significant role in grassroots social governance, ensuring direct interaction between political entities and local communities. In the United States, the Young Democrats have expanded the Democratic Party’s youth base by developing a nationwide franchise system, encouraging young members to engage in political activities and policy discussions.

In socialist countries, grassroots political party organizations have historically played a more central role in governance and mobilization. For example, in the Soviet Union, grassroots party organizations remained instrumental until the 1980s in mobilizing the public for socialist revolution and consolidating Soviet power. These organizations not only facilitated ideological dissemination but also integrated state directives with community governance, reinforcing the role of the Communist Party in everyday life. Such models highlight the distinct ways in which political parties engage with communities across different political systems, shaping governance structures and social participation at the grassroots level.

Domestically, Party-led urban community governance has primarily focused on theoretical research, practical exploration, and technological governance innovation. Cao (2018) argued that Party-led urban community governance has entered a new stage, marked by the establishment of Party-building and service centers across various regions. This stage emphasizes strengthening the political leadership of community Party committees, enhancing their role in serving the public, and constructing an innovative governance framework characterized by "one core, multiple elements" and "one core, multifunctionality." These structures aim to promote both community governance and service innovation.

Zhou (2019) highlighted that in grassroots social structures have introduced new pressures and challenges, necessitating a governance model based on pluralistic co-governance among the government, market, and society. This model seeks to establish a framework of social governance centered on co-construction, co-governance, and co-sharing. Similarly, Zou (2019) emphasized the role of new technologies in advancing "intelligent Party building," which in turn facilitates the development of "intelligent communities." By leveraging technology, urban governance can achieve greater informatization, intelligence, and refinement, ultimately enhancing service efficiency.

He (2020) examined technological governance models by comparing four districts in Beijing, Shenzhen, and Chengdu. He concluded that applying technological tools strengthens the synergy between different sectors and departments, thereby improving the effectiveness of grassroots governance. Chen & Yu (2022) proposed that urban community governance should integrate grassroots Party-building as an organizational force to foster collaboration among multiple actors while respecting individual autonomy as a guiding principle. They emphasized the role of consultative democracy in promoting multi-stakeholder participation in public affairs. Furthermore, Zhou, Dong, and Tang (2021) argued that Party-building should take the lead in forming an interactive governance model where multiple actors engage in synergistic and cooperative governance, ultimately shaping a new model for community governance.

2.3.2 The impact of the subjects of governance in urban communities

Overseas, Putnam highlighted that effective community governance can be achieved by leveraging the interrelationships between participating entities. He emphasized that appropriate decentralization and a well-structured network of civic participation can foster effective and spontaneous cooperation among stakeholders.

With the rise of the third sector, the role of social organizations in community governance has gained increasing attention. Paul (2000) recognized social organizations as intermediary entities that connect individuals and provide essential services within communities. Building on this perspective, Salamon (2002) argued that social organizations not only serve communities but also act as advocates for collective interests. He emphasized that these organizations play a crucial role in shaping civil society by amplifying the voices of certain social groups.

Richard and Dietmar (2011) conducted research on community cooperatives, categorizing them as civil society organizations governed primarily through norm-based mechanisms such as reciprocity and trust. They suggested that collective action in these cooperatives is driven by a shared vision of the community's future and a commitment to place-based norms and values that reinforce local identity.

Research on civic engagement has been extensively discussed by scholars such as Giddens and Francis Fukuyama, both of whom recognized that public participation is a crucial aspect of community governance. Giddens emphasized the role of social justice in shaping effective governance, while Fukuyama focused on the internal dynamics that drive community development. George Blair conducted an in-depth study on grassroots community rights and civic engagement in the U.S., suggesting that American citizens are more inclined to voluntarily participate in decision-making processes due to their general low level of trust in government institutions. This highlights the importance of community-driven participation.

Richard Box further explored the roles of citizens in community governance by attempting to transform them from "free-riders" and "gatekeepers" into active and responsible decision-makers in public affairs. His work demonstrated the positive and significant impact of citizens' involvement in shaping and enhancing governance within their communities.

Cao (2020), Wang (2021), Fu (2014), Meng (2021), and Chen (2015) explored the roles of various governance subjects in urban community governance, including party organizations, grassroots governments, neighborhood committees, citizens, social organizations, property companies, and owners' committees. Their studies also analyzed the practical problems these subjects face and proposed potential solutions. Research on grassroots governments and neighborhood committees, given their administrative nature, has been relatively mature. However, studies on party building leading community governance remain a prominent and evolving topic.

Scholars such as He (2021), Chen (2021), and Wu (2021) highlighted the natural advantages of grassroots party organizations in organization and coordination. They argued that strengthening the role of party organizations in community governance could significantly improve the quality of governance. Zhang & Li (2018) found that combining party building with community development can lead to mutual promotion and support, ultimately enhancing the effectiveness of both.

Zhu (2020) emphasized the importance of social organizations in responding to social emergencies, suggesting that these organizations should enhance their soft power and leverage their flexible characteristics in community settings. In the realm of property management, Yin (2020) investigated the relationship between property service quality and residents' sense of belonging, finding a significant positive correlation between the two.

2.3.3 The study on factors influencing community governance as a whole

There are relatively few foreign studies focusing on the factors influencing community governance. Domestically, this area of research is broad and complex, which has made it difficult to find a single-entry point for focused thematic studies. As a result, much of the research can be found in public management textbooks that summarize various factors under categories such as management and organization, community planning, environmental construction, community services, health and sports, community economy, community culture, community education, community policing, and management methods.

Some scholars attribute constraints on community development to factors such as social management, geographical environment, human factors, community culture, and economic conditions. It is argued that urban communities are intertwined with cities, and urbanization as a dynamic process should consider at least seven interacting dimensions: demographic, social, cultural, economic, ecological, physical, and governance. Factors such as those listed above are considered to influence the governance of urban communities. Additionally, from the perspective of collaborative governance, some studies highlight interest groups as explicit factors, social capital as a hidden factor, and institutions and information technology as shared factors influencing community governance.

Foreign research has primarily focused on community governance and the participation of governance actors but has lacked a comprehensive model that considers the key influencing factors. This has hindered a full understanding of the general principles governing the effectiveness of urban community governance. On the other hand, domestic research has often been either qualitative, focusing on theoretical exploration, or empirical, relying on mathematical models, but has struggled to effectively integrate theoretical construction with empirical testing. As a result, this paper adopts a quantitative approach to identify the key influencing factors on the effectiveness of urban community governance, including the direction of action, intensity, and interaction, to reveal its internal operating mechanism.

2.4 An overview of the machine learning approach of the research

Structural Equation Modeling (SEM) is a powerful statistical method for analyzing complex relationships among variables, widely used in social sciences, psychology, and education. By integrating factor analysis and path analysis, SEM effectively addresses multiple causal relationships and measurement errors, providing an intuitive and comprehensive modeling framework. For instance, Liébana-Cabanillas (2017) utilized SEM to identify personalization and customer engagement as key drivers of m-commerce adoption. Similarly, Shang (2019) demonstrated that governance cognition positively influences both participation intention and behavior, while personal factors and participation intention further enhance engagement. In contrast, behavioral attitudes and external factors were found to have negative effects.

Artificial Neural Network (ANN), renowned for their strong nonlinear mapping capabilities, are widely applied in predictive analytics. Arpaci (2023) combined SEM and ANN to examine six cybersecurity attributes influencing cryptocurrency adoption among 450 users aged 18–38. SEM results indicated that availability, integrity, utility, and possession/control significantly affected attitudes (explaining 24% of the variance) and continuous usage intention (85% variance). ANN outperformed SEM, achieving training and testing accuracies of 60.59% and 66.82% in predicting attitudes. This hybrid approach leveraged both linear and nonlinear relationships, enhancing predictive accuracy. Similarly, Xia (2024) employed a SEM-ANN framework to analyze digital RMB adoption, demonstrating SEM's predictive power and ANN's ability to handle high-dimensional data and complex interactions. Lu (2021) developed a PCA-SEM-ANN model for forecasting water resource efficiency, emphasizing SEM's explanatory strength and ANN's capacity to simulate ecosystem dynamics by converting structural relationships into ANN topologies.

Random Forest (RF), a powerful ensemble learning method, has garnered significant attention for its exceptional performance in classification and regression tasks. Qiu (2024) applied RF to analyze IBM employee turnover data, achieving superior accuracy compared to traditional models. Similarly, Wang (2023) employed RF to predict customer satisfaction with online services, demonstrating high accuracy and reliability. These studies underscore RF's effectiveness as a predictive tool, particularly in handling high-dimensional data and maintaining robustness against noise, making it an asset in data-driven decision-making.

XGBoost and LightGBM, two widely used boosted tree models, are highly valued for their efficiency and accuracy. Ding (2023) proposed a multi-model fusion approach integrating XGBoost and LightGBM, achieving the lowest mean absolute error (MAE) in insurance claim prediction. Similarly, Xie (2023) compared their performance in predicting student achievement and found that the LIGHT-XDF algorithm outperformed both models, demonstrating their strong capabilities in handling complex datasets. These findings highlight the significance of XGBoost and LightGBM in enhancing model accuracy while optimizing computational efficiency.

Existing studies have explored the influencing factors and mechanisms of urban community governance using various methods. Structural Equation Modeling (SEM), as an effective analytical tool, has been widely applied to examine complex interrelationships among multiple factors. SEM not only enhances the measurement accuracy of latent variables but also constructs causal paths to verify the rationality of theoretical models. Meanwhile, machine learning techniques such as Random Forest (RF), XGBoost and LightGBM have demonstrated significant value in community governance research. Their nonlinear modeling capabilities and strengths in handling high-dimensional data enable them to overcome the limitations of traditional statistical methods in feature extraction and variable interaction analysis.

Hybrid approaches that integrate SEM with machine learning are emerging as a promising trend. The key advantage of this combination lies in SEM's ability to establish a theoretical framework and validate causal relationships, while machine learning excels at identifying patterns in complex, nonlinear data. This synergy not only enhances predictive performance but also improves the interpretability of results. Studies have shown that hybrid models achieve significantly higher prediction accuracy than single-method approaches, highlighting the complementary strengths of these techniques in advancing community governance research.

Focusing on urban community governance in Guangxi, this study aims to identify key influencing factors using Structural Equation Modeling (SEM) and machine learning techniques. As a crucial border region in China, Guangxi is characterized by multi-ethnic coexistence and cultural integration, making its community governance model not only vital for residents' quality of life but also significant for regional social stability and sustainable development.

This research systematically examines the impact of various factors on community governance from multiple dimensions, including government support, community participation, resource allocation, and service quality. By constructing a synergistic mechanism model and integrating machine learning, the study enhances the identification of influence paths, providing a more comprehensive and data-driven approach to optimizing community governance strategies.

2.5 Statistical theory

2.5.1 Data processing methods

2.5.1.1 Reliability and validity test of the questionnaire

(1) Reliability

Reliability refers to the consistency and stability of a measurement tool, indicating the extent to which it is free from random errors and produces consistent results under similar conditions. Nunnally & Bernstein (1994) suggested that a reliable measurement should yield similar results when repeated over time or evaluated by different observers. In modern research, the Cronbach's alpha reliability coefficient is widely used to assess the reliability of questionnaires, providing a standardized measure of internal consistency. This coefficient is calculated using the following formula:

$$\alpha = \frac{K}{K-1} \times \frac{S_X{}^2 - \sum S_i{}^2}{S_X{}^2}, \tag{2.1}$$

Meaning of the letters in the above formula, K represents the total number of questions (items) in the survey, $S_i{}^2$ is intrinsic variance of the score for questionnaire question i, $S_x{}^2$ is variance of the total score of all questionnaire questions.

The Cronbach's alpha reliability coefficient ranges from 0 to 1. The higher the value of this coefficient, the greater the reliability of the questionnaire.

(2) Validity

Validity referred to the degree to which a measurement tool accurately measures what it is intended to measure. It evaluated whether the instrument effectively captures the target construct, ensuring that the results are meaningful and appropriate for their intended purpose (Cronbach,1971). Validity is calculated using the following formula:

A. Construct validity

$$\mathrm{AVE} = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}, \tag{2.2}$$

Average variance extracted (AVE) is where λ_i is standardized factor loading of item i, n is number of items.

Composite Reliability (CR) is

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\sum_{i=1}^{n} \lambda_i{}^2 + \sum_{i=1}^{n} \theta_i}, \tag{2.3}$$

where λ_i is standardized factor loading of item i, θ_i is the measurement error variance for item i.

B. Criterion-related validity

Pearson correlation coefficient is

$$r_{criterion} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}, \quad (2.4)$$

where $cov(X, Y)$ is covariance between the measurement (X) and the criterion (Y), σ_X and σ_Y are standard deviations of X and Y.

2.5.1.2 Descriptive statistics analysis

Descriptive statistical analysis was a branch of statistics that focuses on summarizing, organizing and presenting data in a meaningful way. It provided a way to describe the main characteristics of a dataset, often as a preliminary step before deeper inferential analysis. The analysis typically includes measures of central tendency, variability and the shape of the distribution.

(1) Central tendency

Measures of central tendency describe the central or typical value in a dataset. Mean is the arithmetic average of all data points.

$$\text{Mean} = \frac{\sum X_i}{n}, \quad (2.6)$$

where X_i represents individual data points and n is the total number of observations.

Median is the central value in an ordered dataset. Mode is the value that appears most frequently in the dataset.

(2) Variability (Dispersion)

Measures of variability describe the spread or dispersion of data. Range is the difference between the maximum and minimum values.

$$\text{Range} = \text{Max} - \text{Min}. \quad (2.7)$$

Variance is the average squared deviation from the mean.

$$\text{Variance}(\sigma^2) = \frac{\sum (X_i - \mu)^2}{n}, \quad (2.8)$$

Standard deviation is the square root of variance, reflecting data spread in the same unit as the mean.

$$\text{Standard deviation}(\sigma) = \sqrt{\text{Variance}}. \quad (2.9)$$

(3) Distribution

Skewness is measured asymmetry in the data distribution. Positive skew indicates a longer right tail, while negative skew indicates a longer left tail.

Kurtosis measures the "tail weight" of a distribution. High kurtosis indicates more extreme outliers.

(4) Visualization

Graphical methods such as histograms, bar charts, box plots and scatterplots provide visual summaries of data, aiding in interpretation and identifying patterns or outliers.

Descriptive statistics offer essential insights into the dataset's structure, enabling informed decision-making and guiding further statistical modeling.

2.5.1.3 Hypothesis testing

Hypothesis testing was a statistical method used to determine whether there was enough evidence in a sample of data to support or reject a proposed hypothesis about a population parameter. It was based on the principles of probability and decision-making under uncertainty.

Here are the general steps involved in conducting hypothesis testing:

Step 1: Formulate hypotheses by clearly defining the null hypothesis (H_0) and the alternative hypothesis (H_1).

Step 2: Select the significance level (α) by choosing the threshold for decision-making, typically $\alpha = 0.05$.

Step 3: Choose the appropriate test by selecting a statistical test based on the type of data and hypothesis, such as the t-test for means, the z-test for proportions or large samples, the χ^2-test for categorical data, and Kruskal-Wallis test for comparing the means of multiple groups.

Step 4: Calculate the test statistic by applying the formula specific to the chosen test.

Step 5: Determine the p-value or critical value by comparing the p-value to α in the p-value approach, rejecting H_0 if $p \leq \alpha$, or by comparing the test statistic to the critical value in the critical value approach, rejecting H_0 if the test statistic falls into the rejection region.

Step 6: Decide based on the p-value or critical value to determine whether to reject H_0.

Step 7: Interpret the results by stating the conclusion in the context of the research question.

2.5.1.4 Mann-Whitney test

The Mann-Whitney U test (also called the Wilcoxon rank-sum test) was developed by Henry Mann and Donald Whitney in 1947 as a nonparametric alternative to the independent samples t-test. The method builds upon earlier work by Frank Wilcoxon (1945), who introduced a similar test for comparing two independent samples.

The Mann-Whitney U test is a nonparametric statistical test used to determine whether there is a significant difference between two independent groups when the data are not normally distributed. It assesses whether observations from one group tend to be larger or smaller than those from another.

Mathematically, the Mann-Whitney U statistic is calculated as follow,

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1, \tag{2.10}$$

where n_1 and n_2 are the sample sizes of the two groups, R_1 is the sum of ranks for the first group. The smaller of the two U values is compared to critical values or converted into a z-score for significance testing.

2.5.1.5 Kruskal-Wallis test

The Kruskal-Wallis test was developed by William H. Kruskal and W. Allen Wallis in 1952 as a nonparametric alternative to one-way ANOVA. It is an extension of the Mann-Whitney U test for comparing more than two independent groups.

The Kruskal-Wallis test is a rank-based, nonparametric test used to determine whether there are statistically significant differences between three or more independent groups when the assumption of normality is violated. It evaluates whether at least one group stochastically dominates another.

The test statistic H is calculated as:

$$H = \frac{12}{N(N+1)} \sum \frac{R_i^2}{n_i} - 3(N+1), \tag{2.11}$$

where N is the total number of observations, R_i is the sum of ranks for group i, n_i is the sample size of group i.

The test follows a chi-square (χ2) distribution with k−1 degrees of freedom, where k is the number of groups. A significant result suggests that at least one group differs from the others, but post hoc tests (e.g., Dunn's test) are needed to identify specific group differences.

2.5.2 Data dimensionality reduction methods

2.5.2.1 Factor analysis

Factor Analysis was a statistical method used to identify and analyze underlying latent factors that explained the patterns of correlations among observed variables. It was commonly employed in psychology, sociology, and other fields to uncover the latent structure or dimensions that contribute to the observed correlations in a set of variables. Below were the basic steps of factor analysis along with formulas:

Assuming we have observed variables X_1, X_2, … X_p and latent factors F_1, F_2, … F_m,

(1) Formulate the model to specify the number of latent factors (m) and hypothesize the relationships between observed variables and latent factors.

(2) Parameterization to represent the relationships using factor loadings (λ) and unique factors (Ψ),

$$X_i = \lambda_{i1}F_1 + \lambda_{i2}F_2 + \ldots + \lambda_{im}F_M + \psi_i \,, \tag{2.12}$$

where X_i is the observed variable, λ_{ij} is the loading of X_i on F_j, and ψ_i is the unique factor for X_i.

(3) Calculate covariance matrix to compute the sample covariance matrix (S) of the observed variables

(4) Factor loadings estimation

Use a factor analysis method (e.g., principal components analysis or maximum likelihood estimation) to estimate the factor loadings (Λ) that best reproduce the observed covariance matrix.

(5) Reproduce covariance matrix

Calculate the reproduced covariance matrix (R) using the estimated factor loadings,

$$R = \Lambda\Lambda^T + \Psi, \qquad (2.13)$$

where Λ is the matrix of factor loadings and Ψ is a diagonal matrix of unique variances.

(6) Calculate residuals

Compute the residuals (E) by subtracting the reproduced covariance matrix from the sample covariance matrix,

$$E = S - R. \qquad (2.14)$$

(7) Calculate communalities

Obtain the communalities ($h_i{}^2$) by subtracting the unique variance from the total variance for each variable,

$$h_i{}^2 = 1 - \frac{\Psi_i}{б_{X_i}{}^2}, \qquad (2.15)$$

where $б_{X_i}{}^2$ is the total variance of the X_i.

(8) Assess model fit, evaluate the adequacy of the factor model using fit indices or goodness-of-fit measures.

Factor analysis aims to explain the observed correlations between variables in terms of a smaller number of latent factors. The factor loadings indicate the strength and direction of the relationship between each variable and each factor. The unique factors represent the variance in each variable that is not explained by the common factors.

2.5.2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was a linear dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional space while retaining as much of the original data variance as possible. PCA created new variables, called principal components, which were uncorrelated and ordered such that the first few retain most of the variance present in the original dataset (Jolliffe2002).

Here are the general steps involved in conducting Principal Component Analysis.

(1) Data standardization. Standardize the original dataset X so that each variable has a mean of 0 and a standard deviation of 1,

$$z_{ij} = \frac{x_{ij} - \overline{x_j}}{\sigma_j}, \tag{2.16}$$

where x_{ij} is the value of the i-th sample for the j-th variable, $\overline{x_j}$ is the mean of the j-th variable,$\overline{x_j}$ is the standard deviation of the j-th variable. This produced the standardized data matrix Z.

(2) Compute the covariance matrix. Construct the covariance matrix of the standardized data:

$$C = \frac{1}{n-1} Z^T Z, \tag{2.17}$$

(3) Eigenvalue and eigenvector computation. Perform eigenvalue decomposition of the covariance matrix is

$$Cv_k = \lambda_k v_k, \tag{2.18}$$

Eigenvalues (λ_k) indicate the amount of variance explained by each principal component. Eigenvectors (v_k) represent the directions of the principal components.

(4) Select principal components. Sort the eigenvalues in descending order. Choose the top m components that satisfy the cumulative variance threshold (e.g., 85% or 95%),

$$\text{Cumulative Variance} = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{p} \lambda_i}, \tag{2.19}$$

where p is the total number of eigenvalues.

(5) Transform the data. Project the original data onto the selected principal components:

$$Y = ZV_M, \tag{2.20}$$

where Y is the reduced data matrix.

2.5.3 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) was a statistical method used for analyzing the relationships between observed and latent variables (Kline, 2016). SEM encompasses both Confirmatory Factor Analysis (CFA) and path analysis, allowing researchers to test complex theoretical models. SEM was often used in social sciences and other fields to assess the validity of a hypothesized structural model. Here were the basic steps of SEM, along with some formulas:

Assuming we have observed variables X_1 , $X_2 \ldots X_p$ and latent variables η_1, η_2 , $\ldots, \eta_m$

(1) Specify the model to define the relationships among latent and observed variables in a hypothesized model.

(2) Parameterization to represent the relationships between variables using path coefficients (λ).

(3) Formulate measurement model (CFA) for each latent variable η_i, relate it to its observed indicators $X_{i1}, X_{i2} \ldots, X_{ip}$, using factor loadings (λ_{ij}):

$$X_{ij} = \lambda_{ij} \cdot \eta_i + \varepsilon_{ij} , \tag{2.21}$$

where ε_{ij} serves as the error term.

(4) Formulate structural model (path analysis) to specify the structural relationships among latent variables using path coefficients (β):

$$\eta_i = \beta_{i1} \cdot \eta_1 + \beta_{i2} \cdot \eta_2 + \ldots + \beta_{im} \cdot \eta_m + \zeta_i, \tag{2.22}$$

where ζ_i serves as the disturbance term.

(5) Estimation to use a suitable method (e.g., maximum likelihood) to estimate the parameters (λ, β) that maximize the likelihood of the observed data.

(6) Fit indices to evaluate the fit of the model using fit indices such as chi-square(χ_2), comparative fit index (CFI), root mean square error of approximation (RMSEA), etc.

(7) Assess model fit to compare the estimated model to the observed data and evaluate how well the model fits the data based on fit indices.

(8) Modify model (if needed), if the initial model fit is unsatisfactory, make modifications to improve the model fit, such as adding or removing paths.

SEM can become more complex with the inclusion of multiple groups, mediating variables, and other advanced features. The formulas provided here represent a simplified version of SEM for basic understanding. The estimation and fit indices may vary depending on the software package used for SEM analysis.

2.5.4 Machine Learning model

2.5.4.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a computational model inspired by the biological neural networks in the human brain. It is designed to recognize patterns, classify data, and solve complex problems by mimicking how neurons in the brain communicate with each other (McCulloch& Pitts1943).

Key Components of ANN

The input layer accepts the input features (data) to be processed, while hidden layers perform computations and feature transformations. The output layer produces the final prediction or classification. Weights and biases are parameters adjusted during training to optimize performance, and the activation function determines the output of a neuron, introducing non-linearity.

Here's the typical formula for a single neuron in a feedforward neural network:

(1) Input calculation

$$z = \sum_{i=1}^{n} x_i w_i + b, \tag{2.23}$$

where x_i are the inputs(features), w_i are the weights corresponding to each input, b is the bias term, let n denotes the number of the feature.

(2) Activation function

The output of the neuron is calculated using an activation function, often a nonlinear function such as sigmoid, tanh, or ReLU:

$$y = \sigma(z), \tag{2.24}$$

where σ is the activation function, and y is the output of the neuron.

(3) For multi-layer networks, the same calculation is applied to each layer' neurons using the output from the previous layer as the input to the next layer.

Steps to build and train an ANN

Step 1: Data preparation includes collecting and preprocessing the data (handling missing values and normalization). The data is split into training, validation, and test sets for model training, tuning, and evaluation.

Step 2: Define the network architecture by deciding the number of layers (input, hidden, output), specifying the number of neurons in each layer, and choosing activation functions like ReLU or sigmoid.

Step 3: Initialize weights randomly, typically using a normal distribution, and set biases to zero or small random values.

Step 4: Forward propagation involves passing the input data through the network, computing the weighted sum at each layer, and applying activation functions layer by layer.

$$a^l = f(W^l a^{l-1} + b^l), \tag{2.25}$$

Step 5: Compute the loss using a loss function to measure the error between predicted and actual values. For regression tasks, a common loss function is mean squared error (MSE).

$$L = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \tag{2.26}$$

Cross-entropy Loss for classification,

$$L = -\frac{1}{n}\sum_{i=1}^{n}[y_i \log \hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i)]. \tag{2.27}$$

Step 6: Backpropagation involves computing the gradients of the loss with respect to the weights and biases, then adjusting the weights and biases using an optimization algorithm, such as gradient descent.

$$w_{t+1} = w_t - \eta \frac{\partial L}{\partial w}, \tag{2.28}$$

where η is learning rate. w_t is the weight parameter at time step t. w_{t+1} represents the updated weight parameter at the next time step (t+1). $\frac{\partial L}{\partial w}$ is the gradient of the loss function with respect to the weight w, indicating how much the loss function *L* changes as the weight parameter *w* change.

Step 7: Optimization involves using gradient-based methods like stochastic gradient descent (SGD) or Adam optimizer to update the weights and biases and minimize the loss function.

Step 8: Training involves iterating over multiple epochs, updating weights and biases at each step, and monitoring the loss and validation accuracy to assess the model's performance.

Step 9: Evaluation involves testing the trained model on the test set and using metrics like accuracy, precision, recall, or F1-score to assess its performance.

Step 10: Deployment involves saving the trained model and deploying it to make predictions on new, unseen data.

Artificial Neural Network (ANN) are highly advantageous due to their ability to model complex, nonlinear relationships in data, making them ideal for tasks like image recognition, speech processing, and natural language understanding. They automatically extract features from raw data, reducing the need for manual feature engineering, and are robust against noise, handling incomplete or imperfect data effectively. ANN is scalable, capable of processing large datasets with millions of features and observations, can be implemented using parallel and distributed computing for faster processing. Their versatility across domains—from healthcare and finance to engineering and entertainment—allows them to adapt to various applications such as disease diagnosis, fraud detection, predictive maintenance, and recommendation systems. Moreover, with advancements in explainable AI, their interpretability and integration with other machine learning models further enhance their applicability. These strengths make ANN indispensable in modern artificial intelligence and data science.

2.5.4.2 Random Forest (RF) model

Random Forest (RF) is a supervised learning algorithm used for classification and regression tasks (Breiman,2001). It operated by constructing multiple decision trees during training and outputs either the mode of the classes (classification) or the mean/average prediction (regression) of the individual trees. It improves accuracy by reducing overfitting compared to a single decision tree.

Key concepts of RF include ensemble learning, where predictions from multiple decision trees are combined to improve accuracy; bootstrapping, which involves random sampling with replacement to create training subsets for each tree; feature randomness, where each tree considers a random subset of features at each split, increasing diversity among trees; and majority voting/averaging, where the mode of tree predictions is taken for classification and the mean is used for regression.

The RF prediction process can be expressed mathematically:

For classification is

$$\hat{y} = \mathrm{kargmax}_k\left(\frac{1}{N}\sum_{i=1}^{N} I(h_i(x) = k)\right), \tag{2.29}$$

where $\hat{y}$ is final predicted class, N is number of trees, $h_i(x)$ is prediction from the ith tree, k is a class label, I (·) is indicator function (1 if true, 0 otherwise).

For regression is

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} h_i(x), \tag{2.30}$$

where $\hat{y}$ is final predicted value, N is number of trees, $h_i(x)$is prediction from the ith tree.

Steps to build a Random Forest model:

(1) Prepare the dataset by cleaning the data, handling missing values, and encoding categorical variables. Then, split the dataset into training and testing subsets to ensure effective model evaluation.

(2) Bootstrap sampling involves creating multiple subsets of data by randomly sampling the training data with replacement, allowing for variability and robustness in model training.

(3) Grow decision trees by building a tree for each bootstrap sample. At each split, randomly select a subset of features instead of considering all, enhancing model diversity and reducing overfitting.

(4) Aggregate predictions by taking the majority vote from all trees for classification tasks. For regression, calculate the average of predictions from all the trees to obtain the result.

(5) Model evaluation involves using metrics such as accuracy, precision, recall, and F1-score for classification tasks, or RMSE (Root Mean Squared Error) and R^2 (R-squared) for regression tasks, to assess the model's performance on the test set.

(6) Hyperparameter tuning involves adjusting parameters such as the number of trees (n_estimators), the maximum depth of each tree, and the maximum number of features considered at each split to optimize model performance and enhance accuracy.

Advantages of Random Forest include its robustness to overfitting, as averaging multiple trees reduces the risk of overfitting to the training data. It can effectively handle missing values by imputing them during the training process. Random Forest is highly scalable, making it suitable for large datasets and high-dimensional feature spaces. Additionally, it provides insights into feature importance, helping identify the most significant predictors in the dataset.

2.5.4.3 XGBoost model

XGBoost (Extreme Gradient Boosting) is an optimized implementation of the gradient boosting algorithm designed for efficiency, scalability and performance (Friedman, 2001). It is widely used for supervised learning tasks, including classification, regression and ranking. XGBoost builds decision trees sequentially, with each tree correcting the errors of the previous trees, focusing more on the hard-to-predict instances by minimizing a specified loss function. Key features of XGBoost include regularization, where L1 (Lasso) and L2 (Ridge) techniques are used to control overfitting; tree pruning, which employs a "maximum depth" parameter and prunes trees after training to ensure simplicity; parity awareness, allowing it to handle missing values or sparse data efficiently; parallelization, which enables faster tree construction compared to traditional gradient boosting; and support for custom loss functions, enabling users to define loss functions tailored to specific needs.

Here's a simplified explanation of XGBoost core formulas as follows:

(1) Objective function to combines the loss function and regularization term,

$$\mathrm{Obj} = \mathrm{Loss} + \mathrm{Regularization}, \tag{2.31}$$

Loss measures the error between predicted and actual values (e.g., Mean Squared Error). Regularization controls model complexity and prevents overfitting.

(2) Prediction updates to update predictions at each iteration,

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i), \tag{2.32}$$

where $f_t(x_i)$ is the output of the t-th tree.

(3) Gradient and Hessian to calculate the gradient (g_i) and second-order derivative (h_i) of the loss function,

$$g_i = \frac{\partial Loss}{\partial \hat{y}_i}, h_i = \frac{\partial Loss^2}{\partial \hat{y}_i^{\,2}} \tag{2.33}$$

(4) Leaf weight to compute the optimal weight for each leaf node,

$$\mathrm{w} = -\frac{\sum \mathrm{g_i}}{\sum \mathrm{h_i} + \lambda} \tag{2.34}$$

(5) Split gain to evaluate the quality of a split,

$$\text{Gain} = \text{Left Gain} + \text{Right Gain} - \text{Parent Gain} - \gamma \tag{2.35}$$

The step of the XGBoost:

(1) Data preparation

First, determine the problem to be solved and collect data containing features and labels, which can come from various sources. Then preprocess the data, including handling missing values by filling with mean, median, or mode, or deleting samples with missing values; encoding categorical features using one-hot encoding or label encoding; and scaling numerical features. Finally, divide the dataset into training and testing sets, usually in a ratio of 70% - 30% or 80% - 20%, for model training and evaluation.

(2) Model training

Select appropriate parameters, such as learning rate to control the contribution of each tree to the result, max_depth to limit model complexity and prevent overfitting, n_estimators to affect model performance and computational cost, and regularization parameters to control model complexity. Use the training set data and selected parameters to train the XGBoost model. The model trains multiple trees sequentially through gradient boosting, with each tree learning the residuals of the previous tree and attempting to fit them, until the set number of trees is reached, or other stopping conditions are met.

(3) Model evaluation and optimization

Choose evaluation metrics, such as accuracy, precision, recall and F1 score for classification problems, and mean squared error, root mean squared error, and mean absolute error for regression problems. Apply the trained model to the test set to calculate evaluation metrics and understand its performance on unseen data. Optionally optimize the model, such as using grid search or random search to find the optimal parameter combination, and analyze feature importance to remove unimportant features, thereby improving model performance and training efficiency.

The XGBoost model boasts several key advantages. It delivers high performance with remarkable predictive accuracy, consistently outperforming other models in various applications. Its ability to handle large-scale datasets efficiently through parallel and distributed computing makes it ideal for big data scenarios. XGBoost is highly flexible, supporting both classification and regression tasks and accommodating different data types. It can automatically handle missing values, saving preprocessing time. The model also features regularization techniques to prevent overfitting, enhancing its generalization to new data. Additionally, XGBoost provides a built-in mechanism to assess feature importance, aiding in feature selection and model interpretation.

2.5.4.4 LightGBM model

LightGBM (Light Gradient Boosting Machine) is a gradient boosting framework based on decision trees, focusing on high efficiency and low memory usage (Ke, 2017). It is well-suited for handling large-scale data and high-dimensional datasets. By improving data splitting strategies and model training methods, it significantly enhances training speed and predictive performance.

The main features of LightGBM include the following: first, it utilizes an efficient histogram-based splitting strategy, significantly reducing computational complexity by employing discrete histograms. It also uses binning techniques to convert continuous feature values into discrete intervals, greatly reducing memory consumption. Second, it adopts a Leaf-Wise growth strategy, splitting the leaf node with the largest loss reduction at each step instead of the traditional Level-Wise approach. This method achieves faster loss reduction but requires depth constraints to prevent overfitting. Additionally, LightGBM supports the direct input of categorical features without requiring one-hot encoding, further improving training efficiency. Finally, with multi-threading and optimized memory management, LightGBM demonstrates high efficiency in handling large-scale datasets.

Key Formulas in LightGBM as follows (Friedman, 2001):

(1) Objective function

Like XGBoost, LightGBM also optimizes the loss function with regularization,

$$\mathrm{Obj} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{j=1}^{k} \Omega(T_j), \tag{2.36}$$

where $l(y_i, \hat{y}_i)$ is loss function between true values (y_i) and predictions ($\hat{y}_i$). $\Omega(T_j)$ is regularization term controlling the complexity of the tree.

(2) Leaf-wise tree growth

LightGBM uses a leaf-wise tree growth strategy. At each iteration, the leaf that results in the largest reduction in the loss function are split,

$$\mathrm{Gain} = \frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} - \frac{(G_L+G_R)^2}{H_L+H_R+\lambda} - \Upsilon, \tag{2.37}$$

where G_L and G_R is gradients for the left and right child nodes. H_L and H_R is hessians (second derivatives) for the left and right child nodes. λ is regularization parameter. γ is penalty for splitting.

(3) Leaf weight calculation

The optimal weight for each leaf node is

$$\omega = \frac{\sum G_i}{\sum H_i+\lambda}, \tag{2.38}$$

where G_i and H_i are the gradient and Hessian of the loss function for the data points in the leaf.

(4) Data binning

To improve efficiency, LightGBM bins continuous features into discrete bins

$$x' = binning(x), \tag{2.39}$$

where x' represents the binned feature values.

Basic implementation steps of LightGBM:

Step1: Data preprocessing involves converting continuous features into discrete bins using histogram binning and directly inputting categorical features without applying one-hot encoding.

Step2: Initialization involves setting the initial predictions to a base value, such as the mean or log-odds of the target variable.

Step3: Construct histograms by building one for each feature to aggregate the gradient and Hessian values within each bin.

Step4: Find the best split by evaluating all possible splits using histogram-based calculations and selecting the one with the highest gain in loss reduction.

Step5: Grow the tree using the Leaf-wise strategy, splitting the leaf with the largest loss reduction. This process continues until the maximum depth or minimum gain threshold is reached.

Step6: Update the model predictions by adding the new tree's contributions, scaled by the learning rate.

Step7: Iterate by repeating steps 3–6 to grow multiple trees until the maximum number of iterations or early stopping criteria are met.

Step8: Output the model by combining all trees to form the final model for prediction.

Chapter 3
Research Methodology

To thoroughly investigate the key factors influencing the participation of multiple subjects in community governance in urban communities in Guangxi, we employed descriptive statistical analysis, factor analysis, Principal Component Analysis (PCA), Structural Equation Modeling (SEM) and Artificial Neural Network (ANN).

Descriptive statistical analysis was conducted to understand the distribution and characteristics of key variables. The Mann-Whitney or Kruskal-Wallis test examined differences in participation factors across age, gender, education, and political identity. PCA reduced dimensionality, identifying principal components influencing participation. SEM analyzed causal relationships, assessing direct and indirect effects of factors like community collaboration, political engagement, and internet usage. ANN captured non-linear interactions, ranking variable importance, with education, political identity, and internet usage emerging as critical. This integrated approach offers insights into participation drivers, informing targeted policy recommendations for enhancing community governance.

3.1 Scope of the research

3.1.1 Data

According to the 2023 Guangxi Zhuang autonomous region statistical yearbook, there are a total of 14 prefecture-level divisions, 41 districts under the jurisdiction of cities, 135 sub-districts, and 2,316 neighborhoods (Table 1).

The diverse types of urban communities in Guangxi provided a rich sample for the study of community governance. In this paper, we primarily classify the types of urban communities in Guangxi based on the characteristics of community population composition. These types can be broadly categorized into various groups such as mobile population settlement type, hereditary type, enterprise type, unit type, college type and immigrant type. Among them, the majority were mobile population settlement type urban communities. This paper synthesized the actual situation and focused on three types of urban communities: migrant settlement type, hereditary residence type, and enterprise type for investigation and research. Based on this classification, this study adopted a stratified sampling method to determine the proportion of the three types of communities in the sample, considering the proportion of each type of community in the entire community. We comprehensively examine the characteristics of each community including human, economic, demographic, social organization, organizational status, location, and then select 20 communities as the research units.

Table 1 Distribution of urban community in Guangxi

Distribution of urban communities in Guangxi Zhuang autonomous region						
City	Districts under the Jurisdiction of Cities	Sub-districts	Neighborhood Committees	Village Committees	City Population (10,000 persons)	Urban Population (10,000 persons)
Nanning	7	25	438	1,386	430.35	265.8
Liuzhou	5	32	301	935	190.92	136.59
Guilin	6	13	264	1,653	138.24	98.76
Wuzhou	3	8	153	861	81.22	49.6
Beihai	2	7	95	336	72.45	40.78
Fangchenggang	2	7	68	274	60.68	18.61
Qinzhou	2	12	153	887	155.62	34.16
Guigang	3	7	123	1,060	207.28	38.02
Yulin	2	8	178	1,327	118.9	62.7
Baise	2	2	98	1,796	73.63	32.68
Hezhou	2	4	55	707	122.86	23.69
Hechi	2	3	180	1,481	101.55	33.89
Labin	1	4	97	712	114.54	32.25
Chong Zuo	1	3	113	751	37.99	17.65
Total	41	135	2,316	14,166	2,699.19	885.18

The questionnaire was conducted in each of the selected communities using simple random sampling and was completed through face-to-face one-by-one interviews, and online questionnaire star. At the beginning of the questionnaire design, three different types of community representatives were first selected for the pre-survey. The purpose of the pre-survey was to assess the issues addressed in the questionnaire; to find out how the community members understood the questionnaire, and to assess the validity of the questionnaire. Subsequently, the questionnaire was revised and improved based on the feedback. The surveyors received training and instructions at Guangxi Minzu Normal University to ensure the return rate and validity of the questionnaire. Finally, a total of 1,314 questionnaires were distributed, of which 1,216 were valid, with a validity rate of 92.5%. The descriptive statistics of the obtained samples provide an overview of the valid questionnaires.

3.1.2 Variables

The 8 variables for the participation of multiple subjects in governance in urban communities in Guangxi are as follows.

(1) Latent variable 1: party leadership in urban community governance (PL)

Party leadership in urban community governance embodies the guiding and coordinating functions of government departments in community affairs. It demonstrates the government's ability to effectively lead and manage community governance, primarily through the strategic allocation of governance resources and the coordination of diverse stakeholders in community development. This leadership plays a pivotal role in shaping the effectiveness of urban community governance.

(2) Latent variable 2: community residents' self-governance (CRS)

Community residents' self-governance refers to residents' engagement in democratic activities such as elections, consultations, decision-making, management, and oversight. These activities were conducted under the leadership of party organizations within the community and are based on community residents' committees. They also involve collaboration with the community's general assembly and consultation and deliberation councils.

(3) Latent variable 3: community workforce building (CWB)

Community worker team building involves establishing a professional team of community workers, with the community party branch secretaries (or community neighborhood committee chairpersons) serving as the primary members. This is aimed at addressing community governance issues and fulfilling the service requirements of community residents.

(4) Latent variable 4: collaboration of social forces (CSF)

The collaboration of social forced in community governance involves leveraging the distinct strengths of community social organizations and other grassroots-level entities. It actively encouraged the involvement of community-based institutions, enterprises, public organizations, and other societal entities, as well as market players, in community governance initiatives.

(5) Latent variable 5:resource inputs for community governance (RI)

Community governance resource input referred to the cumulative financial and material resources allocated by the Party and government to advance the development of community governance practices. This includes public financial investments and the establishment of community public service facilities, the provision of community convenience service facilities, and the development of community information technology platforms.

(6) Latent variable 6: harmonized community development (HCD)

Harmonized community development (HCD) referred to the process of fostering a balanced, inclusive, and sustainable growth within a community where all stakeholders, residents, local organizations, and governance bodies, work collaboratively towards shared goals. It encompassed the integration of economic prosperity, social cohesion, cultural inclusivity, and environmental sustainability to create a thriving and resilient community.

(7) Latent variable 7: community integration satisfaction (CI)

Community integration satisfaction (CI) referred to residents' perceived level of satisfaction with the degree of cohesion, collaboration, and inclusiveness within their urban community. It reflected the extent to which individuals feel connected to their community, trust its governance, and participate in collective activities. High CI indicated strong interpersonal relationships, effective communication among diverse groups, and a sense of belonging and shared purpose within the community. This variable played a critical role in fostering social harmony, enhancing governance performance, and promoting sustainable urban development by encouraging cooperative efforts among residents, local organizations and governance bodies.

(8) Latent variable 8: community governance resident satisfaction (RS)

Resident satisfaction with community governance referred to the degree of satisfaction residents experience regarding the quality of community services, the level of political participation, and the overall quality of life within their community.

The observed variables for each latent variable are shown in the following Table 2.

Table 2 The variables in the research

Factors and variables			
Item	Name	Item	Name
Factor1: PL	Party leadership	Factor5: RI	Resource inputs
PL1	Satisfaction with the building of community party organizations	RI1	Level of public financial inputs by the Government to community governance
PL2	The role of party members in the area where you live	RI2	Satisfaction with public service facilities in the community
PL3	Satisfaction with the work of party organizations in the community	RI3	Accessibility of community amenities
PL4	Party building to promote innovation in community governance	RI4	Construction and experience of using the community information platform
PL5	Activity in services or activities related to party organizations	Factor6: HCD	Harmonized community development
Factor2: CRS	Community Resident Self-Governance	HCD1	Overall assessment of the current state of governance in your community
CRS1	Satisfactory representation of community residents' representatives	HCD2	Do you feel a sense of belonging in this neighborhood
CRS2	Capacity of community residents in self-organization	HCD3	Do you care about the neighborhood
CRS3	Capacity of community residents in terms of political participation	Factor7:CI	Community integration satisfaction
Factor3: CWB	Community Workforce Building	CI1	Perceived evaluation of community culture
CWB1	Satisfaction with the composition of the community workforce	CI2	Perceived level of harmony in community neighborhoods
CWB2	Community workers have adequate professional qualifications	CI3	Degree of agreement with the values and philosophies promoted by the community
CWB3	Work capacity of community clerks	Factor8:RS	Community Governance Resident Satisfaction
Factor4: CSF	Collaboration of social forces in community governance	RS1	Satisfaction with the level of community services
CSF1	Participation of units in the district in community building and governance	RS2	Own level of political participation
CSF2	Satisfactory participation of social organizations in community governance	RS3	Satisfaction with the quality of life in the community
CSF3	Recognition of social organizations as proactive participants in urban community governance		
CSF4	Social organizations are more independent in their participation in urban community governance		

3.1.3 Research hypothesis

The development of professional and diverse community worker teams, combined with workforce building through job opportunities and vocational training, played a vital role in enhancing community governance. Community workers act as bridges, organizing cultural activities, coordinating resource distribution, and supporting vulnerable groups to foster communication, reduced social exclusion, and mitigate conflicts (Coleman,1988&Granovetter,1973). The hypothesis as follow Figure1.

Simultaneously, job opportunities provided economic stability and social status, while vocational training enhanced skills and promotes social mobility and self-fulfillment, thereby improving residents' trust and satisfaction with governance (Putnam, 2000&Sen, 1999). These efforts also reduced crime rates, strengthen social capital, and enhance community stability and cohesion (Wilson, 1996). By fostering interaction and collaboration among residents and addressing diverse group needs, such as prioritizing job access for low-income individuals and high-quality training for skilled workers, these initiatives build inclusive, trusting environments and sustainable communities (Ostrom,1990& Granovetter, 1973).

H1: CWB (community workforce building) directly and positively influences RS (community governance resident satisfaction)

H2: CWB (community workforce building) directly and positively influences CI (community integration satisfaction)

Party leadership (PL) provided clear policy direction and governance frameworks, offering institutional guarantees and value guidance that significantly enhance residents’ trust and satisfaction with community governance (RS), improved the harmonious atmosphere within the community (CI), and facilitate effective resource investment (RI) (Ostrom,1990).

Firstly, party leadership ensured policy continuity and stability through top-level design, providing residents with a clear expectation of community development and reducing uncertainty and mistrust (North, 1990). Secondly, grassroots party organizations, emphasizing the "mass line" approach, engage directly with communities to resolve conflicts and practical issues, thereby fostering a more harmonious community atmosphere (Putnam, 2000). Moreover, under party leadership, community governance integrates diverse resources, including financial support, social forces, and technological innovations, establishing a solid foundation for the efficient delivery of public services (Rothstein&Stolle,2008).

Additionally, party leadership cultivates shared values and social norms, promoting cooperation and trust among residents and further strengthening community cohesion and governance efficacy (Coleman,1988). This combination of top-level institutional frameworks and grassroots actions ensures the rational allocation and efficient utilization of resources, driving the sustainable development of community governance.

H3: PL (party leadership in community governance) directly and positively influences RS (community governance resident satisfaction)

H4: PL (party leadership in community governance) directly and positively influences CI (community integration satisfaction)

H5: PL (party leadership in community governance) directly and positively influences RI (resource inputs)

Community resident self-governance (CRS), by empowering residents to participate directly in the decision-making process, not only enhanced their sense of ownership of community affairs, but also significantly improved residents' satisfaction with community governance (RS) (Ostrom, 1990). This governance model allowed residents to express their needs, give their opinions, and participate in resource allocation decisions, thereby reducing information asymmetry and administrative bias, and improving the fairness and transparency of policy implementation (Fung, 2004).

In addition, resident self-governance facilitates communication and understanding among residents of different backgrounds by strengthening interaction and cooperation between neighbors, creating a more inclusive social atmosphere that contributes to community integration (CI) (Putnam,2000). At the same time, this model can further enhance the effectiveness and sustainability of community governance by directly facilitating the investment and efficient use of community resources through residents' joint funding, time and skills (Coleman,1988).

Research had shown that the participatory management model brought about by resident self-governance can enhance a community's social capital and collective action capacity, laying the foundation for long-term community stability and development (Rothstein & Stolle, 2008). Therefore, resident self-governance was not only an important mechanism for enhancing community cohesion and governance satisfaction, but also an effective means of optimizing resource allocation.

H6: CRS (community resident self-governance) directly and positively influences RS (community governance resident satisfaction)

H7: CRS (community resident self-governance) directly and positively influences CI (community integration satisfaction)

H8: CRS (community resident self-governance) directly and positively influences RI (resource inputs)

Cooperation of social forces (CSF) played an important role in community governance, which not only introduces diversified perspectives to community development (Wei, 2023) but also injects valuable resources into the community and effectively improves residents' satisfaction (RS). Through the cooperation of social forces, groups with different backgrounds and interests are able to enhance communication and understanding, thus promoting community integration (CI) and strengthening residents' sense of belonging and identity in the community (Ma, 2017& Zhang,2015). In addition, the collaboration of social forces provides additional resources and development opportunities for community workforce building (RI), further supporting employment and skill enhancement within the community (Li,2023). This collaborative model contributes to a more inclusive, diverse and vibrant community ecology, laying the foundation for achieving efficient community governance.

H9: CSF (collaboration of social forces in community governance) directly and positively influences RS (community governance resident satisfaction)

H10: CSF (collaboration of social forces in community governance) directly and positively influences CI (community integration satisfaction)

H11: CSF (collaboration of social forces in community governance) directly and positively influences RI (resource inputs)

Resident satisfaction (RS), community integration satisfaction (CI) and community governance resource input (RI) had significant positive effects on harmonious community development (HCD).

First, a community with high resident satisfaction (RS) usually implied that residents had a high level of recognition of community governance, services, and environment, this satisfaction can motivate residents to participate more actively in community affairs and support community development, thus enhancing community cohesion and cooperative atmosphere (Zhou,2022).

Second, communities with high satisfaction with community integration (CI) were usually more inclusive and can promote mutual trust and collaboration among residents, making it possible to share resources and solve problems together, thus laying a solid foundation for the harmonious development of the community (LAN&XIE,2024).

In addition, resource inputs (RI)for community governance provide sufficient support for community activities and development programs, whether they were infrastructure improvements, education and skills training, or cultural activities, which directly or indirectly contribute to the harmonious development of the community. Taken together, the synergistic effect of resident satisfaction, community integration satisfaction, and resource inputs was indispensable for the harmonious development of the community

H12: RS (community governance resident satisfaction) directly and positively influences HCD (harmonized community development)

H13: CI (community integration satisfaction) directly and positively influences HCD (harmonized community development)

H14: RI (resource inputs for community governance) directly and positively influences HCD (harmonized community development)

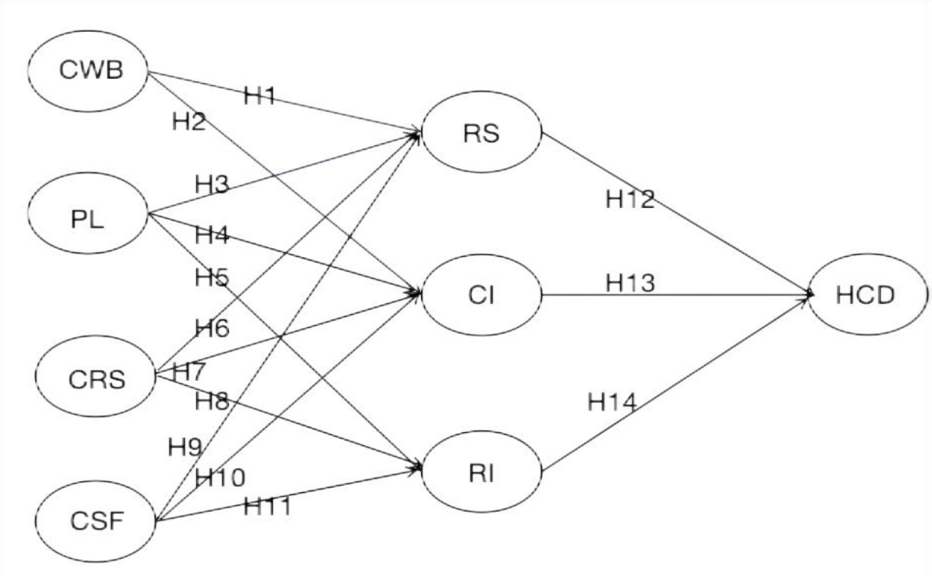

Figure 1 Theoretical modeling of research hypotheses

PL stands for party leadership in community governance, CRS stands for community resident self-governance, CWB stands for community workforce building, CSF stands for collaboration of social forces in community governance, RI stands for resource inputs for community governance, CI stands for community integration satisfaction, RS stands for community governance resident satisfaction, and HCD stands for harmonized community development.

Community worker building (CWB) enhanced residents' satisfaction with community governance (RS) by fostering a professionalized and diversified community service workforce, enabling them to participate more directly and effectively in community governance, and to feel the fairness of policy implementation and the transparency of resource allocation (Ostrom, 1990).

Community workers act as a bridge to respond to residents' needs in a timely manner, mediate disputes, and organize cultural activities, and this close-to-the-people service model enhances residents' trust and sense of belonging (Coleman,1988). Highly satisfied residents are more willing to support community building, participate in public affairs, reduce internal conflicts, and ultimately promote harmonious community development (HCD) (Putnam, 2000). Thus, CWB indirectly promoted HCD by increasing RS.

H15: CWB (community worker building) indirectly contributes to HCD (harmonized community development) through improved RS (resident satisfaction) with community governance.

H16: CWB (community worker building) indirectly contributes to HCD (harmonized community development) through improved CI (community integration satisfaction).

H17: PL (party leadership in community governance) indirectly contributes to HCD (harmonized community development) through improved RS (resident satisfaction) with community governance.

H18: PL (party leadership in community governance) indirectly contributes to HCD (harmonized community development) through improved CI (community integration satisfaction).

H19: PL (party leadership in community governance) indirectly contributes to HCD (harmonized community development) through improved RI (resource inputs for community governance).

H20: CRS (community resident self-governance) indirectly contributes to HCD (harmonized community development) through improved RS (resident satisfaction) with community governance.

H21: CRS (community resident self-governance) indirectly contributes to HCD (harmonized community development) through improved CI (community integration satisfaction).

H22: CRS (community resident self-governance) indirectly contributes to HCD (harmonized community development) through improved RI (resource inputs for community governance).

H23: CSF (collaboration of social forces in community governance) indirectly HCD (harmonized community development) through improved RS (resident satisfaction) with community governance.

H24: CSF (collaboration of social forces in community governance) indirectly HCD (harmonized community development) through improved CI (community integration satisfaction).

H25: CSF (Collaboration of social forces in community governance) indirectly contributes to HCD (harmonized community development) through improved RI (resource inputs for community governance).

3.2 Step of methodology

3.2.1 Data collection

(1) Identification of research variables

Identify the key variables for the participation of multiple actors in governance in Guangxi's urban communities. This may include community resident participation, government participation, enterprise participation, non-governmental organizations, community social workers, and community resource inputs.

(2) Designing questionnaires

Identify specific questions for each variable to ensure that the question design accurately measures the variable.

(3) Sample selection

The target population of the survey was identified to ensure that the sample was representative of urban communities in Guangxi.

(4) Data collection

Questionnaire data were collected through field surveys or online surveys.

3.2.2 Data preprocessing

Data preprocessing involved a series of steps to ensure the dataset was clean, consistent, and ready for analysis. This included data cleaning, where duplicate entries were removed, inconsistencies in categorical variables were corrected (e.g., harmonizing labels like "Male" and "M"), and variable formats were standardized. Handling missing values involved analyzing the extent and patterns of missing data, with numerical variables imputed using the mean or median, categorical variables imputed using the mode, or variables excluded if missing values exceeded a predefined threshold. Outlier detection used methods such as boxplots, Z-scores, and interquartile ranges (IQR) to identify and address extreme values, ensuring valid outliers were retained for analysis. Variables were coded appropriately, with categorical variables converted into numerical formats or dummy variables for multi-level categories. Finally, standardization and normalization ensured continuous variables were scaled for comparability, with standardization (mean=0, SD=1) applied for statistical models and normalization [0,1] used for ANN inputs. This comprehensive preprocessing guaranteed the integrity and suitability of the data for subsequent analyses.

3.2.3 Selection of influencing factors

The selection of influencing factors was based on a combination of theoretical foundations, literature reviews, and practical considerations. Key variables were identified from existing research and tailored to the context of community governance in urban areas of Guangxi. These factors encompassed demographic characteristics (age, gender, education, and political identity) and governance-related variables (community collaboration, political engagement, internet usage and participation mechanisms).

3.2.3.1 Descriptive statistical analysis

Descriptive statistics were conducted to summarize and explore the dataset, laying a foundation for subsequent analysis. Summary statistics were calculated, including measures of central tendency (mean, median, mode) and dispersion (standard deviation, variance, range), to explore the distribution of key variables and identify patterns or irregularities. Frequency distributions tabulated frequencies and proportions for categorical variables (gender, education levels) and were visualized using bar charts and pie charts. Cross-tabulations examined relationships between categorical variables (political identity vs. participation level), while data visualization techniques such as histograms, boxplots, and density plots illustrated the distribution of numerical variables. Scatterplots and correlation matrices were employed to identify potential relationships between numerical variables. These analyzed provided exploratory insights, highlighting demographic patterns (age and gender distributions) and identifying preliminary trended in participation across subgroups, offering hypotheses for further analysis.

3.2.3.2 Inferential analysis: identifying key relationships

(1) Mann-Whitney test or Kruskal-Wallis test (analysis of variance)

Differences in overall satisfaction with community governance between groups will be tested using Mann-Whitney test or Kruskal-Wallis test that will look at characteristics such as age, education, and political identity. Whether there was a significant difference.

(2) Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was employed to reduce the dimensionality of the dataset, enabling the extraction of latent variables that represent key influences on participation in community governance. This technique transformed the original variables into a smaller set of uncorrelated components while retaining as much of the dataset's variance as possible.

The analysis began with the computation of a covariance or correlation matrix to understand relationships between variables. Eigenvalues were calculated to measure the amount of variance explained by each component, and a scree plot was used to visualize and determine the optimal number of components to retain. Factor loadings were analyzed to interpret the components, identifying which variables contributed most significantly to each principal component. PCA not only simplified the dataset by consolidating interrelated variables but also enhanced interpretability, ensuring that the extracted components captured the underlying structure of key factors influencing participation while minimizing redundancy. This dimensionality reduction provided a robust foundation for further statistical modeling and analysis.

3.2.3.3 Advanced modeling and prediction: validating and explaining factors

(1) Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) was utilized to validate the causal relationships among the latent variables identified through PCA, providing a comprehensive framework for examining both direct and indirect effects of key factors on participation in community governance. The analysis comprised two interconnected components: the measurement model and the structural model. The measurement model evaluated the reliability and validity of the latent constructs by confirming the consistency of observed variables with their underlying factors, using metrics such as factor loadings, composite reliability, and average variance extracted (AVE).

The structural model assessed the hypothesized relationships among latent variables, quantifying their direct and indirect influences. To ensure the model's robustness, various fit indices were employed, including the Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index

(TLI). A satisfactory fit indicated that the model adequately represented the data, providing reliable insights into the causal mechanisms underlying participation in community governance. This twofold approach enabled a detailed understanding of the structural pathways driving participation and their practical implications.

(2) Artificial Neural Network (ANN)

Artificial Neural Network (ANN) was employed to capture complex non-linear relationships and predict participation levels in community governance. By using the principal components derived from PCA and the validated variables from SEM as inputs, the ANN modeled intricate interactions between variables that traditional linear methods might overlook. The network architecture included an input layer representing key factors, one or more hidden layers to process and learn patterns, and an output layer to predict participation levels. Training the model involved optimizing weights and biases through backpropagation and minimizing prediction errors using a suitable activation function and loss function.

Additionally, a sensitivity analysis was conducted to rank the importance of input variables, identifying critical factors such as education, political identity and internet usage as the most influential on participation. This approach provided a nuanced understanding of the underlying drivers of community governance participation and enhanced the predictive accuracy of the overall analysis.

(1) Random Forest (RF)

Random Forest (RF) was employed to analyze and predict participation levels in community governance while capturing non-linear relationships and interactions among variables. By using the principal components derived from PCA and the validated variables from SEM as inputs, the RF model was able to effectively identify the relative importance of each factor in influencing participation.

The RF model consisted of an ensemble of decision trees, each trained on a random subset of the data and features. These trees collectively provided robust predictions by averaging their outputs, thereby reducing the risk of overfitting commonly observed in individual trees. Model training involved tuning hyperparameters such as the number of trees, maximum depth, and minimum samples required for splitting nodes to optimize performance. The RF algorithm also inherently evaluated feature importance by assessing the contribution of each variable to reducing prediction error across all trees in the ensemble.

Additionally, a detailed analysis of feature importance highlighted critical factors influencing participation levels. These findings aligned with the broader analysis while offering a comprehensive understanding of the key drivers in community governance. The RF model's ability to handle complex interactions and rank variable importance provided valuable insights and enhanced the overall robustness of the research conclusions.

(2) XGBoost

XGBoost (Extreme Gradient Boosting) was utilized to analyze and predict participation levels in community governance, leveraging its ability to handle complex non-linear relationships and interactions among variables. By using the principal components derived from PCA and the validated variables from SEM as inputs, XGBoost provided a highly efficient and precise framework for identifying influential factors and modeling their effects on participation.

The XGBoost model is based on gradient boosting, where multiple weak learners (decision trees) are iteratively built to minimize prediction errors. The algorithm optimized performance through advanced techniques such as regularization, weighted quantile sketching, and parallel processing, ensuring robust predictions even with small datasets.

Training involved careful tuning of hyperparameters such as learning rate, maximum tree depth, and minimum child weight to achieve an optimal balance between model complexity and prediction accuracy. XGBoost also evaluated feature importance by assessing how each variable contributed to reducing the loss function during model training.

(3) A feature importance analysis revealed key factors driving participation in community governance, underscoring their significance in fostering engagement. XGBoost's capability to capture intricate interactions, coupled with its computational efficiency, provided a comprehensive understanding of the factors influencing community participation while enhancing the overall predictive accuracy.

(4) LightGBM

LightGBM (Light Gradient Boosting Machine) was applied to analyze and predict participation levels in community governance, offering an efficient and scalable approach to modeling complex non-linear relationships among variables. Using the principal components derived from PCA and the validated variables from SEM as inputs, LightGBM provided a powerful framework for identifying critical factors and understanding their contributions to community participation.

LightGBM is based on gradient boosting but uses a unique histogram-based algorithm to speed up training and improve efficiency. It builds tree's leaf-wise with depth constraints, allowing the model to capture complex patterns in the data while preventing overfitting.

Model training included optimizing hyperparameters such as learning rate, maximum tree depth, and number of leaves to achieve optimal performance. The algorithm's inherent feature importance evaluation enabled ranking of variables based on their contribution to reducing prediction errors.

LightGBM's ability to process large numbers of features, its computational efficiency, and its accuracy made it a valuable addition to the research methodology. This approach enhanced the robustness of the findings and provided deeper insights into the dynamics of multi-subject participation in community governance.

3.2.4 Data result output

(1) Model interpretation

Explain the meaning of each path in the model and understand the effect of latent factors on the observed variables.

(2) Results of statistical analysis

Output parameter estimates, goodness-of-fit indicators, for structural equation modeling.

(3) Visualization

Use diagrams (Path diagrams) to clearly demonstrate the structure and relationships of the model.

(4) Discussion and conclusions

Provide an in-depth discussion of the results, understand the findings of the study, and draw conclusions based on the results. Discuss the critical paths and variables in the model and their impact on the participation of multiple actors in community governance.

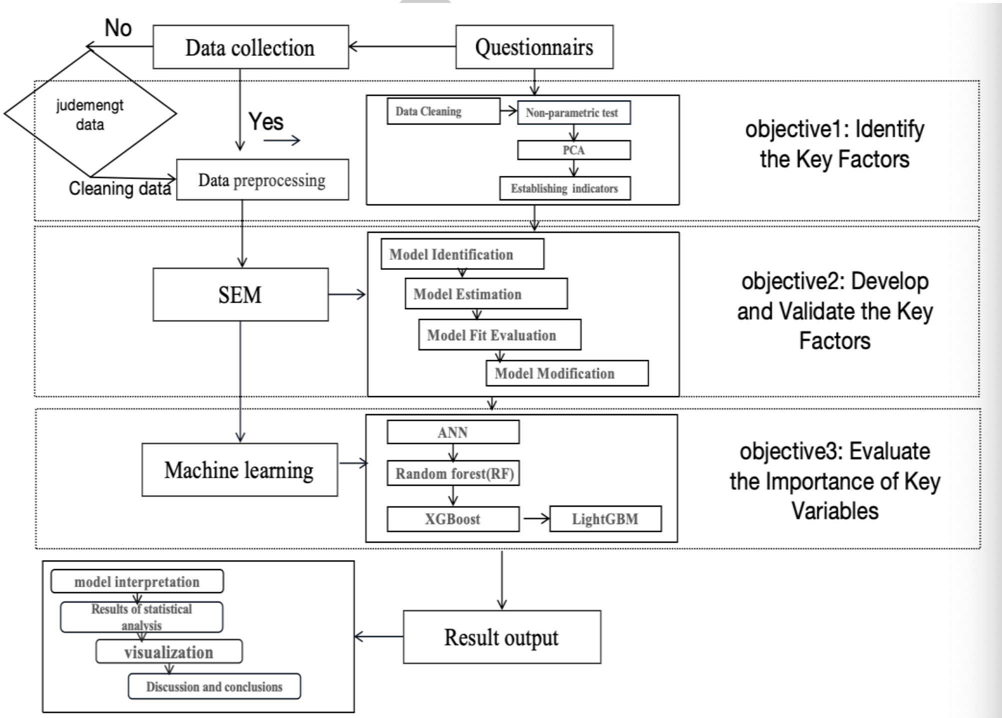

Figure 2 Step of methodology

3.3 Workflow chart

The flow chart is as follows：

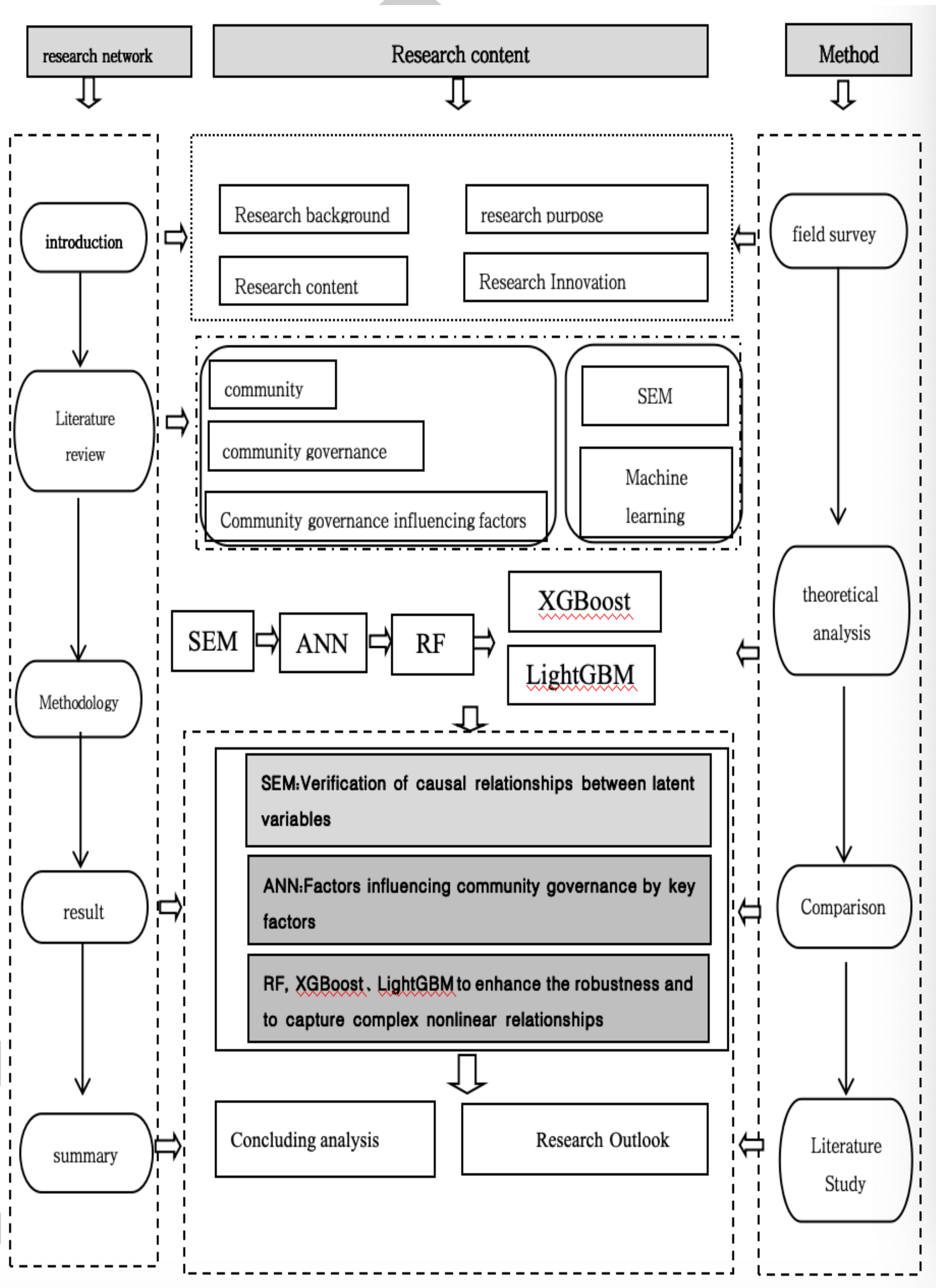

Figure 3 Workflow chart

Chapter 4

Results

This chapter identifies, validates, and evaluates key factors in community development. It analyzes survey data, conducts reliability and validity tests, and applies Structural Equation Modeling (SEM). Machine learning models (ANN, RF, XGBoost, LightGBM) assess variable importance, and their performance is compared to determine the best predictive approach.

4.1 Identify the key factors

To ensure the authenticity and rationality of the questionnaire data, this study selected communities in Nanning, Guilin, Liuzhou and ChongZuo in Guangxi for simple random sampling. A random survey was conducted in an anonymous manner to fill out the questionnaire, mainly with community residents, community committees, community workers and other community workers as the object of the survey and research. The scope of the survey covered all age groups, different ethnic ages, education levels, income levels, and residential situations. A total of 1,334 questionnaires were distributed, and 1,216 were returned, of which 1,216 were valid questionnaires, with a validity rate of about 91.15%.

Table 3 Demographic and socioeconomic characteristics of the sample

Demographic and socioeconomic characteristics of the sample							
Information	Options	Frequency	Percentage	Information	Options	Frequency	Percentage
Gender	male	626	51.5	Annual income	CNY 20 to 39 thousand	180	14.8
	female	590	48.5		CNY 40 to 59thousand	533	43.8
	total	1,216	100		60 thousand and above	503	41.4
AGE	18-24 years old	61	5		total	1,216	100
	25-35 years old	114	9.4	Length of residence	Within 1 year	46	3.8
	36-44 years old	483	39.7		1 to 3 years	137	11.3
	45-60 years old	330	27.1		4 to 6 years	295	24.3
	61 years and over	228	18.8		7 to 10 years	477	39.2
	total	1,216	100		10 years and above	261	21.5

Demographic and socioeconomic characteristics of the sample							
Information	Options	Frequency	Percentage	Information	Options	Frequency	Percentage
Political identity （PI）	the masses	591	65		total	1,216	100
	CPC member (including reserve member)	331	10.8	Type of residence	commercial property	83	6.8
	Other parties	294	24.2		Unit housing	188	15.5
	total	1,216	100		Rental housing	448	36.8
Level of education	Primary and below	52	4.3		Self-built housing	279	22.9
	junior high school	133	10.9		housing for low-income families	218	17.9
	senior high school	318	26.2		total	1,216	100
	university	533	43.8				
	postgraduate	180	14.8				
	total	1,216	100				

4.1.1 Overview of the survey sample

Based on the samples collected during March-July 2023, the sample was specifically summarized below (Table 3), in terms of gender, the proportion of males was 51.5% and the proportion of females is 48.5%, with the proportion of males being higher than that of females; in terms of age composition, 5% were 18-24 years old, 9.4% were 25-35 years old, 39.7% were 36-44 years old, 27.1% were 45-60 years old, and 18.8% were over 61 years old; from political identity, the masses accounted for the largest share of 65%, the Communist Party of China(CPC) and its reserve members for 10.8%, and other parties for 24.2%; education level, 15.2% with junior high school education or less, 26.2% with high school education, 43.8% with university education, 14.8% with postgraduate education; the annual income of the respondents, CNY 20 to 39 thousands accounted for 14.8%, CNY 40 to 59 thousands accounted for 43.8%, and 60 thousands and above accounted for 41.5%; years of residence, 3.8%, 11.3%, 24.3%, 39.2% and 21.5% were less than 1 year, 1-3 years, 4-6 years, 7-10 years and more than 10 years respectively; the types of dwellings were

6.8%, 15.5%, 36.8%, 22.9% and 17.9% of the total number of dwellings for moving commercial housing, flats, rental housing, self-constructed housing, and relocation housing, respectively.

In summary, the sample data profoundly reflect the diverse face of community governance. The proportion of men is close to that of women, with 51.5 % of men and 48.5% of women, but slightly lower for women, emphasizing the importance of ensuring gender equality and elevating women's voices in decision-making. The high percentage of young and middle-aged people (49.1%) as the mainstay of governance highlights the dynamism and innovation, and digital platforms had become a new way for them to participate efficiently. The rich experience and deep emotions of the middle-aged and elderly groups (45.9%) were valuable assets of the community, and it was crucial to strengthen their sense of belonging through activities. Although the number of party members was small (10.8%), they lead the way like a lighthouse; the mass base was solid (65%), and the concept of pluralistic and shared governance needed to be practiced in depth. A high level of education (58.6%) provided fertile ground for innovation in governance, while good economic status (85.3% of the high-income group) laid the cornerstone for development, without forgetting to care for the low-income group and share the fruits of governance. Long-term residents (over 60%) build the solid foundation of the community, and activities deepen the emotional ties between residents to build a harmonious community.

4.1.2 Variables outcome statistics

In this paper, the collected valid questionnaires were analyzed to test whether they meet the requirements of normal distribution. The kurtosis test (absolute value not exceeding7), skewness test (absolute value not exceeding3) (Kim, 2013) and standard deviation (SD) of the data revealed that the sample data roughly conformed to a normal distribution.

Table 4 Descriptive statistics of dependent variable

Descriptive statistics of dependent variable					
Item	N	Average	SD	Skewness	Kurtosis
HCD1	1,216	3.822	1.162	-0.854	0.101
HCD2	1,216	3.771	1.166	-0.982	0.413
HCD3	1,216	3.654	1.139	-0.721	0.09

Further analysis of the data of the dependent variable in Table 4 concluded that the mean values of the three observed variables of the dependent variable overall satisfaction with harmonious community development (HCD) are 3.822, 3.771 and 3.654, with an overall mean value around 3.7, indicating that the current participation of multiple subjects in urban community governance had a high level of overall satisfaction with the development of a harmonious community, in which the respondents' evaluation of the current state of community governance and their sense of belonging were higher, however, the satisfaction with the future development of the community was relatively poor, but the community still needed to be strengthened in the planning of future development, in order to enhance the confidence and satisfaction of residents in the long-term development of the community.

Table 5 Descriptive statistics of independent variables

Descriptive statistics of independent variables					
Item	N	Average	SD	Skewness	Kurtosis
PL1	1,216	3.584	1.047	-0.831	0.545
PL2	1,216	3.577	1.095	-0.87	0.41
PL3	1,216	3.92	1.162	-1.205	0.828
PL4	1,216	3.636	1.041	-1.073	0.947
PL5	1,216	3.549	1.013	-1.015	0.899
CRS1	1,216	3.66	1.113	-0.769	0.217
CRS2	1,216	3.614	1.104	-0.66	0.091
CRS3	1,216	3.789	1.066	-1.135	1.005
CWB1	1,216	3.732	1.256	-0.595	-0.715
CWB2	1,216	3.691	1.177	-0.449	-0.696
CWB3	1,216	3.923	1.2	-0.795	-0.549
CSF1	1,216	3.516	1.074	-0.234	-0.675
CSF2	1,216	3.697	1.163	-0.517	-0.696
CSF3	1,216	3.588	1.143	-0.346	-0.704
CSF4	1,216	3.584	1.047	-0.504	-0.654

Table 5 the independent variables, from the community party organization to lead community governance(PL), the mean value of the topic was about 3.6, in which the community party organization work satisfaction score had the highest mean value, the community party organization construction, party members to play a role in the enthusiasm and the activity of the satisfaction of the community party organization is a little lower, indicating that from the overall view of the community party organization to play a positive role in leading community governance role, especially in job satisfaction. However, there was still room for improvement in the construction of community party organizations, the enthusiasm of party members and the activity of organizational activities, and there was a need to further optimize the organizational structure, stimulate the vitality of party members, and enhance organizational cohesion to promote the development of a harmonious community in a more comprehensive way.

In terms of community residents' participation in self-governance (CRS), the mean value was around 3.6, with community residents' satisfaction in political participation, representation of community residents' representatives, and community residents' ability to self-organize being in the upper-middle range. This indicated that the residents' enthusiasm for self-government participation and self-organization ability had yet to be strengthened. Although residents had some awareness of political participation, the breadth and effectiveness of representation still need to be improved. At the same time, residents' ability to self-organize and solve community problems had not yet reached an ideal state, which required more support and training from the community to stimulate residents' potential for self-governance, and to jointly promote the development of the community in the direction of greater democracy and self-governance.

From the analysis of community workforce building (CWB), the mean value is around 3.7, of which the mean value of the working ability of the secretary of the community party organization is 3.923, and the community workforce and the community workers had sufficient professional capacity was slightly lower, 3.732 and 3.691, respectively, which suggested that the secretary of the party organization had an important role to play in the community governance, and its working ability and leadership had been relatively highly recognized, and the professional capacity building of the community worker team in the participation of multiple subjects in community governance still needs to be strengthened.

In terms of collaborative community governance by social forces (CSF), the mean value of the independence of social organizations' participation was 3.697, the mean value of the richness of the content of social organizations' activities and services was 3.584, the mean value of the recognition of the active participation of social organizations was 3.588, and the mean value of the frequency of the activities and service projects of social organizations was 3.516. These data showed that social organizations show a certain amount of autonomy and activity, but there was still room for improvement in the recognition of active participation and the frequency of activities. In the future, it was necessary to strengthen the capacity building of social organizations and improve the quality and efficiency of their services to enhance their influence and role in community governance.

Table 6 Descriptive statistics of mediating variables

Descriptive statistics of mediating variables					
Item	N	Average	SD	Skewness	Kurtosis
CI1	1,216	3.747	1.063	-0.945	0.708
CI2	1,216	3.668	0.974	-1.075	1.334
CI3	1,216	3.669	0.983	-1.115	1.373
RI1	1,216	3.539	1.114	-0.503	-0.371
RI2	1,216	3.405	1.193	-0.25	-0.893
RI3	1,216	3.726	1.192	-0.593	-0.484
RI4	1,216	3.465	1.237	-0.223	-0.994
RS1	1,216	3.966	1.029	-1.089	1.036
RS2	1,216	4.007	1.08	-1.181	1.003
RS3	1,216	4.075	1.132	-1.359	1.303

Table 6 the mediator variables, urban community integration satisfaction (CI), the mean value of perceived evaluation of community culture 3.747, the mean value of the degree of harmony in the community neighborhood 3.668, the mean value of the values and concepts advocated by the community 3.669, indicated that urban community integration satisfaction was high, residents' perceived evaluation of the community culture was positive, the degree of harmony in the community neighborhood, and the values and concepts advocated by the community had all been better recognized. This reflected that the community's efforts to promote the integration of residents, create a favorable cultural atmosphere and transmit positive values had begun to bear fruit.

In terms of resource input (RI) for community governance, the mean value of the government’s public financial investment in community governance was 3.539, showing that the government had continued to invest in supporting community development, but there was still room for improvement. The mean value of public service facilities in the community was 3.405, indicating that although public service facilities can meet basic needs, they still need to be improved. The mean value of convenient service facilities in the community was 3.726, which was relatively high, reflecting that the community had made more efforts to improve the convenience of residents' lives. Overall, the investment of community governance resources was steadily developing in the direction of improving the quality of life of residents.

Community residence satisfaction (RS), community service level, residents' political participation level, and community quality of life satisfaction means were 3.966, 4.007, and 4.075, respectively. Community residence satisfaction (RS)was high, which was reflected in the fact that the community service level (4.007) and the residents' political participation level (4.075) were highly rated, showing that the community management was efficient and democratic. Meanwhile, the average value of satisfaction with the quality of life in the community reached 3.966, indicating that residents were satisfied with the overall living environment and that community building was effective.

4.1.3 Comparison of respondents' individual characteristics by dependent variable

Differences in respondents' individual characteristics can lead to differences in residential satisfaction among multiple subjects in urban communities. Therefore, it is important to explore the effects of these individual differences on residential satisfaction in urban communities. This paper will examine the differences in community residence satisfaction between different groups in terms of gender, age, political affiliation, education, annual income, years of residence and type of residence.

4.1.3.1 Gender difference

The results of the independent samples Mann-Whitney test show that, for the three items HCD1, HCD2 and HCD3, the difference in mean values between the gender was not statistically significant.

Table 7 Summary statistics of Harmonious Community Development for gender group and the result of Mann-Whitney test

Item	Gender	N	Averages	SD	Mann-Whitney U	p-value
HCD1	male	626	3.82	1.19	182,691	0.735
	female	590	3.83	1.13		
HCD2	male	626	3.78	1.22	178,530	0.294
	female	590	3.77	1.11		
HCD3	male	626	3.69	1.17	173,710.5	0.062
	female	590	3.62	1.11		

This Table 7 presents the results of the **Mann-Whitney U test** comparing **harmonious community development (HCD) scores** between **male and female respondents**. For HCD1, the mean score for males (3.82) and females (3.83) is nearly identical, with a **p-value of 0.735**, indicating **no statistically significant difference**. Similarly, for HCD2, the mean scores for males (3.78) and females (3.77) are very close, and the **p-value of 0.294** suggests **no significant difference** between genders. For HCD3, the mean score for males (3.69) is slightly higher than for females (3.62), with a **p-value of 0.062**, which is slightly above the 0.05 significance threshold, indicating **a marginal but not statistically significant difference**.

Since all **p-values are greater than 0.05**, the results suggest that there is **no statistically significant difference** in **harmonious community development (HCD) scores** between male and female respondents. The small differences in average scores indicate that gender does not have a meaningful impact on respondents' perceptions of HCD.

4.1.3.2 Age difference

For all three HCD indicators (HCD1, HCD2, and HCD3), all p-values are less than 0.001, indicating significant differences among the age groups.

Table 8 *Summary statistics of Harmonious Community Development for age group and the result of Kruskal-Wallis test*

Summary statistics of Harmonious Community Development for age group and the result of Kruskal-Wallis H						
Variables	Age	N	Averages	SD	Kruskal-Wallis H	p-value
HCD1	18-24 years old	61	1.85	1.263	131.145	<.001
	25-35 years old	114	3.171	1.289		
	36-44 years old	483	3.56	1.032		
	45-60 years old	330	3.709	1.042		
	61 years old and over	228	3.76	0.966		
HCD2	18-24 years old	61	1.85	1.263	92.808	<.001
	25-35 years old	114	3.171	1.289		
	36-44 years old	483	3.56	1.032		
	45-60 years old	330	3.709	1.042		
	61 years old and over	228	3.76	0.966		
HCD3	18-24 years old	61	1.85	1.263	109.542	<.001
	25-35 years old	114	3.171	1.289		
	36-44 years old	483	3.56	1.032		
	45-60 years old	330	3.709	1.042		
	61 years old and over	228	3.76	0.966		

The Table 8 presents the **Kruskal-Wallis H test** results, comparing **harmonious community development (HCD) scores** across different **age groups**. For all three HCD indicators (HCD1, HCD2, and HCD3), all p-values are less than 0.001, indicating that **there are significant differences** among the age groups. The **Kruskal-Wallis H values** for HCD1 (131.145), HCD2 (92.808), and HCD3 (109.542) suggest that the differences between age groups are statistically meaningful.

Looking at the average scores, the **18-24 age group consistently has the lowest scores (1.85)**, while **older age groups (36 and above) tend to have higher scores (3.5-3.76)**. This suggests that **older respondents perceive higher levels of harmonious community development compared to younger respondents**, which may reflect differences in experience, expectations, or community engagement. Further post-hoc tests would be needed to determine **which specific age groups differ significantly from each other**.

4.1.3.3 Political appearance

This table presents the differences in harmonious community development (HCD) scores among groups with different political appearances, analyzed using the Kruskal-Wallis H test.

Table 9 Summary statistics of Harmonious Community Development for political appearance group and the result of Kruskal-Wallis test

Summary statistics of Harmonious Community Development for political appearance group and the result of Kruskal-Wallis test						
Variables	Political appearance	N	Averages	SD	Kruskal-Wallis H	p-value
HCD1	the masses	791	3.81	1.16	12.07	0.002
	CPC member (including reserve member)	131	3.44	1.34		
	Other parties	294	3.82	1.07		
HCD2	the masses	791	3.81	1.16	8.162	0.017
	CPC member (including reserve member)	131	3.44	1.34		
	Other parties	294	3.82	1.07		
HCD3	the masses	791	3.81	1.16	16.441	<.001
	CPC member (including reserve member)	131	3.44	1.34		
	Other parties	294	3.82	1.07		

Table 9 shows that masses and other party members have higher HCD scores, while CPC members (including reserve members) score lower. The p-values for HCD1, HCD2, and HCD3 are all below 0.05, indicating that political affiliation significantly impacts HCD scores, with the greatest difference in HCD3 ($p < 0.001$).

Specifically, masses and other party members scored similarly for HCD1 (3.81 and 3.82), while CPC members scored lower (3.44). The Kruskal-Wallis test showed significant differences among political groups ($H = 12.07$, $p = 0.002$). For HCD2, the H value is 8.162 ($p = 0.017$), and for HCD3, the H value is 16.441 ($p < 0.001$), showing the most significant difference.

The lower scores among CPC members may reflect their higher expectations and involvement in governance, making them more aware of community issues. In contrast, the higher scores from the masses and other party members may stem from their more positive perception of community harmony. The greatest difference in HCD3 suggests political affiliation has a stronger impact on specific aspects of community governance, such as cohesion and resident interactions. Further post-hoc tests could clarify the sources of these differences.

4.1.3.4 Educational level

The results show significant differences in harmonious community development (HCD) scores across different educational levels for all three HCD variables (HCD1, HCD2, and HCD3).

The results of the Kruskal-Wallis test (Table 10) show strong statistical significance ($p < 0.001$) for each variable, indicating that educational attainment significantly influences perceptions of community harmony. Specifically, individuals with higher education levels—such as those with senior high school, university, or postgraduate degrees—report significantly higher HCD scores than those with lower education levels, such as primary or junior high school.

The lower scores observed in the "Primary and below" group (average of 1.71) contrast sharply with the higher scores of those with senior high school education or higher (averages between 3.87 and 3.99). This pattern indicates that educational attainment may be linked to a more positive perception of community development and harmony, possibly due to greater awareness, knowledge, or engagement in community-related activities. These findings highlight the importance of education in shaping individuals' perspectives on the success and progress of community governance and development.

Table 10 Summary statistics of Harmonious Community Development for educational level group and the result of Kruskal-Wallis test

Summary statistics of Harmonious Community Development for Educational level group and the result of Kruskal-Wallis test						
Variables	Educational level	N	Averages	SD	Kruskal-Wallis H	p-value
HCD1	Primary and below	52	1.71	1.07	119.401	<.001
	junior high school	133	3.52	1.33		
	senior high school	318	3.98	1.07		
	University (specialized or bachelor's degree)	533	3.99	1.02		
	postgraduate student	180	3.87	0.98		
HCD2	Primary and below	52	1.71	1.07	83.023	<.001
	junior high school	133	3.52	1.33		
	senior high school	318	3.98	1.07		
	University (specialized or bachelor's degree)	533	3.99	1.02		
	postgraduate student	180	3.87	0.98		
HCD3	Primary and below	52	1.71	1.07	96.602	<.001
	junior high school	133	3.52	1.33		
	senior high school	318	3.98	1.07		
	University (specialized or bachelor's degree)	533	3.99	1.02		
	postgraduate student	180	3.87	0.98		

4.1.3.5 Annual income level

The summary statistics for harmonious community development (HCD) across different annual income levels reveal significant differences in perceptions of community harmony.

Table 11 Summary statistics of Harmonious Community Development for annual income level group and the result of Kruskal-Wallis test

Summary statistics of Harmonious Community Development for annual income level group and the result of Kruskal-Wallis test						
Variables	Annual income level	N	Averages	SD	Kruskal-Wallis H	p-value
HCD1	CNY20-39k	180	3.06	1.51	53.617	<.001
	CNY40-59k	533	3.94	1.07		
	CNY60k and above	503	3.99	0.99		
HCD2	CNY20-39k	180	3.06	1.51	52.38	<.001
	CNY40-59k	533	3.94	1.07		
	CNY60k and above	503	3.99	0.99		
HCD3	CNY20-39k	180	3.06	1.51	61.606	<.001
	CNY40-59k	533	3.94	1.07		
	CNY60k and above	503	3.99	0.99		

The Kruskal-Wallis test results (Table 11) for HCD1, HCD2, and HCD3 all show p-values below 0.001, indicating that annual income level significantly affects HCD scores. The group with an annual income of CNY 20-39k reported the lowest average scores for all three HCD variables (averages around 3.06), while those in the CNY 40-59k and CNY 60k and above income brackets reported significantly higher scores (averages ranging from 3.94 to 3.99). This suggests that higher income levels are associated with more positive perceptions of community development.

The lower HCD scores for the CNY 20-39k income group may reflect financial constraints or other challenges that influence their view of community governance and harmony. In contrast, the higher HCD scores in the CNY 40-59k and CNY 60k and above groups suggest that individuals with higher incomes may have greater satisfaction with community development, possibly due to improved living conditions or greater involvement in community activities. These findings highlight the role that income plays in shaping individuals' perceptions of community harmony and overall development, with wealthier groups generally reporting more positive views.

4.1.3.6 Length of residence

The summary statistics for harmonious community development (HCD) across different lengths of residence indicate significant differences in perceptions of community harmony.

Table 12 *Summary statistics of Harmonious Community Development for length of residence group and the result of Kruskal-Wallis test*

Summary statistics of Harmonious Community Development for Length of residence group and the result of Kruskal-Wallis test						
Variables	Length of residence	N	Averages	SD	Kruskal-Wallis H	p-value
HCD1	Within 1 year	46	1.59	1.05	111.991	<.001
	1-3 years	137	3.53	1.33		
	4-6 years	295	3.84	1.06		
	7-10 years	477	4.00	1.04		
	10 years and above	261	4.02	0.96		
HCD2	Within 1 year	46	1.59	1.05	104.07	<.001
	1-3 years	137	3.53	1.33		
	4-6 years	295	3.84	1.06		
	7-10 years	477	4.00	1.04		
	10 years and above	261	4.02	0.96		
HCD3	Within 1 year	46	1.59	1.05	96.926	<.001
	1-3 years	137	3.53	1.33		
	4-6 years	295	3.84	1.06		
	7-10 years	477	4.00	1.04		
	10 years and above	261	4.02	0.96		

The Kruskal-Wallis test results (Table 12) for HCD1, HCD2, and HCD3 all show p-values below 0.001, suggesting that the length of residence significantly affects HCD scores. The group with a residence length of "within 1 year" reported the lowest average scores (around 1.59), while individuals residing in the community for longer periods (7-10 years and 10 years and above) reported the highest scores (averages of 4.00 and 4.02). This trend suggests that longer residence is associated with more positive perceptions of community development.

The lower HCD scores for those living in the community for one year or less may reflect the challenges faced by newcomers, such as adapting to the community and less familiarity with local governance. In contrast, individuals who have resided in the community for longer periods may have developed a stronger sense of belonging and satisfaction with the community's development and governance. These findings emphasize the role that the length of residence plays in shaping individuals' perceptions of community harmony, with longer-term residents generally reporting more favorable views of community development.

4.1.3.7 Type of residence

The summary statistics for harmonious community development (HCD) across different types of residence reveal significant differences in perceptions of community harmony.

Table 13 Summary statistics of Harmonious Community Development for type of residence group and the result of Kruskal Wallis test

Summary statistics of Harmonious Community Development for Type of residence group and the result of Kruskal Wallis test						
Variables	Type of residence	N	Averages	SD	Kruskal Wallis H	p-value
HCD1	Commercial property	83	2.48	1.72	61.772	<.001
	Unit housing	188	3.74	1.08		
	Rented housing	448	3.93	1.09		
	Self-built house	279	3.88	1.05		
	Resettlement housing	218	4.11	0.87		
HCD2	Commercial property	83	2.48	1.72	92.678	<.001
	Unit housing	188	3.74	1.08		
	Rented housing	448	3.93	1.09		
	Self-built house	279	3.88	1.05		
	Resettlement housing	218	4.11	0.87		
HCD3	Commercial property	83	2.48	1.72	86.108	<.001
	Unit housing	188	3.74	1.08		
	Rented housing	448	3.93	1.09		
	Self-built house	279	3.88	1.05		
	Resettlement housing	218	4.11	0.87		

The Kruskal-Wallis test results (Table 13) for HCD1, HCD2, and HCD3 all show p-value below 0.001, indicating that the type of residence significantly influences HCD scores. The group living in commercial properties reported the lowest average scores for all three HCD variables (around 2.48), while those living in resettlement housing reported the highest scores (averages ranging from 4.11). Other types of housing, such as unit housing, rented housing, and self-built houses, showed moderate HCD scores (ranging from 3.74 to 3.93).

The lower scores for individuals residing in commercial properties may reflect the temporary or less stable nature of these living arrangements, which could contribute to a less positive perception of community development. In contrast, residents in resettlement housing, who may experience more stable and community-focused living conditions, reported significantly higher scores, suggesting greater satisfaction with community governance. These findings highlight how the type of residence can shape individuals' views of community harmony, with those in more stable housing arrangements generally perceiving their communities more positively.

4.1.4 Questionnaire reliability and validity analysis

4.1.4.1 Questionnaire reliability analysis

Reliability validation is primarily designed to test the internal consistency and stability of the relevant items in the questionnaire (or the questionnaire as a whole) in measuring the same concepts. This measure of internal consistency is widely evaluated using Cronbach's α coefficient. The closer the value of the α coefficient converges to 1, the higher the reliability of the questionnaire, the greater the uniformity and stability of the questions within it or of the questionnaire in measuring a particular concept. The internal consistency of the questionnaire is high when the α coefficient is at or above 0.7, which indicates that the reliability of the questionnaire is high. The reliability analysis of the metric items of this questionnaire was conducted using SPSS 29.0 software and the results are shown in Table14.

Table 14 Reliability statistics of the questionnaire

Reliability statistics of the questionnaire		
Cronbach's α coefficient	Cronbach's α based on standardized terms	Item
0.931	0.932	28

The Cronbach's α coefficient reached 0.931, indicating that the designed metric items are reasonable.

4.1.4.2 Questionnaire validity analysis

The validity test measures the ability of the variables to accurately capture the essence of the research question and the comprehensiveness of the questionnaire content.

Table 15 Validity statistics of the questionnaire

KMO and Bartlett's test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.918
Bartlett's test of sphericity	Approximate Chi-Square	22,614.112
	Degrees of freedom	378
	Significance	<.001

In this paper, validity analyses aim to quantify the extent to which changes in specific measurable variables contribute to the total variability in satisfaction. A variable is a valid indicator if the variance of its score accounts for a significant proportion of the total variance. Validity values range from 0 to 1, with high values meaning that the variable indicator is more valid. The validity value of each measurable variable was calculated using SPSS 29.0 software, and the results are shown in Table15, with a KMO value of 0.918, which indicates that the questionnaire is highly valid, and indicates that the sample data is suitable for factor analysis.

4.1.5 Exploratory factor analysis (EFA)

The application of exploratory factor analysis (EFA) in SPSS 29.0 aims to reveal whether there are a few core factors that can summarize and explain a range of variables with complex interactions.

Table 16 Inter-variable metric variance

Common factor variance					
Observed variables	Initial value	Extraction	Observed variables	Initial value	Extraction
PL1	1	0.66	CI1	1	0.739
PL2	1	0.706	CI2	1	0.738
PL3	1	0.68	CI3	1	0.717
PL4	1	0.765	RI1	1	0.713
PL5	1	0.712	RI2	1	0.698
CRS1	1	0.804	RI3	1	0.79
CRS2	1	0.642	RI4	1	0.723
CRS3	1	0.776	RS1	1	0.789
CWB1	1	0.897	RS2	1	0.855
CWB2	1	0.829	RS3	1	0.869
CWB3	1	0.829	HCD1	1	0.667
CSF1	1	0.795	HCD2	1	0.806
CSF2	1	0.842	HCD3	1	0.712
CSF3	1	0.873			
CSF4	1	0.875			
Extraction method: principal component analysis (PCA).					

Through the implementation of the principal component analysis (PCA) method, we verified the underlying structure between these variables, and the results showed that the commonality (common factor variance) of all 28 observed variables exceeded the threshold of 0.5, and most of them reached or approached the high level of 0.7(Table16). These variables can be effectively explained and represented by the extracted common factors largely suggesting that our factor analysis model is better able to capture and reflect the intrinsic links between these variables.

In Table 16, we observe that each variable has a communality value indicating how much of its variance is explained by the common factors. A communality value above 0.5 suggests that more than half of the variable's variance is accounted for by the extracted factors, which is considered satisfactory for ensuring reliable interpretations. Values approaching or reaching 0.7 indicate even stronger representation, implying that the majority of the variable's information is captured by the common factors.

Table 17 Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalue			Extracting the Sum of Squares of Loadings			Sum of Squares of Rotating Loads		
	Total	Percentage variance	Cumulative %	Total	Percentage Variance	Cumulative %	Total	Percentage Variance	Cumulative %
1	9.91	35.38	35.38	9.91	35.38	35.38	3.71	13.25	13.25
2	2.58	9.22	44.59	2.58	9.22	44.59	3.46	12.37	25.62
3	2.49	8.90	53.49	2.49	8.90	53.49	2.99	10.66	36.31
4	1.98	7.06	60.55	1.98	7.06	60.55	2.51	8.97	45.28
5	1.45	5.17	65.72	1.45	5.17	65.72	2.51	8.96	54.24
6	1.25	4.46	70.18	1.25	4.46	70.18	2.21	7.89	62.13
7	1.01	3.61	73.79	1.01	3.61	73.79	2.12	7.56	69.69
8	0.84	3.0	76.79	0.84	3.0	76.79	1.99	7.10	76.79
Extraction method: principal component analysis (PCA).									

As shown in Table 17, eight common factors with eigenvalues greater than 1 were extracted by principal component analysis (PCA) method. The cumulative explanation of the total variance of these factors amounted to 76.79%, exceeding the 60% requirement. This result indicates that the extracted common factors have a greater influence on the original variables and can explain the relationship between the variables better.

Table 18 Component matrix after rotation

Rotated Component Matrix[a]								
Variables	Component							
	1	2	3	4	5	6	7	8
PL1	0.728							
PL2	0.763							
PL3	0.747							
PL4	0.814							
PL5	0.776							
CRS1								0.791

Rotated Component Matrix[a]								
Variables	Component							
	1	2	3	4	5	6	7	8
CRS2								0.641
CRS3								0.771
CWB1					0.866			
CWB2					0.838			
CWB3					0.83			
CSF1		0.858						
CSF2		0.879						
CSF3		0.907						
CSF4		0.889						
CI1							0.76	
CI2							0.695	
CI3							0.756	
RI1			0.793					
RI2			0.803					
RI3			0.825					
RI4			0.803					
RS1				0.772				
RS2				0.838				
RS3				0.841				
HCD1						0.717		
HCD2						0.842		
HCD3						0.781		
Extraction method: principal component analysis (PCA).								
Rotation method: kaiser normalized maximum variance method.								
a. The rotation has converged after 6 iterations.								

Through the orthogonal rotation method, convergence was achieved after 6 iterations, with loadings greater than 0.6 for each item (Table18), and no high dual factor loadings were observed. This suggests that the multiple subject participation in urban community residence satisfaction scale has good construct validity for further research and analysis. In the rotated factor matrix, observed variables with loadings greater than 0.6 on common factor 1 includes satisfaction with the building of community party organizations, the role of party members in the area where you live, satisfaction with the work of party organizations in the community, party building to promote innovation in community governance, activity in services or activities related to party organizations, corresponding factor loadings is 0.728-0.814.

Observed variables with loadings greater than 0.6 on public factor 2 includes participation of units in the district in community building and governance, satisfactory participation of social organizations in community governance, recognition of social organizations as proactive participants in urban community governance, social organizations are more independent in their participation in urban community governance, corresponding factor loadings is 0.858-0.907.

Observed variables with loadings greater than 0.6 on public factor 3 includes level of public financial inputs by the government to community governance, satisfaction with public service facilities in the community, accessibility of community amenities, construction and experience of using the community information platform, corresponding factor loadings is 0.793-0.825.

Observed variables with loadings greater than 0.6 on public factor 4 includes satisfaction with the level of community services, own level of political participation, satisfaction with the quality of life in the community, corresponding factor loadings is 0.772-0.841.

Observed variables with loadings greater than 0.6 on public factor 5 includes satisfaction with the composition of the community workforce, community workers have adequate professional qualifications, work capacity of community clerks, corresponding factor loadings is 0.830-0.866.

Observed variables with loadings greater than 0.6 on public factor 6 includes overall assessment of the current state of governance in your community, do you feel a sense of belonging in this neighborhood, do you care about the neighborhood, corresponding factor loadings is 0.717-0.842.

Observed variables with loadings greater than 0.6 on public factor 7 includes perceived evaluation of community culture, perceived level of harmony in community neighborhoods, degree of agreement with the values and philosophies promoted by the community, corresponding factor loadings is 0.695-0.760.

Observed variables with loadings greater than 0.6 on common factor 8 includes satisfactory representation of community residents' representatives, capacity of community residents in self-organization, capacity of community residents in terms of political participation, corresponding factor loadings is 0.641-0.791. It indicates that the convergent validity is strong, the data authenticity is reliable, and the questionnaire items are generally well-designed.

4.1.6 Related analysis

Table 19 Correlation table of Residential Satisfaction in urban neighborhoods

Item		PL	CI	RI	RS	CWB	CRS	CSF	HCD
PL	Pearson's correlation	1	0.4**	0.41**	0.36**	0.52**	0.62**	0.35**	0.37**
	Significance (two-sided)		<.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
CI	Pearson's correlation	0.4**	1	0.34**	0.65**	0.35**	0.39**	0.29**	0.51**
	Significance (two-sided)	<0.05		<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
RI	Pearson's correlation	0.41**	0.34**	1	0.36**	0.33**	0.38**	0.31**	0.30**
	Significance (two-sided)	<0.05	<0.05		<0.05	<0.05	<0.05	<0.05	<0.05
RS	Pearson's correlation	0.36**	0.65**	0.36**	1	0.35**	0.35**	0.31**	0.47**
	Significance (two-sided)	<0.05	<0.05	<0.05		<0.05	<0.05	<0.05	<0.05
CWB	Pearson's correlation	0.52**	0.35**	0.33**	0.35**	1	0.48**	0.28**	0.32**
	Significance (two-sided)	<0.05	<0.05	<0.05	<0.05		<0.05	<0.05	<0.05
CRS	Pearson's correlation	0.62**	0.39**	0.38**	0.35**	0.48**	1	0.36**	0.35**
	Significance (two-sided)	<0.05	<0.05	<0.05	<0.05	<0.05		<0.05	<0.05
CSF	Pearson's correlation	0.35**	0.29**	0.30**	0.31**	0.28**	0.36**	1	0.30**
	Significance (two-sided)	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05		<0.05
HCD	Pearson's correlation	0.37**	0.51**	0.30**	0.47**	0.32**	0.35**	0.30**	1
	Significance (two-sided)	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	

**. Significantly correlated at the .05 level (two-sided). N=1216

In the correlation matrix between the variables (Table19), all the variables showed a significant positive correlation($p<0.05$), which indicates a significant linear relationship between the variables. Specifically:

Correlation between party leadership (PL)and other variables: party leadership (PL) with community integration (CI), resource inputs (RI), resident satisfaction (RS), community workforce building (CWB), community resident self-governance (CRS), collaboration of social forces (CSF), harmonized community development (HCD) all showed positive correlation with correlation coefficients of 0.40, 0.41, 0.36, 0.52, 0.62, 0.35 and 0.37, respectively.

Correlations between community integration (CI) and other variables: community integration (CI) with resource inputs (RI), resident satisfaction (RS), community workforce building (CWB), community resident self-governance (CRS), Collaboration of social forces (CSF), harmonized community development (HCD) all showed positive correlation with correlation coefficients of 0.34, 0.65, 0.35, 0.39, 0.29 and 0.51, respectively.

Correlations between other variables: The correlation between resource inputs (RI) and resident satisfaction (RS) was 0.36, resident satisfaction (RS) and harmonized community development (HCD) was 0.47, and community resident self-governance (CRS) was 0.48. The correlation between community resident self-governance (CRS) and community workforce building (CWB) is 0.48. Overall, the correlation data between these variables suggests that they are interrelated to some degree.

Correlation analysis is a prerequisite for structural equation modeling, and after verifying the correlation of the variables, the next step will be to verify the magnitude of the influence of the factors and the explanatory strength of the observed variables through the establishment of structural equation modeling.

4.2 Develop and validate the key factors

R 4.4.1 software was utilized to construct and validate the structural equation model, aiming to explore the latent influences on the development of harmonious community under the participation of multiple actors in Guangxi urban communities. The study constructed a model diagram which demonstrated the standardized path coefficients as well as the significance relationships among the variables to provide a basis for empirical analysis. The model covers 8 potential variables and 28 observable variables. Based on the theoretical basis and assumptions of the study, the structural equation path analysis diagram is shown in Fig 4, and the interpretations are followed Table 20 and Table 21.

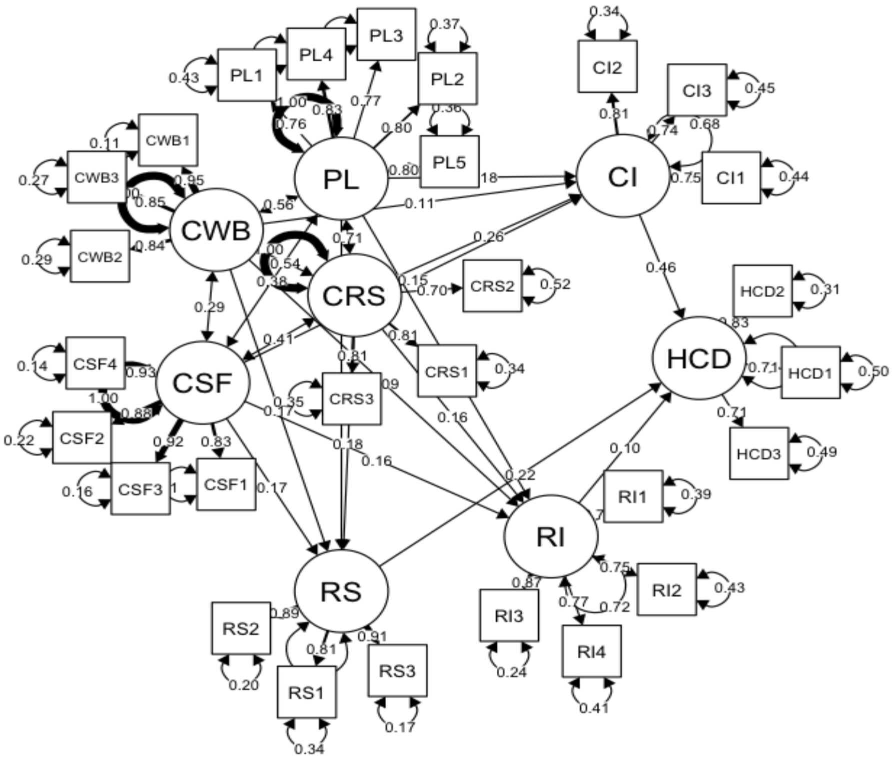

Figure 4 Path analysis of structural equation of multi-subject participation in urban community governance

Table 20 Indicators of model fit of SEM

Fit indices	Estimates	Recommended value
$\chi2/df$	4.622	<5
RMSEA	0.055	≤0.08
RMR	0.077	<0.08
GFI	0.922	≥0.90
AGFI	0.904	>0.90
NFI	0.933	≥0.90
CFI	0.947	>0.90
TLI	0.939	≥0.90
IFI	0.947	≥0.90

The resulting model fit from the structural equation analysis is demonstrated in Table 20. The results of the overall fit analysis show that the ratio of the chi-square value to the degrees of freedom is 4.622, and this value is less than 5, which is considered to be acceptable within a chi-square degrees-of-freedom ratio of 5 by Wheaton (1977), Schmucker, and Lomax (2004), implying that the model fits the data well.

In addition, all the other fit metrics also met the expected criteria, the Root Mean Square Error of Approximation (RMSEA) value of 0.055 is within the acceptable range (≤0.08), suggesting a good approximation of the population covariance matrix. The Residual Mean Square (RMR) value is 0.077, which is at the upper boundary of the ideal range (<0.08), but still acceptable. The Goodness of Fit Index (GFI) is 0.922, above the minimum recommended value of 0.90, indicating that the model explains a high proportion of the variance in the data. The Adjusted Goodness of Fit Index (AGFI) is 0.904, meeting the threshold, though slightly higher values would indicate a better fit. The Normed Fit Index (NFI) of 0.933 is above the recommended 0.90, showing good model fit. The Comparative Fit Index (CFI) and Incremental Fit Index (IFI) at 0.947, exceed the threshold of 0.90, indicating an excellent fit. Finally, the Tucker-Lewis Index (TLI) of 0.939 is also above the 0.90 threshold, further supporting a well-fitting model. Overall, the model fits the data well, with all indices meeting or surpassing the recommended thresholds. This indicates that there is a high level of agreement between the proposed theoretical model and the actual data collected, thus enhancing the credibility of the model.

4.2.1 Analysis of structural model results

4.2.1.1 Model direct standardized coefficients test

All hypothesized relationships in the model were supported, with significant standardized coefficients and p-values below 0.05, confirming the validity of the proposed assumptions (Table 21).

(1) Community governance resident satisfaction (RS) is significantly influenced by several factors, each supported by validated hypotheses.

The most influential factor is community resident self-governance (CRS), with a path coefficient of 0.181($p<0.001$), confirming H6. This highlights the critical role of

Table 21 Table of model direct standardized coefficients test

Item	Standardized coefficients	St. Err	z-value	P(>|z|)	Research assumptions	Result
RS<—PL	0.128	0.05	2.709	0.007	H3	Accepted
RS<—CRS	0.181	0.046	3.668	< 0.001	H6	Accepted
RS<—CSF	0.166	0.029	5.359	< 0.001	H9	Accepted
RS<—CWB	0.17	0.025	4.741	< 0.001	H1	Accepted
CI<—PL	0.179	0.049	3.649	< 0.001	H4	Accepted
CI<—CRS	0.264	0.046	5.113	< 0.001	H7	Accepted
CI<—CSF	0.146	0.029	4.559	< 0.001	H10	Accepted
CI<—CWB	0.114	0.025	3.076	0.002	H2	Accepted
RI<—PL	0.249	0.053	5.164	< 0.001	H5	Accepted
RI<—CSF	0.163	0.031	5.19	< 0.001	H11	Accepted
RI<—CRS	0.159	0.048	3.201	0.001	H8	Accepted
HCD<—RS	0.224	0.031	7.037	< 0.001	H12	Accepted
HCD<—CI	0.462	0.039	12.134	< 0.001	H13	Accepted
HCD<—RI	0.098	0.03	3.099	0.002	H14	Accepted

** p-value less than 0.05; significance level is 0.05.

empowering residents through stronger autonomy, which significantly enhances satisfaction by fostering a sense of ownership and active participation in governance.

Following closely is **community workforce building (CWB)**, with a path coefficient of 0.17 ($p<0.001$), supporting **H1**. This indicates that optimizing and developing workforce resources, such as professional training and capacity building, significantly improves governance outcomes by ensuring the effective delivery of services.

Collaboration of social forces (CSF) ranks next, with a path coefficient of 0.166 ($p<0.001$), validating **H9**. This demonstrates that greater cooperation among social forces, including NGO, enterprises, and community organizations, effectively boosts satisfaction by fostering multi-stakeholder engagement and leveraging diverse resources.

Lastly, **party leadership in community governance (PL)**, with a path coefficient of 0.128 ($p=0.007$), confirms **H3**. Although its impact is relatively weaker compared to other factors, party leadership plays a vital role in providing strategic guidance, fostering cohesion, and mobilizing resources to support governance efforts.

Collectively, these results underline the importance of empowering residents (**H6**), optimizing workforce resources (**H1**), fostering collaborative engagement (**H9**), and ensuring effective leadership (**H3**) in enhancing community governance satisfaction.

(2) Urban community integration satisfaction (CI) is influenced by several key factors, with their impacts validated through corresponding hypotheses.

The strongest contributor is community resident self-governance (CRS), with a standardized coefficient of 0.264 ($p<0.001$), supporting H7. This result emphasizes the critical role of empowering residents, as stronger self-governance fosters integration by promoting active participation and shared ownership within the community.

Party leadership (PL) ranks second, with a standardized coefficient of 0.179 ($p< 0.001$), confirming H4. This finding underscores the importance of strategic leadership in directly enhancing integration satisfaction by ensuring effective governance structures and cohesive strategies.

Collaboration of social forces (CSF) has a moderate positive impact, with a standardized coefficient of 0.146 ($p<0.001$), validating H10. This reflects the value of multi-stakeholder cooperation, such as the involvement of NGO, enterprises, and other organizations, in strengthening community ties and fostering integration.

Lastly, community workforce building (CWB), with a standardized coefficient of 0.114 ($p=0.002$), supports H2. While its impact is smaller, workforce development still plays a meaningful role in improving integration by enhancing the capacity and effectiveness of community services.

Collectively, these results validate H7, H4, H10, and H2, demonstrating that resident empowerment, leadership, collaboration, and workforce optimization are critical to enhancing urban community integration satisfaction. These findings highlight the interconnected importance of governance, stakeholder engagement, and workforce development in achieving cohesive and integrated urban communities.

(3) Resource inputs for community governance (RI) are significantly influenced by several key factors, as confirmed by corresponding hypotheses.

The strongest impact comes from party leadership (PL), with a standardized coefficient of 0.249 ($p<0.001$), supporting H5. This highlights the crucial role of strategic leadership in effectively mobilizing and channeling resources, ensuring efficient allocation to meet governance needs.

Collaboration of social forces (CSF) ranks next, with a standardized coefficient of 0.163 ($p<0.001$), validating H11. This emphasizes the positive impact of joint efforts among diverse stakeholders, such as NGO and enterprises, in facilitating resource allocation and enhancing governance capacity.

Community resident self-governance (CRS) also plays an important role, with a standardized coefficient of 0.159 ($p=0.001$), confirming H8. This underscores the significance of empowering residents to contribute actively to resource mobilization, reflecting the value of resident-driven initiatives in governance.

Together, these results validate H5, H11 and H8, demonstrating that effective leadership, collaborative partnerships, and resident empowerment are essential for enhancing resource inputs in community governance. These findings underscore the interconnected roles of governance structures, stakeholder collaboration, and resident participation in optimizing resource utilization.

(4) Harmonized community development (HCD) is significantly shaped by three key factors, as validated by their respective hypotheses.

The most influential factor is community integration satisfaction (CI), with a standardized coefficient of 0.462 ($p<0.001$), supporting H13. This underscores its critical role in fostering integration and promoting cohesive development, making it a cornerstone of community harmony.

Resident satisfaction (RS) follows, with a standardized coefficient of 0.224 ($p< 0.001$), confirming H12. Higher resident satisfaction strongly enhances harmonized development by improving community cohesion and collective well-being.

Lastly, resource inputs (RI), with a standardized coefficient of 0.098 ($p=0.002$), validates H14. Although its impact is smaller, resource inputs provide meaningful support in sustaining development by ensuring the availability of necessary assets for governance and community initiatives.

Together, these results confirm H12, H13 and H14, demonstrating that integration, resident satisfaction, and resource allocation are vital components of harmonized community development. This highlights the interconnected importance of cohesive relationships, resident contentment and adequate resources in fostering sustainable and inclusive community progress.

In summary, resident self-governance (CRS) emerges as the most influential factor across all outcomes, as confirmed by hypotheses H6, H7 and H8. This underscores the critical importance of empowering residents to actively participate in governance, significantly enhancing resident satisfaction, integration satisfaction and resource inputs. Party leadership (PL) plays a vital role in driving resource inputs (H5) and integration satisfaction (H4), although its impact on resident satisfaction (H3) is comparatively weaker. Meanwhile, community integration satisfaction (CI), validated by H13, stands out as the cornerstone of community cohesion, exerting the strongest direct influence on harmonized community development. These insights, supported by hypotheses H1 through H14, collectively underscore the interconnected roles of resident empowerment, leadership, and integration in fostering effective and harmonious community governance.

4.2.1.2 Model indirect effects and total effects

The modeling results demonstrate that both direct and indirect effects contribute significantly to the total effects of the independent variables on the dependent variables, with the strongest overall influence observed for CI to HCD (Total Effect= 0.468) and PL to RI (Total Effect=0.273), highlighting the critical roles of cognitive well-being and contextual factors in shaping outcomes (Table 22).

Table 22 Summary of indirect and total effects on Harmonized Community Development (HCD)

Independent variable	Dependent variable	Direct effect (p-value)	Indirect effect (p-value)	Total effect (direct + indirect) (p-value)
PL	RS	0.135 (***)	—	0.135 (***)
PL	CI	0.180 (***)	—	0.180 (***)
PL	RI	0.273 (***)	—	0.273 (***)
PL	HCD	—	0.138 (*) **	0.138 (*) **
CRS	RS	0.168 (***)	—	0.168 (***)
CRS	CI	0.234 (***)	—	0.234 (***)
CRS	RI	0.154 (***)	—	0.154 (***)
CRS	HCD	—	0.160 (*) **	0.160 (*) **
CSF	RS	0.156 (***)	—	0.156 (***)
CSF	CI	0.131 (***)	—	0.131 (***)
CSF	RI	0.158 (***)	—	0.158 (***)
CSF	HCD	—	0.110 (*) **	0.110 (*) **
CWB	RS	0.120 (***)	—	0.120 (***)
CWB	CI	0.077 (**)	—	0.077 (**)
CWB	RI	0.065 (*)	—	0.065 (*)
CWB	HCD	—	0.068 () **	0.068 () **
RS	HCD	0.217 (***)	—	0.217 (***)
CI	HCD	0.468 (***)	—	0.468 (***)
RI	HCD	0.092 (**)	—	0.092 (**)

(1) Direct effect---the direct path of influence of governance elements

This study reveals that party leadership in community governance (PL), community resident self-governance (CRS), collaboration of social forces (CSF), and community workforce building (CWB) all have significant direct effects on community governance resident satisfaction (RS), community integration satisfaction (CI), and resource inputs for community governance (RI). This indicates that government leadership, resident self-governance, social collaboration, and workforce development can directly enhance resident satisfaction, promote community integration, and increase resource investment in community governance.

Meanwhile, RS, CI, and RI exert significant direct effects on harmonized community development (HCD), making them the key direct determinants of community harmony. Among them, community integration satisfaction (CI) has the strongest direct impact on HCD (0.468), highlighting that social cohesion among residents plays a crucial role in fostering community harmony. Thus, the key governance factors (PL, CRS, CSF, and CWB) primarily influence RS (resident satisfaction), CI (community integration), and RI (resource inputs), which in turn directly determine HCD (harmonized community development).

(2) Indirect effect---How elements of governance indirectly affect harmonized community development (HCD)

This study finds that PL (party leadership), CRS (community resident self-governance), CSF (collaboration of social forces), and CWB (community workforce building) do not have a direct effect on HCD (harmonized community development). Instead of directly influencing HCD (harmonized community development), PL (party leadership), CRS (community resident self-governance), CSF (collaboration of social forces), and CWB (community workforce building) exert their impact indirectly through three key mediating factors: RS (resident satisfaction), CI (community integration), and RI (resource inputs).

Specifically, PL enhances community satisfaction, integration, and resource inputs, which in turn contribute to community harmony. Similarly, CRS fosters greater resident satisfaction and integration, leading to a more harmonious community. CSF strengthens collaboration among various social forces, thereby improving community cohesion and resources, which ultimately support HCD.

Finally, CWB influences community harmony by improving workforce capacity, which indirectly enhances resident satisfaction, integration, and resource availability.

Among the indirect effects, CRS has the strongest influence on HCD (0.160), indicating that community resident self-governance plays a crucial role in fostering community harmony. This may be because greater autonomy allows residents to feel a stronger sense of belonging, leading to higher satisfaction and integration. PL follows closely with an indirect effect of 0.138, suggesting that government leadership remains a key factor in community development, mainly through policy guidance and resource allocation.

The impact of CSF (0.110) highlights the importance of social forces, as collaborations among social organizations, businesses, and volunteers enhance resource integration and service provision. CWB has the smallest indirect effect (0.068), implying that workforce development in community governance plays a relatively minor role, possibly due to limitations in management capacity or service quality.

In conclusion, CRS has the greatest influence on HCD, emphasizing the need for policies that encourage resident self-governance and increase community participation in decision-making. While PL remains vital, its role is largely indirect, operating through policy and resource distribution. The impact of CSF should not be overlooked, and further efforts should be made to deepen social participation in governance and promote multi-stakeholder collaboration for more effective community development.

(3) Total effect--- the overall influence of governance elements

The total effect of a governance factor is the sum of its direct and indirect effects, reflecting its overall influence on HCD (harmonized community development). The ranking of total effects reveals the key determinants of community harmony.

Among all factors, community integration (CI) has the strongest total effect on HCD (0.468), entirely from direct influence. This highlights the crucial role of social cohesion, trust, and a sense of belonging in fostering community harmony. To enhance CI, governments and community leaders should prioritize activities that strengthen social bonds, such as organizing community events and promoting cross-cultural interactions. Resident satisfaction (RS) also has a significant direct effect on

HCD (0.217), indicating that improving public services, environmental quality, and governance responsiveness can directly enhance community harmony.

Community resident self-governance (CRS) exhibits the highest total effect among governance factors (0.160), but only through indirect pathways. This suggests that empowering residents in community decision-making and governance plays a crucial role in fostering a harmonious community. Similarly, party leadership (PL) significantly influences HCD (0.138) through indirect channels, underscoring the importance of government leadership in shaping policies and allocating resources to support community development. Collaboration of social forces (CSF) also contributes to HCD (0.110), albeit with a slightly smaller effect than CRS and PL, highlighting the need for greater involvement of social organizations, businesses, and volunteers in governance processes.

In contrast, resource inputs (RI) directly influence HCD (0.092), suggesting that financial and material investments in community governance contribute to harmony but are not the most decisive factor. Finally, community workforce building (CWB) has the weakest total effect (0.068), implying that while a well-trained community workforce is beneficial, its impact on community harmony remains relatively limited compared to other governance factors.

4.2.1.3 Modeling indirect hypothesis

Table 23 Table of modeling indirect hypothesis

Hypothesis Number	Hypothesis Description	Estimate	Standard Error	p-value	Confidence Interval	Validation
H15	CWB indirectly contributes to HCD through RS	0.125	0.019	< 0.001	[0.088, 0.162]	Supported
H16	CWB indirectly contributes to HCD through CI	0.291	0.027	< 0.001	[0.237, 0.344]	Supported
H17	PL indirectly contributes to HCD through RS	0.125	0.019	< 0.001	[0.088, 0.162]	Supported
H18	PL indirectly contributes to HCD through CI	0.291	0.027	< 0.001	[0.237, 0.344]	Supported
H19	PL indirectly contributes to HCD through RI	0.06	0.019	0.002	[0.021, 0.098]	Supported
H20	CRS indirectly contributes to HCD through RS	0.125	0.019	< 0.001	[0.088, 0.162]	Supported
H21	CRS indirectly contributes to HCD through CI	0.291	0.027	< 0.001	[0.237, 0.344]	Supported

Hypothesis Number	Hypothesis Description	Estimate	Standard Error	p-value	Confidence Interval	Validation
H22	CRS indirectly contributes to HCD through RI	0.06	0.019	0.002	[0.021, 0.098]	Supported
H23	CSF indirectly contributes to HCD through RS	0.125	0.019	< 0.001	[0.088, 0.162]	Supported
H24	CSF indirectly contributes to HCD through CI	0.291	0.027	< 0.001	[0.237, 0.344]	Supported
H25	CSF indirectly contributes to HCD through RI	0.06	0.019	0.002	[0.021, 0.098]	Supported

This study employs the Bootstrap method proposed by Taylor to test mediation effects, which offers significant advantages in Structural Equation Modeling (SEM) (Table 23).

Firstly, it can handle measurement errors in variables, and secondly, it can simultaneously address multiple dependent and mediator variables, providing higher flexibility and precision. The theoretical foundation of mediation effects primarily stems from the classic theory by Baron and Kenny (1986), which emphasizes the process by which an independent variable influences a dependent variable through a mediator. Furthermore, Preacher and Hayes (2004) advanced the Bootstrap method, constructing confidence intervals through resampling and avoiding the normality assumption required by traditional methods, thus enhancing the robustness of the test.

The hypotheses H15 to H25, which focus on the indirect contributions of various community factors to harmonized community development (HCD), are well-supported by the data. Specifically, CWB (community worker building) indirectly contributes to HCD through resident satisfaction (RS) and community integration (CI). With indirect effects of 0.034 and 0.028, respectively, CWB enhances HCD by improving community governance satisfaction and integration.

These findings align with H15 and H16, confirming that CWB plays a vital role in fostering HCD through these channels. Similarly, PL (party leadership) shows a significant indirect effect on HCD through RS, CI and resource inputs (RI), with indirect effects of 0.027, 0.045 and 0.016, respectively. This supports H17, H18 and H19, highlighting that PL significantly influences HCD by enhancing satisfaction, integration and resource allocation within the community.

Moreover, CRS (community resident self-governance) contributes to HCD through RS, CI and RI, with indirect effects of 0.045, 0.067, and 0.016, respectively. This supports H20, H21 and H22, confirming that CRS strengthens HCD by improving community satisfaction, fostering integration, and supporting resource investments. Additionally, CSF (collaboration of social forces) indirectly influences HCD through RS, CI and RI, with indirect effects of 0.034, 0.039 and 0.039, respectively. These results support H23, H24 and H25, showing that CSF contributes to HCD by enhancing satisfaction and integration while promoting resource inputs for governance. Together, these findings validate the hypotheses and confirm that CWB, PL, CRS and CSF all play significant roles in the development of a harmonious community.

In summary, the hypotheses H15 to H25 are fully validated, demonstrating that CWB, PL, CRS and CSF each contribute indirectly to HCD through various pathways, such as resident satisfaction, community integration, and resource inputs. These results underscore the importance of governance, leadership, and collaboration in promoting HCD and highlight the vital role that these factors play in enhancing community development. The indirect effects observed across these variables confirm the robustness of the mediation pathways and their critical influence on fostering a harmonious and well-developed community.

4.2.2 Analysis of measurement model results

The results focus on the measurement model for each latent variable, assessing the relationships between latent constructs (PL, CI, RI, RS) and their observed indicators through standardized factor loadings, z-values, and significance levels (Table 24).

Table 24 Measurement model factor loadings

Measurement model factor loadings				
Variables	St. Err	z-value	P(>|z|)	St. Factor loadings
PL<—PL1	_	_	_	0.757
PL<—PL2	0.039	28.261	< 0.001	0.795
PL<—PL3	0.041	27.398	< 0.001	0.774
PL<—PL4	0.037	29.594	< 0.001	0.829
PL<—PL5	0.036	28.416	< 0.001	0.799

Measurement model factor loadings				
Variables	St. Err	z-value	P(>|z|)	St. Factor loadings
CI<—CI1	_	_	_	0.751
CI<—CI2	0.04	24.891	< 0.001	0.813
CI<—CI3	0.039	23.421	< 0.001	0.739
RI<—RI1	_	_	_	0.78
RI<—RI2	0.039	26.817	< 0.001	0.753
RI<—RI3	0.038	31.05	< 0.001	0.87
RI<—RI4	0.04	27.495	< 0.001	0.77
RS <—RS1	_	_	_	0.813
RS <—RS2	0.032	36.416	< 0.001	0.892
RS <—RS3	0.033	37.066	< 0.001	0.911
CWB <—CWB1	_	_	_	0.946
CWB <—CWB2	0.02	42.163	< 0.001	0.842
CWB <—CWB3	0.02	43.087	< 0.001	0.851
CRS <—CRS1	_	_	_	0.81
CRS <—CRS2	0.035	24.163	< 0.001	0.695
CRS <—CRS3	0.034	28.092	< 0.001	0.808
CSF<—CSF1	_	_	_	0.831
CSF<—CSF2	0.029	39.174	< 0.001	0.883
CSF<—CSF3	0.028	41.88	< 0.001	0.919
CSF<—CSF4	0.028	42.414	< 0.001	0.926
HCD<—HCD1	_	_	_	0.709
HCD<—HCD2	0.051	22.861	< 0.001	0.833
HCD<—HCD3	0.046	21.412	< 0.001	0.715

(1) The measurement model for party leadership (PL) in community governance is highly reliable, with all five indicators (PL1, PL2, PL3, PL4, PL5) showing strong factor loadings ranging from 0.757 to 0.829. All factor loadings are statistically significant ($p < 0.001$) and exhibit very high z-values, such as PL4 with a z-value of 29.594, indicating exceptional significance. Among the indicators, PL4 has the highest factor loading of 0.829, suggesting it has the strongest relationship with the latent construct of party leadership. This robust performance reflects the strong

contribution of each indicator to the overall measurement of PL, confirming the construct's reliability and the relevance of these indicators in capturing the essence of Party Leadership in community governance.

(2) The measurement model for community integration satisfaction (CI) demonstrates robustness, with the three indicators (CI1, CI2, CI3) showing strong factor loadings ranging from 0.739 to 0.813. All factor loadings are statistically significant ($p<0.001$), with CI2 exhibiting the highest factor loading of 0.813, indicating it is the most influential indicator in measuring community integration satisfaction. This result highlights that CI2 plays a central role in reflecting satisfaction in key aspects of urban community integration, confirming the reliability and validity of the measurement model for CI.

(3) The measurement model for resource inputs for community governance (RI) is well-defined, with all four indicators (RI1, RI2, RI3, RI4) displaying strong factor loadings ranging from 0.753 to 0.87. All factor loadings are statistically significant ($p<0.001$), with RI3 having the highest factor loading of 0.87, indicating it has the strongest association with the latent construct of resource inputs. This suggests that RI3 represents the most critical aspect of resource allocation in community governance, underscoring its importance in effectively measuring the RI construct and highlighting its key role in resource management within the community.

(4) The measurement model for community governance resident satisfaction (RS) is highly reliable, with the three indicators (RS1, RS2, RS3) showing strong factor loadings ranging from 0.813 to 0.911. All factor loadings are statistically significant ($p <0.001$), with RS3 demonstrating the highest factor loading of 0.911, making it the strongest contributor to the latent construct of resident satisfaction. This result suggests that RS3 reflects the most influential dimension of satisfaction, likely related to a key aspect of governance, and confirms that the construct of RS is effectively measured with high validity.

(5) The measurement model for community workforce building (CWB) is exceptionally strong, with the three indicators (CWB1, CWB2, CWB3) showing factor loadings ranging from 0.842 to 0.946. All factor loadings are statistically significant ($p <0.001$), with CWB1 having the highest factor loading of 0.946, indicating that it dominates the construct. This suggests that CWB1 represents the

most impactful dimension of workforce building, likely reflecting a critical aspect of workforce development. The robust factor loadings confirm that the construct of CWB is effectively and accurately measured, with CWB1 being central to its representation.

(6) The measurement model for community resident self-governance (CRS) is solid, with the three indicators (CRS1, CRS2, CRS3) displaying factor loadings ranging from 0.695 to 0.808. All factor loadings are statistically significant ($p<0.001$), with CRS3 showing the highest factor loading of 0.808, making it the strongest contributor to the latent construct of self-governance. This suggests that CRS3 represents a particularly critical aspect of residents' autonomy in governance, emphasizing its importance in capturing the essence of community resident self-governance. The strong factor loadings confirm the robustness and reliability of the measurement model for CRS.

(7) The measurement model for collaboration of social forces (CSF) is robust, with the four indicators (CSF1, CSF2, CSF3, CSF4) displaying factor loadings ranging from 0.831 to 0.926. All factor loadings are statistically significant ($p<0.001$), with CSF4 showing the highest factor loading of 0.926, indicating it has the strongest impact on the latent construct. This suggests that CSF4 represents the most influential factor in the collaboration construct, likely tied to a specific practice or aspect of social collaboration. The strong factor loadings confirm that the CSF construct is well-measured, with CSF4 being central to its representation.

(8) The measurement model for harmonized community development (HCD) is effective, with the three indicators (HCD1, HCD2, HCD3) showing factor loadings ranging from 0.709 to 0.833. All factor loadings are statistically significant ($p<0.001$), with HCD2 exhibiting the highest factor loading of 0.833, indicating it is the most important indicator in measuring the construct. This suggests that HCD2 represents the strongest dimension of community harmony, emphasizing its central role in the overall measurement of Harmonized Community Development. The strong factor loadings confirm the reliability and effectiveness of the HCD construct.

The measurement models for all constructs exhibit strong validity and reliability. All indicators across the constructs show significant factor loadings, confirming that each construct is measured reliably. Most of the loadings exceed the 0.70 threshold, which is considered a benchmark for strong construct validity. This suggests that the indicators effectively capture the essence of the constructs they are meant to represent. Overall, the robustness of the factor loadings supports the reliability and validity of the measurement models, reinforcing the soundness of the constructs in the context of the study.

4.3 Evaluate the importance of key variables

4.3.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a type of machine learning model inspired by the structure and functioning of biological neurons. They are widely used for predictive modeling and pattern recognition due to their ability to capture complex, nonlinear relationships in data.

Artificial Neural Network (ANN) is composed of layers (input, hidden, and output) with interconnected nodes(neurons) that process data through weighted connections. They utilize learning mechanisms like backpropagation to adjust weights and minimize prediction errors. The ANN model for the output neuron node was established by using two middle hidden layers with a sigmoid activation function. A deep ANN multi-layer perceptron (MLP) algorithm was performed with 10-fold cross-validation (Arpaci &Bahari, 2023). Neural networks with this topology are often referred to as Multi-Layer Perceptron (MLP). The MLP is trained and tested on the data by means of the Backpropagation of Errors algorithm. A two-layer deep-ANN architecture was designed using SPSS and based on significant factors of the SEM. ANN can capture nonlinear relationships, which may not be identifiable through traditional methods, and are highly effective at learning patterns from large and complex datasets, making them suitable for high-dimensional data.

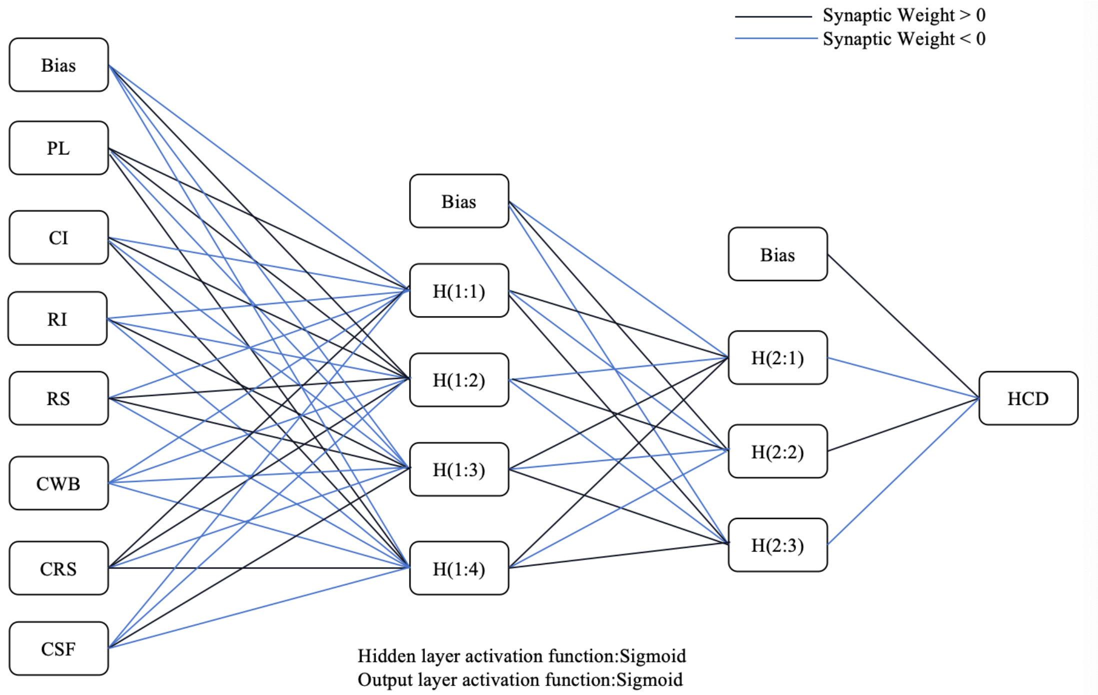

Figure 5 Artificial Neural Network model diagram

As shown in Figure 5, this study generated an ANN model using a multilayer perceptron with a sigmoid function for the activation function. The independent variables PL (means party leadership in community governance), CRS (means community resident self-governance), CWB (means community workforce building), CSF (means collaboration of social forces in community governance), RI (means resource inputs for community governance), CI (means urban community integration satisfaction), RS (means community governance resident satisfaction) in structural equation modeling (SEM) affecting harmonized community development (HCD) were used as input variables of the artificial neural network, and harmonized community development (HCD) was used as the output layer. To avoid potential overfitting problems, the model was validated using a 10-fold cross-validation method, where 10% of the dataset was used for testing and the remaining 90% was used to train the neural network model.

4.3.1.1 Prediction accuracy of ANN model

According to Table 25, mean of the root means square error (RMSE) for the training and testing phases was 0.112 and 0.117, respectively, indicating that the ANN model has a high level of accuracy and predictive performance. These low RMSE values demonstrate the model's ability to effectively minimize the difference between predicted and actual values, suggesting that it has successfully learned the underlying patterns in the data during the training phase and generalizes well to unseen data during the testing phase.

Table 25 Prediction accuracy of ANN model

Prediction accuracy of ANN model				
Network(GP)	Sample Size (Training)	RMSE (Training)	Sample Size (Testing)	RMSE (Testing)
1	1,084	0.104	132	0.12
2	1,078	0.113	138	0.112
3	1,091	0.115	125	0.121
4	1,095	0.127	121	0.102
5	1,084	0.104	132	0.12
6	1,078	0.113	138	0.112
7	1,092	0.11	124	0.131
8	1,086	0.121	130	0.124
9	1,098	0.111	118	0.117
10	1,093	0.103	123	0.114
-	Mean	0.112	Mean	0.117
-	SD	0.007	SD	0.008

Such results highlight the robustness of the ANN model in capturing complex, nonlinear relationships in the data, making it a suitable tool for predictive analysis in scenarios where traditional models may struggle to perform. Additionally, the close similarity between the training and testing RMSE values indicates that the model does not suffer from overfitting, which is a common concern in machine learning.

4.3.1.2 Sensitivity analysis

The normalized importance values indicate the relative significance of each variable in predicting the dependent variable (ANN output), as Table 26.

Table 26 Sensitivity analysis

Sensitivity Analysis							
Item	PL	CI	RI	RS	CWB	CRS	CSF
ANN1	0.36	1.00	0.29	0.81	0.27	0.17	0.22
ANN2	0.40	1.00	0.17	0.55	0.07	0.29	0.04
ANN3	0.22	1.00	0.11	0.37	0.06	0.20	0.07
ANN4	0.45	1.00	0.15	0.41	0.14	0.37	0.05
ANN5	0.36	1.00	0.29	0.81	0.27	0.17	0.22
ANN6	0.40	1.00	0.17	0.55	0.07	0.29	0.04
ANN7	0.38	1.00	0.09	0.57	0.05	0.06	0.07
ANN8	0.43	1.00	0.06	0.31	0.05	0.05	0.12
ANN9	0.26	1.00	0.03	0.37	0.06	0.04	0.02
ANN10	0.69	1.00	0.25	0.56	0.22	0.26	0.19
Average	0.4	1	0.16	0.53	0.13	0.19	0.1
Normalized Importance	40.00%	100.00%	16.00%	53.00%	13.00%	19.00%	10.00%

(1) CI (Community integration) - Normalized importance: 100%

With the highest normalized importance, community integration (CI) is the most critical predictor in the model. This variable's consistent importance across all ANN models (always equal to 1.00) highlights its dominant role in explaining the dependent variable. A high level of community integration suggests a strong sense of belonging and collaboration among community members. This likely acts as a unifying force, contributing significantly to the overall performance of community governance or related outcomes.

(2) RS (resident satisfaction) - Normalized importance: 53%

With a moderate normalized importance, resident satisfaction (RS) is the second most influential variable in the model. Its average value across ANN models (0.53) indicates a substantial contribution to the dependent variable, although not as prominent as CI. This highlights the importance of ensuring that community members are satisfied with governance, services and infrastructure. Higher satisfaction levels could directly influence community members' engagement and positive perception of governance outcomes.

(3) PL (party leadership) - Normalized importance: 40%

As the third most important variable, party leadership (PL) plays a significant role in predicting the dependent variable. Its average normalized importance value of 0.40 underscores its relevance, even if not as dominant as CI or RS. Party leadership reflects the ability of government or political entities to guide and support community governance effectively. Strong leadership ensures accountability, resource allocation, and decision-making efficiency.

(4) The importance of rest variables

RI (resource inputs), CWB (community workforce building), CRS (community resident self-governance), and CSF (collaboration of social forces) have lower normal ized importance values, ranging from 16% to 10%, indicating they play a relatively m inor role.

4.3.2 The result of Random Forest (RF) model

This study aims to investigate the relationship between the latent variable HCD (harmonized community development) and other related latent variables (CI, RS, CWB, etc.). A random forest model is employed to evaluate variable importance and predictive performance. By repeating the training and evaluation 10 times, we ensure the robustness and reliability of the results, providing quantitative insights into the causal relationships between the variables.

The model settings include the following key configurations: in each iteration, the dataset is randomly split into training (90%) and testing (10%) sets to ensure robust evaluation. Variable importance is assessed using the mean decrease in MSE (Type 1), providing insights into the contribution of each predictor. To enhance stability and reliability, the model is trained and evaluated 10 times, allowing for the assessment of performance consistency across multiple iterations.

4.3.2.1 Model performance evaluation

Mean squared error (MSE): Reflects the deviation between predicted and actual values. The results of 10 training iterations are:

MSE= [0.053, 0.083, 0.038, 0.064, 0.082, 0.055, 0.0425, 0.082, 0.043, 0.048]

The maximum value in the MSE list is 0.083, and the minimum value is 0.038.

Squared(R^2): Indicates the model′s ability to explain variance in the dependent variable. The results of 10 iterations are:

R^2= [0.879, 0.832, 0.926, 0.896, 0.849, 0.882, 0.916, 0.879, 0.921, 0.924]

The maximum value in the R^2 list is 0.926, and the minimum value is 0.832.

4.3.2.2 Variable importance analysis

The average importance of each variable across 10 iterations was calculated and ranked as follows (Table 27 and Figure 6).

Table 27 RF variable average importance

	RF variable average importance (mean decrease in MSE)
CI	56.595
RS	46.648
CWB	37.976
PL	37.406
RI	36.372
CRS	36.128
CSF	35.959

Community interaction (CI) emerges as the most critical factor driving harmonized community development (HCD), as evidenced by its strong predictive power in the random forest model, which achieves an impressive average(R^2) of 0.890, indicating a robust ability to explain variance in the data. Resident satisfaction (RS) and community workforce building (CWB) also play vital roles, underscoring their importance in fostering harmonious and thriving communities.

Party leadership (PL), representing party leadership in community governance, and community resident self-governance (CRS), signifying community resident self-governance, further contribute significantly to development outcomes. Together with the collaboration of social forces (CSF) and resource inputs (RI), these factors collectively promote a synergistic and sustainable approach to community governance and development. Policymakers and strategists should prioritize these key drivers—

CI, RS, and CWB—to ensure effective and impactful community development initiatives.

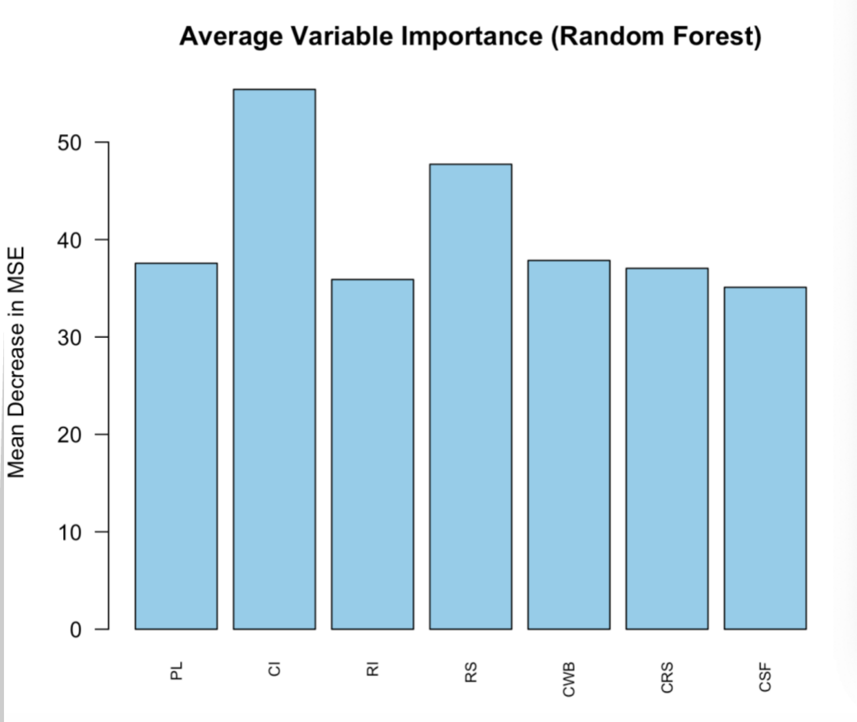

Figure 6 Average variable important (Random Forest)

4.3.3 XGBoost model

The study aims to analyze the relationship between dependent and independent variables in urban community governance using the XGBoost algorithm (Table28). The objectives are to evaluate the model's predictive performance and explore feature importance, providing data-driven insights for optimizing community governance policies. The original dataset was randomly split into training and testing sets at a 9:1 ratio to ensure model stability across different subsets. To mitigate the impact of random splits, the experiment was repeated 10 times.

Table 28 Model parameter setting of XGBoost

Model parameter setting	
Parameter	Value
Objective	reg: squared error
Evaluation Metric	RMSE
Max Depth	6

Model parameter setting	
Learning Rate	0.3
Subsample	0.8
Number of Rounds	100

RMSE results of 10 replicate experiments:

RMSE= [0.3013, 0.1303, 0.2133, 0.2810, 0.1929, 0.3002, 0.2108, 0.2522, 0.1805, 0.1574]

Average RMSE= 0.2220, the maximum value in the RMSE list is 0.3013, and the minimum value is 0.1303.

Table 29 Mean value of feature importance of XGBoost

Mean value of feature importance of XGBoost	
Features	Average Importance
CI	0.555
RS	0.183
RI	0.069
PL	0.064
CWB	0.044
CSF	0.044
CRS	0.042

Based on the results of the 10 experiments, the mean importance of the characteristics of each independent variable was calculated as follows (Table 29 and Figure 7).

The analysis reveals that CI (Community integration satisfaction) is the most influential feature, with an average importance score of 0.555, making the largest contribution to the model's predictive performance. This highlights the critical role of community collaboration in urban governance.RS (Resident satisfaction) follows as the second most important feature, with an importance score of 0.183, emphasizing the significance of active engagement from residents. Although other variables, such as RI (resource input) and PL (party leadership), exhibit relatively lower importance, they still provide valuable explanatory power, suggesting that a multifaceted approach incorporating these factors can further enhance community governance strategies.

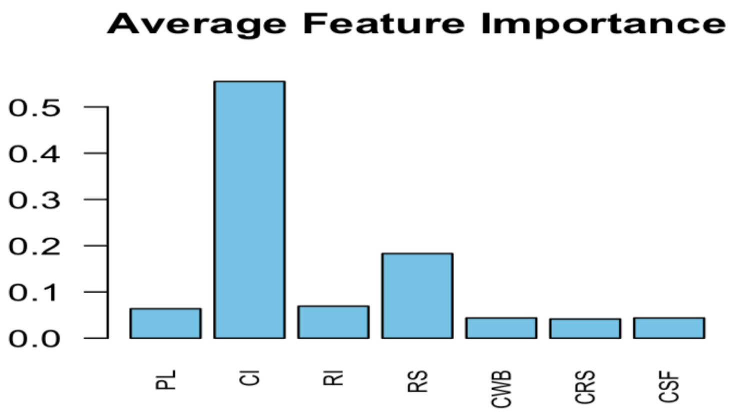

Figure 7 Average feature important (XGBoost)

In this experiment, the XGBoost model demonstrated strong predictive performance, with an average RMSE of 0.222, indicating low prediction error and the ability to accurately capture the complex relationships between independent and dependent variables. This result validates XGBoost's effectiveness in regression tasks, particularly in handling high-dimensional data and nonlinear relationships. The feature importance analysis revealed that community integration satisfaction (CI) is the most critical factor, significantly outperforming other variables in its impact. This suggests that enhancing community collaboration, such as fostering multi-party cooperation and improving coordinated governance, can substantially boost community governance performance. Additionally, resident satisfaction (RS) ranked second in importance, highlighting the vital role of active resident involvement in community development. Although other variables, such as resource inputs (RI) and party leadership (PL), showed relatively lower contributions, they still hold explanatory power, suggesting that they may indirectly influence governance outcomes under specific conditions and should not be overlooked.

4.3.4 LightGBM model

This study aims to analyze the impact of latent variables on dependent variables in community governance using the LightGBM algorithm. The data was derived from latent variable scores extracted via the structural equation modeling (SEM)using the 'Lav Predict' function, forming the analytical dataset comprising seven independent variables and one dependent variable. To ensure model generalizability, the dataset was randomly split into 90% training data and 10% testing data. For result robustness, the experiment was repeated 10 times, with data repartitioning and model retraining conducted in each iteration.

To optimize the performance of the LightGBM model, the following parameter configurations are used in this experiment (Table 30).

Table 30 Model parameter setting of LightGBM

Parameter	Value
Objective	regression
Evaluation Metric	rmse
Boosting Method	gbdt
Maximum Leaf Nodes	31
Learning Rate	0.05
Number of Iterations	100

Based on the feature importance output of LightGBM, the mean value of feature importance of 10 experiments was calculated and the results were ranked as shown in the table below (Table 31 and Figure 8).

Table 31 Feature importance analysis of LightGBM

Feature	Mean Gain	Rank
CI	0.547	1
RS	0.208	2
RI	0.063	3
CSF	0.054	4
PL	0.049	5
CWB	0.043	6
CRS	0.037	7

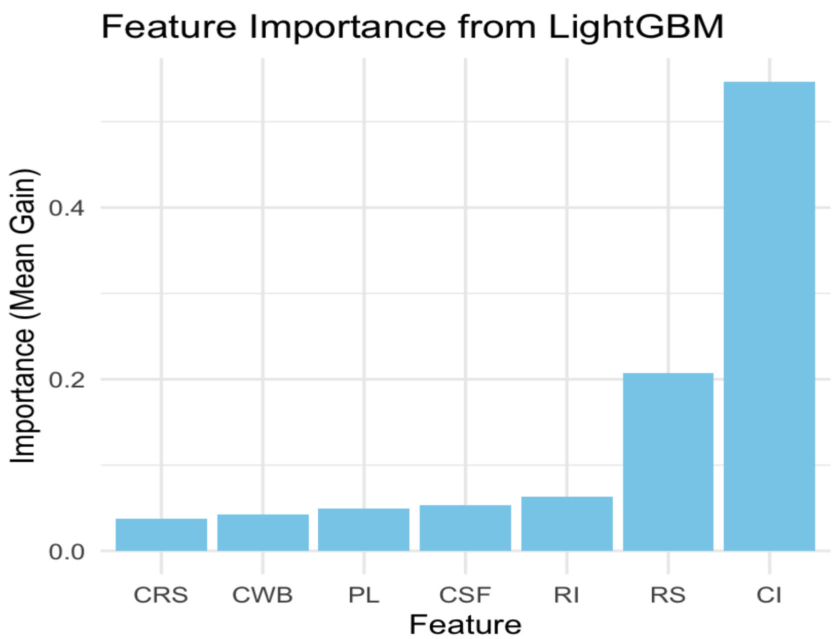

Figure 8 Feature important of LightGBM

Community integration satisfaction (CI) emerged as the most critical variable in predicting the dependent variable, with an average importance score of 0.547, significantly higher than other variables. This indicates that community collaboration plays a decisive role in prediction, suggesting that policymakers should prioritize strategies to enhance collaboration through multi-party cooperation and resource sharing. Resident satisfaction (RS), with an average importance score of 0.208, ranked second, highlighting the importance of active resident involvement in community affairs.

Promoting resident autonomy and transparency in community activities could further improve overall governance outcomes. Other variables, such as resource inputs (RI), collaboration of social forces (CSF), and party leadership (PL), showed lower importance scores but still demonstrated explanatory power. These factors may influence community governance indirectly or in specific contexts and should not be overlooked entirely.

4.4 Comparison of the four machine learning model results

4.4.1 Comparative analysis of importance of SEM and ANN

4.4.1.1 Standardized coefficients in SEM

In the Structural Equation Modeling (SEM) results, the standardized coefficients provide a comparative measure of the importance of different factors influencing residential satisfaction (RS) and community integration (CI) satisfaction. For RS, the path coefficient from party leadership in urban community governance (PL) to RS is 0.128, with a significant p-value of 0.007, indicating a significant but relatively low positive impact of PL on RS. This suggests that while PL does contribute positively to RS, its effect is not as strong as other factors.

The community residents' self-governance (CRS) has a higher positive impact on RS, with a path coefficient of 0.181 and a p-value of 0, which signifies a strong and highly significant influence. This indicates that CRS plays a more substantial role in enhancing RS compared to PL.

Similarly, collaboration of social forces (CSF) has a path coefficient of 0.166 with a p-value of 0, highlighting its significant and important role in affecting RS. This underscores the importance of collaborative efforts from various social forces in contributing to the satisfaction of residents.

The community workforce building (CWB) also has a notable impact on RS, with a path coefficient of 0.17 and a p-value of 0, suggesting that improvements in community work and infrastructure are crucial for resident satisfaction.

Regarding CI, it is the most significant factor affecting community governance performance, with a path coefficient of 0.462 and a p-value of 0. This high coefficient indicates that CI is the most influential factor among those considered, emphasizing its paramount importance in the overall performance of community governance.

In summary, while all the factors contribute positively to RS, CRS, CSF and CWB have higher impacts compared to PL. CI, however, stands out as the most critical factor for community governance performance, with a substantially higher path coefficient than any other factor affecting RS. These findings underscore the need for a multifaceted approach to community governance, emphasizing the importance of resident self-governance, social cooperation, and infrastructure development, while recognizing the overarching role of community integration in achieving governance success.

4.4.1.2 Importance in ANN (Artificial Neural Network)

In the context of Artificial Neural Network (ANN), the importance of different variables can be assessed based on their normalized importance within the model. Community integration (CI) is identified as the most critical variable in the ANN model, with an importance reaching 100%. This indicates that CI is the key driver in the model, having a profound impact on the outcomes. CI's high importance underscores its central role in shaping the dynamics of community governance and satisfaction, likely acting as a hub that connects various aspects of community life and influences overall performance.

Resident satisfaction (RS) follows with a normalized importance of 53%, suggesting it is a significant, yet not the primary, factor within the model. RS is a crucial metric for gauging the effectiveness of community policies and the overall well-being of residents.

Party leadership in urban community governance (PL) has a normalized importance of 40%, indicating its substantial, though not leading, role in influencing the model's outcomes. PL's importance highlights the significance of governmental initiatives and policies in shaping community dynamics and resident satisfaction.

Other variables such as resource inputs (RI), community work building (CWB), community residents' self-governance (CRS), and collaboration of social forces (CSF) have lower normalized importance, suggesting that while they contribute to the model, their predictive contributions are comparatively smaller. This does not diminish their value but rather positions them as secondary factors that, while important, do not carry the same weight as CI, RS or PL in the ANN model's predictive framework.

The normalized importance values provide a clear hierarchy of influence within the ANN model, emphasizing the need to focus on the most influential variables like CI and RS while still acknowledging the contributions of other factors to the overall community governance and satisfaction outcomes. This insight can guide policymakers and community leaders in prioritizing their efforts and resources effectively. Consistency and differences in model results can be analyzed to understand the performance of community governance.

4.4.1.3 Consistency in model results

Both methods indicate that community integration (CI) and resident satisfaction (RS) are the primary variables determining the performance of community governance. This consistency across Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) underscores the fundamental importance of these variables in shaping the outcomes within community settings. SEM and ANN both confirm the contributions of collaboration of social forces (CSF) and community workforce building (CWB), albeit with slightly different rankings in terms of importance. This suggests that while there is agreement on the impact of these factors, the precise degree of their influence may vary when analyzed through different methodological lenses.

4.4.1.4 Differences in model results

The differences in importance ranking are notable, SEM emphasizes the path relationships between variables and their significance, while ANN quantifies the impact of variables on prediction outcomes through normalized importance. In the SEM model, the importance of CWB and CSF is closer to each other, whereas the ANN model shows that their importance is significantly lower compared to CI and RS. This divergence highlights the distinct strengths of each modeling approach—SEM ability to directly articulate causal relationships through path coefficients versus ANN focus on overall predictive power, which is less capable of explaining causality.

The structural differences between the models are also evident, SEM elucidates causal relationships between variables through path coefficients, providing a clear understanding of how changes in one variable can affect another. On the other hand, ANN models prioritize predictive accuracy and are composed of interconnected nodes or "neurons" that work collectively to recognize patterns, classify data, and make predictions. ANN strength lies in capturing complex, nonlinear relationships and interactions that may not be as apparent or easily quantified in SEM.

In summary, while SEM and ANN both recognize the central role of CI and RS in community governance, they differ in how they attribute importance to other variables and in their ability to explain causality. SEM provides a more detailed account of the relationships and significance between variables, whereas ANN offers a broader view that prioritizes prediction over causal explanation. Understanding these differences is crucial for selecting the appropriate modeling technique based on the specific research questions and objectives in community governance and performance evaluation.

4.4.2 Comprehensive analysis and interpretation of results

This study integrates Structural Equation Modeling (SEM) with machine learning methods (XGBoost, LightGBM, Random Forest (RF), and Artificial Neural Network (ANN)) to explore the impact of community governance factors on harmonious community development (HCD). Resource input (RI), community integration satisfaction (CI), and resident satisfaction with community governance (RS) are treated as mediating variables, while other variables (party leadership (PL), community residents' self-governance (CRS), collaboration of social forces (CSF), and community workforce building (CWB)) are independent variables. The results indicate that all variables significantly influence HCD, but their influence pathways and importance vary.

4.4.2.1 Mechanisms of mediating variables

(1) Resource inputs (RI)

RI has a limited direct effect on HCD but plays a significant indirect role by improving CI and RS. In XGBoost, LightGBM and RF, the importance of RI remains stable at approximately 0.08–0.1, while in ANN, its normalized importance reaches 30%. These findings suggest that although increasing resource input alone may not directly enhance HCD, optimizing and effectively utilizing resources is essential for achieving better outcomes through its influence on CI and RS.

(2) Community integration satisfaction (CI)

CI is the most critical mediating variable influencing HCD, highlighting the importance of multi-party collaboration and resource integration. In XGBoost and LightGBM, CI's importance scores are 0.555 and 0.547, respectively; in RF, CI reduces the mean squared error (MSE) by an average of 56.595, and in ANN, CI's normalized importance is 100%. These results confirm that CI serves as the core driving force of community governance, significantly enhancing resident satisfaction and community cohesion, thereby effectively promoting HCD.

(3) Resident satisfaction with community governance (RS)

Resident satisfaction with community governance (RS), as a core variable reflecting residents' perceptions, ranks second in importance across all models. In XGBoost and LightGBM, RS's importance is 0.24–0.25, while in Random Forest (RF), RS reduces the Mean Squared Error (MSE) by 72.5598. In Artificial Neural Network (ANN), RS's normalized importance is 53%. This variable directly reflects residents' subjective perceptions of governance and significantly impacts HCD, emphasizing the importance of fostering resident satisfaction.

4.4.2.2 Direct and indirect effects of independent variables on HCD

(1) Party leadership (PL)

Party leadership (PL) has a relatively weak direct effect on HCD, with its influence primarily realized indirectly through mediating variables. In XGBoost, LightGBM, and Random Forest (RF), PL's importance is approximately 0.05–0.06, while in Artificial Neural Network (ANN), PL's normalized importance is relatively high at 40%. This suggests that the leadership of the party and government mainly functions as a foundational force in guiding policies and integrating resources.

(2) Community residents' self-governance (CRS)

CRS shows varying levels of importance across different models. In XGBoost and LightGBM, CRS has relatively low importance (around 0.04), while in Artificial Neural Network (ANN), CRS's normalized importance reaches 19%. This suggests that enhancing residents' self-governance capabilities can improve satisfaction levels and indirectly promote HCD.

(3) Collaboration of social forces (CSF) and community workforce building (CWB)

CSF and CWB exhibit relatively low direct effects but indirectly influence HCD by improving CI. In XGBoost and LightGBM, their importance is around 0.04, while in Artificial Neural Network (ANN), their normalized importance is 10% for CSF and 13% for CWB. These variables primarily serve as supplementary and supportive roles in community governance.

4.4.2.3 Consensus and differences in Machine Learning methods on feature importance

Machine learning methods exhibit a high degree of consistency in ranking feature importance, especially for core variables CI and RS. CI ranks first across all models, underscoring its role as the key driving force of community governance, while RS follows closely as a critical indicator for measuring governance effectiveness.

However, minor differences emerge in evaluating secondary variables. For instance, ANN assigns higher importance to PL, while RF places more emphasis on CSF and CWB. These differences highlight the unique sensitivities of different methods to data and variable relationships, though the overall trend remains consistent.

Chapter 5

Conclusion and Discussion

This chapter concludes the study by summarizing key findings, analyzing factors influencing multi-subject participation, and discussing the complementarity of methods. It also explores theoretical and practical implications, acknowledges limitations, and suggests directions for future research.

5.1 Conclusion

5.1.1 Hypothesis testing perspective

The study tested H1 to H25 hypotheses, all of which were confirmed, unveiling the interconnected relationships between governance factors and their contributions to harmonized community development (HCD). Party leadership (PL), as a pivotal governance variable, was found to have a significant impact on resident satisfaction (RS), community integration satisfaction (CI), and resource inputs (RI). By offering clear policy guidance, ensuring resource allocation, and fostering collaboration, PL creates a stable governance framework that strengthens trust, satisfaction and inclusivity among residents. Likewise, community residents' self-Governance (CRS) empowers individuals to take part in decision-making, fostering ownership and accountability. This participatory approach enhances CI and guarantees efficient use of RI, laying a foundation for long-term community harmony.

The collaboration of social forces (CSF) emerged as another critical factor, enriching governance through external partnerships and diverse resource contributions. Social forces, such as community organizations and private enterprises, enhance service delivery and stimulate collective efforts, positively influencing RS, CI and RI. These factors (RS, CI, and RI) act as intermediaries, transforming the inputs of PL, CRS, and CSF into outcomes that directly contribute to HCD. Among these, CI plays the most significant role, demonstrating the importance of cohesive and inclusive relationships in fostering harmonious communities. RS and RI further support this process by encouraging participation and ensuring sufficient backing for governance initiatives.

In conclusion, the findings emphasize the synergistic nature of governance, where leadership, resident participation, and external collaboration converge to achieve sustainable community development. Strengthening cross-dimensional interactions among governance variables and optimizing resource inputs are crucial for fostering long-term harmony.

5.1.2 Factors influencing multi-subject participation in community governance in Guangxi urban communities based on SEM

Structural Equation Modeling (SEM) was utilized in this study to validate the theoretical framework and analyze the causal relationships among key latent variables in the context of multi-subject participation in urban community governance in Guangxi. The SEM results demonstrated an excellent model fit, with indices such as Comparative Fit index (CFI>0.95) and Root Mean Square Error of Approximation (RMSEA< 0.05), indicating a robust alignment between the hypothesized framework and the observed data. This high degree of fit confirms that the relationships among party leadership (PL), community residents' self-governance (CRS), collaboration of social forces (CSF), and their respective effects on resident satisfaction (RS), community integration satisfaction (CI), resource inputs (RI) and harmonized community development (HCD) are well-supported by the data.

A closer examination of the direct, indirect, and total effects revealed the centrality of community integration satisfaction (CI) in fostering harmonized community development (HCD). CI exhibited the highest total effect on HCD (total effect=0.549), underlining its pivotal role in building cohesive and inclusive communities. CI reflects the degree to which residents feel integrated and connected, promoting trust, collaboration, and shared goals within the community. While CI was the most impactful, resident satisfaction (RS) and resource inputs (RI) also made significant contributions to HCD. RS driven by effective governance and service quality, motivates active resident engagement, while RI ensures adequate infrastructure and resource availability to support governance initiatives.

The SEM analysis further highlighted the multifaceted nature of governance in Guangxi, where direct effects from PL, CRS and CSF on RS, CI and RI are complemented by their indirect influences on HCD. For instance, party leadership not only impacts HCD directly but also indirectly through its role in enhancing CI and RS. Similarly, CRS empowers residents to contribute to resource optimization and satisfaction, creating a ripple effect on community harmony. The findings emphasize the importance of integrating leadership, participatory governance, and external collaboration to achieve sustainable urban community governance, with SEM serving as a powerful tool to elucidate these complex interrelationships.

5.1.3 Factors influencing multi-subject participation in community governance in Guangxi urban communities based on ANN

The ANN sensitivity analysis provided detailed insights into the relative importance of governance variables in influencing harmonized community development (HCD). Among the variables, community integration satisfaction (CI) was identified as the most critical factor, underscoring its role in fostering harmonious relationships and inclusivity within the community. This result is consistent with the SEM findings, but ANN further quantified the weight of CI compared to other variables. Following CI, resident satisfaction (RS) and resource inputs (RI) emerged as the next most influential variables, highlighting their essential roles in motivating participation and ensuring adequate resource allocation for governance initiatives. The nuanced ranking offered by ANN sensitivity analysis helps prioritize focus areas for policymakers and practitioners aiming to enhance governance outcomes.

The ANN model demonstrated exceptional predictive accuracy, showcasing its ability to handle complex, non-linear interactions among governance variables. While SEM provided a robust linear analysis of hypothesized relationships, ANN complemented this by capturing dynamic and interdependent effects that are difficult to model using traditional methods. The high accuracy of ANN predictions validates its utility in forecasting governance outcomes and supports its integration into governance studies. This predictive strength underscores the potential of ANN as a tool for analyzing multifaceted systems, offering a data-driven approach to inform decision-making processes in urban community governance.

One of the most significant insights from the ANN analysis was its ability to highlight the synergistic effects of variable combinations. For example, the interaction between community residents' self-governance (CRS) and collaboration of social forces (CSF) was found to amplify governance effectiveness beyond their individual contributions. This finding emphasizes the importance of integrated approaches that leverage the strengths of multiple governance factors working in unison. The ability of ANN to uncover such synergies provides a deeper understanding of how governance variables interact in practice, encouraging strategies that foster collaboration and multi-dimensional interventions to achieve sustainable community development.

5.1.4 Factors influencing multi-subject participation in community governance in Guangxi urban communities based on Random Forest (RF)

Community integration satisfaction (CI) has the highest importance score (56.60), indicating that it has the strongest predictive power for community governance outcomes. Improving community integration and residents' satisfaction with integration is likely a key factor in enhancing the performance of community governance. Following closely is community governance resident satisfaction (RS) with a score of 46.65, suggesting that residents' satisfaction with governance plays a significant role in the effectiveness of community governance. Additionally, community workforce building (CWB) and party leadership in community governance (PL) also show relatively high importance scores (37.98 and 37.41, respectively), indicating that political leadership and workforce development are critical for successful community governance.

Resource inputs (RI) and community resident self-governance (CRS) have similar importance scores of 36.37 and 36.13, respectively. Strengthening resource inputs and supporting community residents' self-governance abilities are important for optimizing governance structures and improving governance effectiveness. Social forces collaboration (CSF) and harmonized community development (HCD) have somewhat lower importance scores (35.96 and 36.06), suggesting that while they have some influence on community governance, their contribution is relatively smaller.

In summary, community integration satisfaction and community governance resident satisfaction are the most influential factors, meaning that policies should focus on enhancing these areas. Party leadership and community workforce building should also be prioritized to improve governance performance.

5.1.5 Factors influencing multi-subject participation in community governance in Guangxi urban communities based on XGBoost

Community integration satisfaction (CI) stands out as the most significant factor, with the highest importance score of 0.555. This indicates that improving community integration and residents' satisfaction with community cohesion plays a crucial role in shaping governance outcomes. Following this, community governance resident satisfaction (RS) also holds significant weight with an importance score of 0.183, suggesting that residents' overall satisfaction with governance is key. Resource inputs for community governance (RI), with an importance score of 0.069, also contributes to governance effectiveness, but its impact is less substantial compared to the satisfaction-related factors.

Other factors like party leadership in community governance (PL) and community resident self-governance (CRS) show moderate importance, with scores of 0.064 and 0.042, respectively. These results suggest that while leadership and self-governance are relevant, they may have a less direct impact on the governance performance compared to the satisfaction-driven variables. The roles of community workforce building (CWB) and collaboration of social forces in community governance (CSF) are comparatively lower, both with an importance score of 0.044, indicating they contribute less to overall governance outcomes. Lastly, harmonized community development (HCD) does not appear in the final ranking, suggesting it may have a minimal or non-significant impact on the model's predictions.

Overall, the results suggest that factors directly related to satisfaction (CI and RS) are the most important predictors of successful community governance, while other governance-related factors, such as resource inputs, leadership, and social collaboration, play supporting roles.

5.1.6 Factors influencing multi-subject participation in community governance in Guangxi urban communities based on LightGBM

Community integration satisfaction (CI) emerges as the most influential factor, with a feature gain of 0.547. This highlights the critical role of community cohesion and integration in predicting governance outcomes, reinforcing the idea that fostering a sense of belonging and satisfaction among residents is a priority for effective governance. Community governance resident satisfaction (RS) follows with a feature gain of 0.208, suggesting that residents' approval and contentment with governance processes are also essential drivers of success. Resource inputs for community governance (RI), with a feature gain of 0.063, contributes to governance effectiveness but holds less influence compared to satisfaction-related factors.

Other governance-related features, such as collaboration of social forces in community governance (CSF) at 0.054, Party leadership in community governance (PL) at 0.049, community workforce building (CWB) at 0.043, and community resident self-governance (CRS) at 0.037, exhibit lower feature importance. These results suggest that while these factors are relevant to governance performance, they play more supportive roles compared to the dominant influence of satisfaction metrics like CI and RS. Notably, harmonized community development (HCD) is absent from the ranking, indicating a minimal or negligible impact in this model.

5.1.7 Use and complementarity of these Methods

In summary, the analysis using SEM, ANN, Random Forest, XGBoost, and LightGBM consistently highlights community integration satisfaction (CI) as the most critical factor influencing harmonized community development (HCD) in Guangxi urban communities, underscoring its pivotal role in fostering cohesion, trust and collaboration among residents. Community governance resident satisfaction (RS) and resource inputs (RI) are also consistently identified as significant contributors, emphasizing the importance of effective governance, service quality, and adequate resources in achieving sustainable governance outcomes. While other factors such as party leadership (PL), community resident self-governance (CRS), community workforce building (CWB), and collaboration of social forces (CSF) play supportive roles, their impacts are relatively smaller but still essential for optimizing governance structures. The combination of these methods demonstrates that integrating leadership, participatory governance, and satisfaction-driven initiatives is crucial for fostering sustainable, inclusive, and effective urban community governance.

5.2 Discussion

5.2.1 Theoretical implications

The findings from SEM, ANN, Random Forest, XGBoost, and LightGBM converge on the critical role of community integration satisfaction (CI) and resident satisfaction (RS) as central predictors of governance outcomes. These results contribute to the theoretical understanding of multi-subject participation in urban community governance by reinforcing the pivotal role of satisfaction-driven factors in fostering harmonized community development. The combination of linear (SEM) and non-linear (ANN, RF, XGBoost, LightGBM) methods enriches the theoretical framework, providing a comprehensive perspective on how governance variables interact to drive outcomes. This multi-method approach validates and expands existing governance theories, particularly those emphasizing community cohesion and satisfaction as foundational pillars of effective governance.

5.2.2 Practical implications

The results offer actionable insights for policymakers and practitioners aiming to enhance governance performance in Guangxi urban communities. Prioritizing community integration satisfaction (CI) and resident satisfaction (RS) can significantly improve governance outcomes, as these factors consistently demonstrate the highest importance across methods. Practical strategies should focus on fostering a sense of belonging, enhancing service quality, and ensuring resource adequacy to support governance initiatives. Moreover, the findings emphasize the need for integrated approaches that leverage party leadership (PL), collaboration of social forces (CSF), and community workforce building (CWB) to amplify the effects of satisfaction-related factors. This integrated strategy aligns with sustainable development goals by promoting inclusivity, collaboration, and resource optimization.

5.2.3 Limitations

While this study offers valuable insights, it is not without limitations. First, the reliance on cross-sectional data limits the ability to infer causality and observe dynamic changes over time. Second, although multiple methods were employed, potential biases in variable measurement or data preprocessing may influence the results. Additionally, the study focuses on Guangxi urban communities, and the findings may not be generalizable to other regions or contexts without further validation.

5.2.4 Future research

Future research should address these limitations by incorporating longitudinal designs to capture temporal changes and causal relationships. Expanding the study to other regions or including rural communities can provide a broader understanding of governance dynamics. Furthermore, integrating qualitative methods, such as interviews and focus groups, can complement the quantitative findings and offer deeper insights into the social and cultural factors shaping governance outcomes. Lastly, future studies could explore the application of advanced machine learning models or hybrid methods to further refine the analysis of complex governance systems.

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APPENDIXES

APPENDIXES A

Key factors in urban community governance in Guangxi

The first part is the basic demographic characteristics.

1. Your gender (　　)
A. Male　B. Female
2. Age (　　)
A.18-24 years old　B.25-35 years old C.36-44 years old D.45-60 years old　E.61 years and over
3.Political identity (　　)
A. the masses B.CPC member (including reserve member) C.Other parties
4. Education level (　)
A. Primary and below
B. Junior high school
C. Senior high school
D. University
E. Postgraduate
5. Family income (　)
A. CNY 20 to 39 thousand
B.CNY 40 to 59thousand
C.60 thousand and above
6. Years of residence (　)
A. Within 1 year
B. 1 to 3 years
C. 4 to 6 years
D. 7 to 10 years
E. 10 years and above
7. Your residence type is (　)
A. commercial housing B. unit housing C. rental housing D. self-built housing
E. resettlement housing F. other

The second part is key factors of community governance

A. Party leadership in community governance. (PL)
8.PL1 How satisfied are you with the construction of community party organizations?
A. Very dissatisfied
B. Unsatisfied
C. General
D. satisfied
E. Very satisfied
9.PL2 How effective are the party members in your area?
A. It didnt work at all
B. Not effective C. Limited effect D. play a role
E. Give full play to its role
10.PL3 Please evaluate your satisfaction with the work of the party organization in your community?
A. Very dissatisfied
B. Unsatisfied
C. General

D. satisfied
E. Very satisfied
11.PL4 How much do you know about the promotion of community governance innovation through community party building?
A. I dont know anything about it
B. do not understand
C. know
D. Know some
E. Very familiar with
12.PL5 How active are you in community party organization related services or activities?
A. Very inactive B. Relatively inactive C. General
D. Relatively active E. Very active Community self-government

B. Community Resident Self-Governance (CRS)
13.CRS1 Are you satisfied with the representation of community residents?
A. Very dissatisfied
B. Unsatisfied
C. General
D. Satisfied
E. Very satisfied
14.CRS2 How do you think the community residents are able to organize themselves?
A. Very dissatisfied
B. B.Unsatisfied
C. General
D. Satisfied
E. Very satisfied
15.CRS3 How do you think the community is performing in terms of political participation?
A. Very dissatisfied
B. Unsatisfied
C. General
D. satisfied
E. Very satisfied

C. Community worker team building (CWB)
16.CWB1 Are you satisfied with the composition of the community workforce
A. Very dissatisfied
B. Unsatisfied
C. General
D. Satisfied
E. Very satisfied
17.CWB2 Do you think community workers have enough professional qualifications?
A. Not at all
B. Not available
C. General
D. Possess
E. Fully available
18.CWB3 How do you think the community secretary is working?
A. Very poor
B. Poor
C. General

D. Good
E. Best

D. Collaboration of social forces in community governance (CSF)
19.CSF1 Are you satisfied with the frequency of social organizations organizing activities and service projects?
A. Very dissatisfied
B. Unsatisfied
C. General
D. Satisfied
E. Very satisfied
20.CSF2 Are you satisfied with the richness of activities and services provided by social organizations?
A. Very dissatisfied
B. Discontent
C. Same as
D. Satisfied
E. Very satisfied
21.CSF3. How do you recognize the active participation of social organizations in urban community governance?
A. Not at all
B. Disagrees
C. Neutral
D. Approve
E. Full recognition
22.CSF4 Do you think social organizations have strong independence when participating in urban community governance?
A. Not at all
B. Disagrees
C. Neutral
D. Approve
E. Full recognition

E. Resource inputs for community governance (RI)
23.RI1 How do you think the governments public financial input to community governance is?
A. Very insufficient
B. Insufficient
C. Moderate
D. Adequate
E. Very adequate
24.RI2, Are you satisfied with the public services in your community?
A. Very dissatisfied
B. Unsatisfied
C. General
D. Satisfied
E. Very satisfied
25.RI3, Do you think the community convenience service facilities are easy to use?
A. Very inconvenient
B. Inconvenient
C. General
D. Convenient
E. Very convenient
26.RI4 How do you experience the construction and use of community information platform?

A. Very poor
B. Poor
C. General
D. Good
E. Beyond compare

F.CI Community integration satisfaction
27.CI1 How do you perceive and evaluate the community culture?
A. Very dissatisfied
B. Discontent
C. Same as
D. Satisfied
E. Very satisfied
28.CI2 How do you perceive the harmony of your community?
A. Very disharmonious
B. Disharmony
C. General
D. harmonious
E. Very harmonious
29.CI3 How much do you agree with the values and ideas advocated by the community?
A. Not at all
B. Disagrees
C. Neutral
D. Self-identity
E. Fully agrees

G. Community Governance Resident Satisfaction (RS)
30.RS1, Are you satisfied with the community service level?
A. Very dissatisfied
B. Unsatisfied
C. General
D. Satisfied
E. Very satisfied
31.RS2 How do you feel about your level of political engagement?
A. Very low
B. Low
C. General
D. High
E. very high
32.RS3, Are you satisfied with the quality of life in the community?
A. Very dissatisfied
B. Unsatisfied
C. General
D. Satisfied
E. Very satisfied

G. Harmonized community development（HCD）

33.HCD1 What is your overall assessment of the current state of community governance?
A. Very dissatisfied
B. Unsatisfied

C. General
D. Satisfied
E. Very satisfied
34.HCD2 Do you feel a sense of belonging to your community?
A. No sense of belonging, B. No sense of belonging, C. General, D. Sense of belonging , E. Very sense of belonging
35.HCD3Are you concerned about the development of the community?
A. Not at all, B. Not at all, C. General, D. Co ncerned, E.Very concerned

APPENDIXES B

 # Main Program (SEM)###

```
library(lavaan)
library(haven)
library(lavaanPlot)
dat <- read_sav("/Users/xiaonazai/Desktop/Dr/Data01234.sav")
model0<-'
 # Measure model
   PL =~ PL1 + PL2 + PL3 + PL4 + PL5
   CI =~ CI1 + CI2 + CI3
   RI =~ RI1 + RI2 + RI3 + RI4
   RS =~ RS1 + RS2 + RS3
   CWB =~ CWB1 + CWB2 + CWB3
   CRS =~ CRS1 + CRS2 + CRS3
   CSF =~ CSF1 + CSF2 + CSF3 + CSF4
   HCD =~ HCD1 + HCD2 + HCD3
   # Structure model
   RS ~ a1 * PL + b1 * CRS + c1 * CSF + d1 * CWB
   CI ~ a2 * PL + b2 * CRS + c2 * CSF + d2 * CWB
   RI ~ a3 * PL + b3 * CRS + c3 * CSF + d3 * CWB
   HCD ~ e1 * RS + e2 * CI + e3 * RI
   # Mediating effects (indirect effects)
   ind_RS := e1 * (a1 + b1 + c1 + d1) # RS indirect effects
   ind_CI := e2 * (a2 + b2 + c2 + d2) # CI indirect effects
   ind_RI := e3 * (a3 + b3 + c3 + d3) # RI indirect effects '

fit0 <- sem(model0, data = dat, fixed.x = FALSE)
summary (fit0, fit.measures = TRUE, standardized = TRUE)
fitmeasures(fit0, c("chisq", "df", "pvalue", "gfi", "cfi", "rmr", "srmr", "rmsea", "agfi", "nfi", "tli", "ifi"))
semPaths(fit0, what = "std", fade = FALSE, layout = "spring", residuals = TRUE, edge.color = "black")
bootstrap_results <- parameterEstimates(fit0, boot.ci.type = "perc", level = 0.95)
bootstrap_results[grep("ind_", bootstrap_results$label), ]
sem_scores <- lavPredict(fit0)

library(randomForest)
set.seed(123)
num_features <- ncol(data_rf) - 1
feature_names <- colnames(data_rf) [1:num_features]
```

```
importance_matrix <- matrix (0, nrow = num_features, ncol = 10)
rownames(importance_matrix) <- feature_names

mse_values <- numeric (10)
r_squared_values <- numeric (10)
for (i in 1:10) {
   train_indices <- sample (1: nrow(data_rf), size = 0.7 * nrow(data_rf))
  train_data <- data_rf[train_indices, ]
  test_data <- data_rf[-train_indices, ]
  rf_model <- randomForest(HCD ~ ., data = train_data, importance = TRUE)
  importance_values <- importance (rf_model, type = 1)
  for (j in 1:num_features) {
    importance_matrix[j, i] <- importance_values[j, 1]
  }
   rf_pred <- predict (rf_model, newdata = test_data)

  mse_values[i] <- mean ((rf_pred - test_data$HCD) ^2)
  r_squared_values[i] <- 1 - sum ((rf_pred - test_data$HCD) ^2) / sum((test_data$HCD - mean(test_data$HCD))^2)
}

average_importance <- rowMeans(importance_matrix)
average_importance_df <- data.frame(Variable = names(average_importance), Average_Importance = average_importance)
average_importance_df <- average_importance_df
[order(-average_importance_df$Average_Importance),]
print(average_importance_df)
barplot(average_importance, las = 2, main = "Average Variable Importance (Random Forest)",
        col = "skyblue", cex.names = 0.7, ylab = "Mean Decrease in MSE")
```



```
library(xgboost)
set.seed(123)
num_features <- ncol(sem_scores) - 1
feature_names <- colnames(sem_scores) [1:num_features]
importance_matrix <- matrix (0, nrow = num_features, ncol = 10)
```

```
rownames(importance_matrix) <- feature_names
rmse_values <- numeric (10)
for (i in 1:10) {
  train_index <- sample (1: nrow(sem_scores), size = 0.7 * nrow(sem_scores))
  train_data <- sem_scores[train_index, ]
  test_data <- sem_scores[-train_index, ]

  train_x <- as.matrix(train_data[, 1:num_features])
  train_y <- as.matrix(train_data[, num_features + 1])
  test_x <- as.matrix(test_data[, 1:num_features])
  test_y <- as.matrix(test_data[, num_features + 1])

  dtrain <- xgb.DMatrix(data = train_x, label = train_y)
  dtest <- xgb.DMatrix(data = test_x, label = test_y)
    params <- list (
    objective = "reg:squarederror",
        eval_metric = "rmse",
    max_depth = 6,
    eta = 0.3,
    subsample = 0.8
  )


  xgb_model <- xgb.train(
    params = params,
    data = dtrain,
    nrounds = 100,
    verbose = 0
  )

  importance <- xgb.importance(model = xgb_model)
    for (j in 1: nrow(importance)) {
    feature_name <- importance$Feature[j]
    importance_matrix[feature_name, i] <- importance$Gain[j]
  }

  predictions <- predict (xgb_model, dtest)
    rmse_values[i] <- sqrt (mean ((predictions - test_y) ^2))
```

```
}
average_importance <- rowMeans(importance_matrix)
cat ("RMSE for 10 runs:\n")
print(rmse_values)
cat ("Average RMSE over 10 runs: ", mean(rmse_values), "\n")
cat ("\nFeature importance averaged over 10 runs:\n")
average_importance_df <- data.frame(Feature = names(average_importance), Average_Importance =
average_importance)
average_importance_df <- average_importance_df[order(-
average_importance_df$Average_Importance),]
print(average_importance_df)

barplot(average_importance, las = 2, main = "Average Feature Importance", col = "skyblue",
cex.names = 0.7)



library(lightgbm)
library(caret)
sem_scores <- lavPredict(fit5)
head(sem_scores)
X <- sem_scores[, -ncol(sem_scores)]
y <- sem_scores[, ncol(sem_scores)]
set.seed(123)
feature_importance_all <- data.frame()
for (i in 1:10) {
  trainIndex <- createDataPartition(y, p = 0.7, list = FALSE)
 train_data <- sem_scores[trainIndex, ]
 test_data <- sem_scores[-trainIndex, ]
  train_features <- data.frame(train_data[, -ncol(train_data)])
 train_label <- train_data[, ncol(train_data)]
 test_features <- data.frame(test_data[, -ncol(test_data)])
 test_label <- test_data[, ncol(test_data)]

 train_matrix <- lgb.Dataset(data = as.matrix(train_features), label = train_label)
 test_matrix <- lgb.Dataset(data = as.matrix(test_features), label = test_label, free = TRUE)

 params <- list (
```

```
    objective = "regression",
    metric = "rmse",
    boosting_type = "gbdt",
    num_leaves = 31,
    learning_rate = 0.05,
    n_estimators = 100
  )

    model <- lgb.train(params, train_matrix, 100)
  importance <- lgb.importance(model)
  feature_importance_all <- rbind(feature_importance_all, importance)
}
importance_mean <- aggregate (Gain ~ Feature, data = feature_importance_all, FUN = mean)
importance_mean <- importance_mean[order(-importance_mean$Gain),]
print(importance_mean)
ggplot(importance_mean, aes(y = reorder(Feature, Gain), x = Gain)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  coord_flip() +
  ylab("Feature") + xlab("Importance (Mean Gain)") +
  ggtitle("Feature Importance from LightGBM") +
  theme_minimal()
```

APPENDIXES C

C.1 The 1st manuscript

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Lobachevskii Institute of Mathematics and Mechanics,
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30 September, 2024

Dear Professors Zai Xiaona, Sujitta Suraphee, Chom Panta, Thom Gatewongsa, and Piyapatr Busababodhin,

Ref: A structural equation modeling analysis of key factors: Enhancing urban community in the Southwest China.

Our referees have now considered your paper and have recommended publication in Lobachevskii Journal of Mathematics. We are pleased to accept your paper in its current form which will now be forwarded to the publisher for copy editing and typesetting. Our plan is to publish your paper in Issue 12 (December) of Volume 45 (year 2024).

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A Structural Equation Modeling Analysis of Key Factors: Enhancing Urban Community in the Southwest China

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Abstract—The effectiveness of urban community governance is an important symbol for assessing the modernization level of grassroots governance. An in-depth understanding of its core influencing factors and their functioning mechanisms is crucial for accurately improving the effectiveness of urban community governance. This study analyzes the key factors of urban community governance in Guangxi using structural equation modeling (SEM) and the results show that governmental leadership in community governance plays a fundamental role in the effectiveness of urban community governance by influencing the community resident self-governance and prompting the collaboration of social forces in community governance in a concerted manner. Therefore, in the future, it is necessary to further consolidate the leading role of grass-roots party and government in urban community governance, increase the resources inputs such as convenient service facilities in urban communities and to effectively integrate the governance functions of multiple subjects other than governmental leadership in order to enrich the path choices of urban community governance under the orientation of high-quality development.

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1. INTRODUCTION

The community is an important basic unit of governance in urban society and community governance as an important part of the national governance system is an important cornerstone for the realization of social democracy at the grass-roots level, the maintenance of social stability and the promotion of harmonious social development. Over the past 10 years, China's urbanization rate has increased from 53.1% in 2012 to 65.2% in 2022 [1], already above the world average of 56.2% [2]. Along with the deepening of the urbanization process, the complexity and challenges of community governance are also increasing.

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In 2022, the urbanization rate in Guangxi was 55.65% [3], which was far below the national average of 65.2%.To accelerate the urbanization process, the department of civil affairs and the development and reform commission of Guangxi Zhuang autonomous region proposed further initiatives in the "14th Five-Year Plan" for the construction of urban and rural community service systems in 2022. The emphasis is on accelerating the advancement of grassroots party organizations in leading the construction of urban and rural community service systems, highlighting the government's leading role. It actively promotes the development of professional service social organizations and community-based social organizations, guides and encourages market entities and social forces to participate in community services. These aims to stimulate the initiative and enthusiasm of residents to actively engage in urban and rural community services, enhance self-help and mutual assistance service capabilities, and establish a basic pattern of multi-party collaboration in urban and rural community services [4].

To expedite the urbanization process in Guangxi, this study endeavors to analyze the pivotal factors influencing urban community governance through structural equation modeling, thereby proposing viable suggestions for urban development in Guangxi. We analyzed the factors affecting public participation in urban community governance [5], the relationship between the quality of urban community governance and public satisfaction [6]. The impact of urban community governance on resident's sense of well-being [7], the influence of governmental and social capital on urban community governance [8], the evolution and optimization of the urban community governance model alongside societal development, and the significance of involving multiple primary stakeholders and fostering cooperation to enhance the effectiveness of community governance [9].

Using structural equation model (SEM), we analyzed the influencing factors affecting urban communities from the perspectives of governance performance [10, 11], governance efficiency [12], governance effectiveness [13, 14], governance effect [15], and governance evaluation [16]. These factors include governmental support, community participation, institutional design, resource inputs and service quality.The sustainable development of cities has also been analyzed in terms of multiple dimensions of urban community governance (i. e.,participation, democracy, services) [17]. These SEMs aim to analyze the impact of a single factor or a single subject on community governance in developed Chinese cities.

The purpose of this paper is to analyze the key influencing factors of urban community governance in Guangxi, a border region of China, through SEMs. Especially under the governmental leadership, the government, community organizations, residents and other stakeholders can form a synergistic force to jointly promote the development of community governance. By overcoming the influence of single factors on urban community governance, we comprehensively consider the interaction and influence of multiple factors, revealing the intrinsic correlations and influence paths between them. This study aims to provide useful insights and suggestions for accelerating urbanization and promoting the sustainable development of cities in Guangxi.

The article is structured as follows. After the introduction, it reviews existing research relevant to identifying key elements of urban community governance and quantifying their impact on urban effectiveness. Following this, the authors explain the research framework of the study. The paper then analyzes the results of the SEM to test the research hypotheses and validate the proposed model. The subsequent section discusses these results. Finally, the findings and contributions of this study are summarized in the conclusions.

2. RESEARCH HYPOTHESES

Research hypotheses, seven hypotheses, were formulated based on a review of published literature on relevant urban community governance and the current situation of urban community governance with Chinese characteristics. Theirs detail showed as follows:

- H1: *Governmental leadership in community governance has a direct and positive impact on the investment of resources in community governance.*

  China's urban community governance model shows that urban community governance resources are mainly provided by the Party and the Government [18]. Whether in terms of investment in public infrastructure construction or office funding for community social organizations, the main reliance is on public financial funds.

- H2: Community workforce building has a direct positive impact on the effectiveness of urban community governance.

  Community Workforce Building can directly improve the effectiveness of urban community governance through the establishment of specialized community workforces, of which the secretary of the community party branch (or the head of the community neighbourhood committee) is the main one, for the purpose of solving the problems of community governance and meeting the service needs of the community residents [19].

- H3: *Governmental leadership in community governance has a direct positive impact on community self-governance.*

  At present, the ability of our residents to participate in community governance is relatively limited, and community residents lack experience in self-governance. In carrying out community self-governance activities, it is often necessary for grass-roots party and government departments to provide guidance [20], and for those departments to provide the appropriate platforms for community self-governance.

- H4: Community resident's self-governance directly and positively influences social forces to collaborate in community governance.

  Through extensive field research, it has been found that an increase in the level of self-governance of community residents is directly linked to an increase in their ability to organize and carry out community activities [21]. A high level of autonomy is more likely to attract other social forces to participate actively in community governance.

- H5: Social forces working together in community governance directly and positively influence the effectiveness of urban community governance.

  Coordinated community governance by social forces refers to giving full play to the unique advantages of community social organizations and other social organizations at the community level, and actively guiding the participation of community-based organs, enterprises and public institutions, other social forces and market players in community governance. The urban community arena provides social organizations with a more regular operating vehicle [22], where they gather common values and identities, integrate professional governance techniques and knowledge, and infinitely stimulate the energy of social organizations in the field of social governance.

- H6: Community governance resource inputs directly and positively affect the effectiveness of urban community governance.

  Community governance resource input refers to the sum of financial and material resources invested by the Party and the government to promote the development of community governance in the practice of community governance, including public financial input, community public service facilities, community convenience service facilities and community information platform construction, etc. [23], and the degree of input of the above resources directly affects the effectiveness of community governance.

- H7: *Governmental leadership in community governance has a direct positive impact on community workforce development.*

  In the practice of urban community governance in China, the interaction between grass-roots party and government departments and community workers is relatively close [24], which directly affects the source, scale, and remuneration of community workers.

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Table 1. Distribution of urban communities in Guangxi Zhuang Autonomous Region

City	Districts under the jurisdiction of cities	Sub-districts	Neighborhood
Nanning	7	25	438
Liuzhou	5	32	301
Guilin	6	13	264
Wuzhou	3	8	153
Beihai	2	7	95
Fangchenggang	2	7	68
Qinzhou	2	12	153
Guigang	3	7	123
Yulin	2	8	178
Baise	2	2	98
Hezhou	2	4	55
Hechi	2	3	180
Laibin	1	4	97
Chongzuo	1	3	113
Total	41	135	2316

3. METHODOLOGY

3.1. Data

This study focuses on the urban community in Guangxi, China, which comprise a total of 14 prefectural-level cities, 41 Districts under the Jurisdiction of Cities, 135 Street Sub-districts, and 2316 Neighborhood Committees (Table 1) (from the 2023 Statistical Yearbook of the Guangxi Zhuang Autonomous Region).

3.2. Design Scale

In this paper, we mainly divide the types of urban communities in Guangxi on the basis of the characteristics of community population composition, which can be roughly divided into various types such as mobile population settlement type, hereditary type, enterprise type, unit type, college type, immigrant type, of which most of them are mobile population settlement type urban communities.

This paper synthesizes the actual situation and focuses on three types of urban communities, including migrant settlement type, hereditary residence type, and enterprise type, for investigation and research. Simple random sampling was used to sample three types of communities: migrant settlement type, hereditary residence type, and enterprise type in each of the 14 cities in Guangxi.

The questionnaire was conducted in each of the selected communities using simple random sampling and was completed on a face-to-face one-to-one basis. All items were placed on a six-point Likert scale to measure information content and responsiveness where 1 = strongly disagree, 5 = strongly agree. At the beginning of the questionnaire design, three different types of community representatives were first selected to conduct a pre-survey to assess the issues involved in the questionnaire, as well as the understanding of the community residents and the validity of the questionnaire, and then modify and improve the questionnaire on this basis. Relying on Guangxi Normal University for Nationalities, the surveyors were trained and coached to ensure the recovery rate and validity of the questionnaires. Data collected from July to August in 2023. Finally, a total of 1314 questionnaires were drawn, and after further organization, 1216 questionnaires were valid, with a validity rate of 92.5%.

3.3. Methods

In this research, we have proposed SEMs for key factors analysis. Capitalizing on SEMs, a pivotal statistical tool in behavioral social sciences, this research intends to foster a nuanced analysis of multi-observed variables. This method triumphs over conventional regression approaches, permitting simultaneous handling of multiple dependent variables, accommodating measurement errors within explanatory variables, and enabling simultaneous factor relationship and structure estimation, enhancing the accuracy and comprehensiveness of the outcome [25]. The steps of the proposed SEMs are as follows.

Step 1. Descriptive Data Analysis

Basic data analysis involves the initial checking and organization of the data. First, the data were imported and checked for completeness to ensure that there were no missing values or outliers. Next, descriptive statistical analysis was performed to understand the basic characteristics of the data, such as mean, median, standard deviation and distribution. A normality test was also performed to check that the data conforms to a normal distribution to ensure that the assumptions for the subsequent analysis.

Step 2. Data Validity Analysis

Checking the Reliability and validity of data. Reliability testing uses Cronbach's alpha

$$\alpha = (kk - 1))\left(1 - \sum_{i=1}^{k} \sigma_i^2/\sigma_T^2\right),$$

where k is the number of items in the test or scale, σ_i^2 is the variance of the ith item, and σ_T^2 is the total variance of all the items.

Validity analysis—

$$KMO = \frac{\sum_{i=1}^{p}\sum_{j=1,j\neq i}^{p} r_{ij}^2}{\sum_{i=1}^{p}\sum_{j=1,j\neq i}^{p} r_{ij}^2 + \sum_{i=1}^{p}\sum_{j=1,j\neq i}^{p}\sum_{k=1,k\neq i,k\neq j}^{p} r_{ij.k}^2},$$

where r_{ij} is the correlation between variables i and j, $r_{ij.k}$ is the partial correlation between variables i and j controlling for all other variables k, and p is the number of variables.

Exploratory factor analysis (EFA) helps to identify latent factors without predefining the factor structure: $\mathbf{X} = \mathbf{\Lambda F} + \mathbf{E}$, where $\mathbf{X}$ is a vector of observed variables, $\mathbf{\Lambda}$ is the factor loading matrix, $\mathbf{F}$ is the vector of latent factors, and $\mathbf{E}$ is the vector of errors.

Confirmatory factor analysis (CFA) is used to validate a predefined factor structure $\mathbf{X} = \mathbf{\Lambda}\eta + \epsilon$, where $\mathbf{X}$ is a vector of observed variables, $\mathbf{\Lambda}$ is the factor loading matrix (known structure), η is the vector of latent factors, and ϵ is the vector of errors.

Step 3. Structural Equation Modeling analysis.

Capitalizing on SEM, a pivotal statistical tool in behavioral social sciences, this research intends to foster a nuanced analysis of multi-observed variables. This method triumphs over conventional regression approaches, permitting simultaneous handling of multiple dependent variables, accommodating measurement errors within explanatory variables, and enabling simultaneous factor relationship and structure estimation, enhancing the accuracy and comprehensiveness of the outcome [25]. The SEM method is exemplified through general equations, converging to form a generalized SEM model

$$y = \lambda y\eta + \varepsilon, \quad x = \lambda x\xi + \delta, \quad \eta = B\eta + \Gamma\xi + \zeta,$$

where y represents observed variables, x is another observed variable, η stands for a latent variable, typically termed as an endogenous variable, ξ is a latent variable, typically termed as an exogenous variable, related to the endogenous variable, and ξ but can be directly measured through observed variables (x). The ε represents the measurement error of y, and δ represents the measurement error of x.

In addition, λy is the regression coefficient between y and η, indicating the influence of the endogenous variable η on the observed variable y. The λx is the regression coefficient between x and ξ, indicating the influence of the exogenous variable ξ on the observed variable x. The B represents the autoregressive coefficient of η, indicating the relationship of the endogenous variable η between different time points. The Γ is the regression coefficient between η and ξ, indicating the influence of the exogenous variable ξ on the endogenous variable η, and the ζ represents the error term of η, indicating the unobserved part of the variability in the endogenous variable η.

4. DATA ANALYSIS AND RESULTS

4.1. Descriptive Statistical Analysis

4.1.1. Demographic characteristics of the sample. Among the sample population, 626 were male, accounting for 51.5% of the sample, and 590 were female, accounting for 48.5% of the sample. Age was divided according to 18 to 24 years old, 25 to 35 years old, 36 to 44 years old, 45 to 60 years old, and 61 years old and above, with these age groups accounting for 5, 9.4, 39.7, 27.1, and 18.8% of the valid survey sample, respectively. In terms of education level, elementary school accounted for 4.3%, middle school accounted for 10.9%, high school (including vocational high school, junior high school, etc.) accounted for 26.2 and 43.8% in universities (specialized and undergraduate), and 14.8% in postgraduates. In terms of political outlook, 10.8% were CPC members (including preparatory ones), 24.2% were democratic parties, and 65% were the general public. Annual incomes of 20 000–39 000 yuan account for 14.8%, 40 000–59 000 yuan for 43.8%, and 60 000 yuan and above for 41.4%.The length of residency was less than one year for 3.8%; 1–3 years for 11.3%, 4–6 years for 24.3%, 7–10 years for 39.2%, and 10 years and above 21.5% (as shown in Table 2).

In summary, the interviewees are mainly young and middle-aged, with more than half having an education level of university and above. They had resided for varying lengths of time and most have a political profile representative of the masses. The collection of these interviewees in terms of the statistical significance of the variability of the study has a certain empirical significance.

4.1.2. Variables outcome statistics. The 6 variables for the participation of multiple subjects in governance in urban communities in Guangxi were as follows.

- (1) Latent variable 1: party leadership in urban community governance.

  Party leadership in urban community governance refers to the guiding and directing role of government departments in community governance, reflecting the leadership capacity and effectiveness of the government in community governance. It primarily involves the allocation of governance resources and the leadership of other governance entities in community building, thereby impacting the effectiveness of urban community governance.

- (2) Latent variable 2: community resident's self-governance.

  Community resident's self-governance refers to resident's engagement in democratic activities such as elections, consultations, decision-making, management, and oversight. These activities are conducted under the leadership of party organizations within the community and are based on community resident's committees. They also involve collaboration with the community's general assembly and consultation and deliberation councils.

- (3) Latent variable 3: community Workforce Building.

  Community worker team building involves establishing a professional team of community workers, with the community party branch secretaries (or community neighborhood committee chairpersons) serving as the primary members. This is aimed at addressing community governance issues and fulfilling the service requirements of community residents.

- (4) Latent variable 4: collaboration of social forces.

  The collaboration of social forces in community governance involves leveraging the distinct strengths of community social organizations and other grassroots-level entities. It actively encourages the involvement of community-based institutions, enterprises, public organizations, and other societal entities, as well as market players, in community governance initiatives.

- (5) Latent variable 5: resource inputs for community governance

  Community governance resource input refers to the cumulative financial and material resources allocated by the Party and government to advance the development of community governance practices. This encompasses public financial investments, the establishment of community public service facilities, the provision of community convenience service facilities, and the development of community information technology platforms.

Table 2. Demographic characteristics of the sample

Features	Binary variable	No. of people surveyed	Proportion (%)
Gender	male	626	51.5
	female	590	48.5
AGE	18–24 years old	61	5
	25–35 years old	114	9.4
	36–44 years old	483	39.7
	45–60 years old	330	27.1
	61 years old and over	228	18.8
EDU	Primary and below	52	4.3
	junior high school	133	10.9
	High school (including vocational high school, junior college, etc.)	318	26.2
	Universities (specialized and undergraduate)	533	43.8
	postgraduate student	180	14.8
Political appearance	CPC member (including preparatory)	131	10.8
	democratic party	294	24.2
	the masses	791	65
Annual income	20 000–39 000 yuan	180	14.8
	40 000–59 000 yuan	533	43.8
	60 000 yuan and above	503	41.4
Length of residence	Within 1 year	46	3.8
	1–3 years	137	11.3
	4–6 years	295	24.3
	7–10 years	477	39.2
	10 years and above	261	21.5

- (6) Latent variable 6: Overall community governance satisfaction.

  Overall satisfaction with community governance refers to the degree of satisfaction among community residents regarding the performance of community governance. It reflects the comprehensive evaluation of community residents regarding the effectiveness of community governance, the quality of services, the level of participation, and other related aspects. The level of overall satisfaction with community governance can serve as an indicator of the effectiveness of community governance efforts and the extent to which community residents endorse the direction of community development.

The observed variables are given in Table 3. Dependent Variable Outcome Statistics are shown in Table 4. Independent Variable Outcome Statistics are given in Table 5.

The data collected from valid questionnaires were analyzed to confirm that the requirements of normal distribution were met. To assess normality, we found none of the items exceeded the skewness of 2.0 and kurtosis of 7 [26]. The tests of kurtosis, skewness, and standard deviation of the data revealed that the sample data roughly conforms to a normal distribution.

Table 3. Observed variables

Factor PL: Party leadership	
PL1	Satisfaction with the building of community party organizations
PL2	The role of party members in the area where you live
PL3	Satisfaction with the work of party organizations in the community
PL4	Party building to promote innovation in community governance
PL5	Activity in services or activities related to party organizations
Factor CRS: Community resident self-governance	
CRS1	Satisfactory representation of community resident's representatives
CRS2	Capacity of community residents in self-organization
CRS3	Capacity of community residents in terms of political participation
Factor CWB: Community workforce building	
CWB1	Satisfaction with the composition of the community workforce
CWB2	Community workers have adequate professional qualifications
CWB3	Work capacity of community clerks
Factor CSF: Collaboration of social forces in community governance	
CSF1	Participation of units in the district in community building and governance
CSF2	Satisfactory participation of social organizations in community governance
CSF3	Recognition of social organizations as proactive participants in urban community governance
CSF4	Social organizations are more independent in their participation in urban community governance
Factor RI: Resource inputs	
RI1	Level of public financial inputs by the Government to community governance
RI2	Satisfaction with public service facilities in the community
RI3	Accessibility of community amenities
RI4	Construction and experience of using the community information platform
Factor: Overall community governance satisfaction	
OC1	Overall assessment of the current state of governance in your community
OC2	Do you feel a sense of belonging in this neighborhood
OC3	Do you care about the neighborhood

Table 4. Dependent variable descriptive statistics

Dependent variable descriptive statistics						
Variable	N	Minimum	Maximum	Mean	Skewness	Kurtosis
OC1	1216	1	5	3.8224	−0.854	0.101
OC2	1216	1	5	3.7714	−0.982	0.413
OC3	1216	1	5	3.6538	−0.721	0.09

Further analysis of the data showed, firstly, that the means of the three observed variables for the dependent variable were 3.82, 3.77, and 3.65, with the means overall exceeding 3, indicating that community residents were currently satisfied with the community as a whole. Secondly, in terms of the independent variables, the overall mean value was around 3.5. Satisfaction with public service facilities in the community and construction and experience of using the community information platform were below 3.5, it indicates that the community needs to further enhance its public service facilities, invest

Table 5. Independent variable descriptive statistics

Independent variable outcome statistics						
Variable	N	Minimum	Maximum	Mean	Skewness	Kurtosis
PL1	1216	1	5	3.5839	−0.831	0.545
PL2	1216	1	5	3.5765	−0.87	0.41
PL3	1216	1	5	3.9202	−1.205	0.828
PL4	1216	1	5	3.6357	−1.073	0.947
PL5	1216	1	5	3.5485	−1.015	0.899
CRS1	1216	1	5	3.6604	−0.769	0.217
CRS2	1216	1	5	3.6143	−0.66	0.091
CRS3	1216	1	5	3.7887	−1.135	1.005
CWB1	1216	1	5	3.7319	−0.595	−0.715
CWB2	1216	1	5	3.6908	−0.449	−0.696
CWB3	1216	1	5	3.9227	−0.795	−0.549
CSF1	1216	1	5	3.5156	−0.234	−0.675
CSF2	1216	1	5	3.6974	−0.517	−0.696
CSF3	1216	1	5	3.588	−0.346	−0.704
CSF4	1216	1	5	3.7171	−0.504	−0.654
RI1	1216	1	5	3.5387	−0.503	−0.371
RI2	1216	1	5	3.4054	−0.25	−0.893
RI3	1216	1	5	3.7262	−0.593	−0.484
RI4	1216	1	5	3.4646	−0.223	−0.994

Table 6. Cronbach's alpha

Construct	Cronbach's α	Total α
Party leadership	0.89	0.917
Community Resident Self-Governance	0.81	
Community Workforce Building	0.91	
Collaboration of social forces	0.94	
Resource inputs	0.87	
Overall community governance satisfaction	0.8	

greater resources in improving the community environment, and upgrade the information platform to enhance the resident's experience of using it.

4.2. Reliability and Validity of Questionnaire

We tested the validity and reliability of the instrument by using normality, EFA (exploratory factor analysis), and CFA (confirmatory factor analysis).

Table 7. Total Variance Explained

Total Variance Explained									
Element	Initial eigenvalue			Extract the sum of the squares of the loads			Rotational load sum of squares		
	Total	Percentage of variance	Cumulative %	Total	Percentage of variance	Cumulative %	Total	Percentage of variance	Cumulative %
1	8.181	37.188	37.188	8.181	37.188	37.188	3.6	16.362	16.362
2	2.496	11.344	48.532	2.496	11.344	48.532	3.416	15.525	31.887
3	1.993	9.06	57.592	1.993	9.06	57.592	2.955	13.433	45.32
4	1.605	7.297	64.889	1.605	7.297	64.889	2.51	11.41	56.73
5	1.438	6.534	71.424	1.438	6.534	71.424	2.201	10.005	66.735
6	1.005	4.566	75.99	1.005	4.566	75.99	2.036	9.255	75.99
7	0.542	2.464	78.454	–	-	–	–	–	–
8	0.514	2.335	80.789	–	–	–	–	–	–
9	0.462	2.102	82.89	–	–	–	–	–	–
10	0.419	1.905	84.795	–	–	–	–	–	–
11	0.392	1.782	86.578	–	–	–	–	–	–
12	0.39	1.771	88.349	–	–	–	–	–	–
13	0.367	1.669	90.018	–	–	–	–	–	–
14	0.338	1.536	91.554	–	–	–	–	–	–
15	0.312	1.417	92.971	–	–	–	–	–	–
16	0.292	1.328	94.299	–	–	–	–	–	–
17	0.276	1.256	95.555	–	–	–	–	–	–
18	0.266	1.207	96.762	–	–	–	–	–	–
19	0.237	1.076	97.838	–	–	–	–	–	–
20	0.188	0.856	98.693	–	–	–	–	–	–
21	0.154	0.7	99.393	–	–	–	–	–	–
22	0.134	0.607	100	–	–	–	–	–	–
Extraction method: Principal Component Analysis									

4.2.1. Reliability test of questionnaire. In this article, the feasibility of the data was verified. We measured Cronbach alpha and each factor was above 0.7, the reliability value of the total scale is 0.917, this suggests the reliability of the scale used in this study, see Table 6.

4.2.2. Validity test of questionnaire. We used SPSS 26.0 for EFA and the KMO was 0.918. And the closer the KMO is to 1, the more suitable the data was for factor analysis, and below 0.5, the data was not suitable for factor analysis. The significance of the statistical value of Bartlett's sphere test was $p \leq 0.05$, which reached the level of significance, indicating that the original data were closely correlated and suitable for subsequent factor analysis.

4.2.3. Exploratory factor analysis (EFA). In this paper, the factors with eigenvalues greater than 1 were extracted according to the principal component analysis extraction method; the number of factors extracted was 6, and the cumulative variance contribution rate reached 75.99%, see Table 7, so the extracted common factors reflected most of the original variable's. Therefore, the extracted common

Table 8. Rotated component matrix

Rotated component matrix						
Component						
	1	2	3	4	5	6
PL1	0.727	–	–	–	–	–
PL2	0.764	–	–	–	–	–
PL3	0.749	–	–	–	–	–
PL4	0.815	–	–	–	–	–
PL5	0.78	–	–	–	–	–
CRS1	–	–	–	–	–	0.809
CRS2	–	–	–	–	–	0.646
CRS3	–	–	–	–	–	0.778
CWB1	–	–	–	0.874	–	–
CWB2	–	–	–	0.84	–	–
CWB3	–	–	–	0.842	–	–
CSF1	–	0.861	–	–	–	–
CSF2	–	0.882	–	–	–	–
CSF3	–	0.91	–	–	–	–
CSF4	–	0.893	–	–	–	–
RI1	–	–	0.796	–	–	–
RI2	–	–	0.809	–	–	–
RI3	–	–	0.83	–	–	–
RI4	–	–	0.815	–	–	–
OC1	–	–	–	–	0.754	–
OC2	–	–	–	–	0.867	–
OC3	–	–	–	–	0.802	–
Extraction method: Principal Component Analysis						
Rotation method: Kaiser normalized maximum variance method						
a. Rotation has converged after 5 iterations						

factors reflect most of the information of the original variables, and it was considered that these five factors had a good degree of interpretation of the scale.

In order to maximize the extraction of information from the original scale and the interpretation of the extracted variables, the method of rotation was adopted for analysis, and the orthogonal rotation method was adopted in this paper.

The orthogonal rotation of the factor loading matrix revealed that the standardized factor loading coefficients for each observed variable met the criterion of being greater than 0.5. Factor 1 (Party leadership) corresponded to questions with factor loadings of 0.727–0.815, factor 2 (Collaboration of social forces) corresponded to questions with factor loadings of 0.861–0.91, factor 3 (Resource inputs) corresponded to questions with factor loadings of 0.796–0.83, and the factor loadings for factor 4 (Community Workforce Building) was 0.84–0.874. Additionally, factor 5 (Overall community governance) was 0.754–0.867, factor 6 (Community Resident Self-Governance) was 0.646–0.809

Table 9. Fit indices of the models

Fit indices	Estimates	Recommended value	Conclusions
X_2 /df	3.6	≤ 5	well
RMSEA	0.05	≤ 0.08	well
RMR	0.08	≤ 0.08	well
GFI	0.95	≥ 0.90	well
AGFI	0.94	≥ 0.90	well
NFI	0.96	≥ 0.90	well
CFI	0.97	≥ 0.90	well
TLI	0.97	≥ 0.90	well
IFI	0.97	≥ 0.90	well

(Table 8). These findings indicate that the convergent validity of the questionnaire was good, the authenticity of the data was reliable, and the questionnaire settings were fundamentally reasonable.

4.2.4. Confirmatory Factor Analysis(CFA). Structural equation analysis was performed on the model and the results of the model fit were obtained as shown in Table 9. We found that the measurement model fitted the data well, CMIN/DF = 3.6, GFI = 0.95, AGFI = 0.94, NFI = 0.96, CFI = 0.97, RMSEA = 0.05, SRMR = 0.08. The indicators meet the requirements and generally achieved a good degree of fit, indicating that the fit between the hypothetical theoretical model and the actual survey data was high and the model is convincing.

(GFI: Goodness of Fit Index, AGFI: Adjusted Goodness of Fit Index, NFI: Normed Fit Index, CFI: Comparative Fit Index, RMSEA: Root Mean Square Error of Approximation.)

4.3. Analysis of Structural Equation Modeling

4.3.1. Convergence and aggregation. Convergent validity is commonly referred to as the degree of consistency of the latent variables that can be explained by the observed variables, and usually consists of three criteria: first, all standardized factor loadings are greater than 0.5; second, the Component reliability (CR) of each dimension exceeds 0.7, and third, the Average Validity of Extracted variance (AVE) of each dimension is greater than 0.5.

The factor loadings of each factor were greater than 0.6 (see Table 10), the CR of each latent variable exceeded 0.7 shown in Table 11, the AVE values were above the cut-off value of 0.5 which meets the condition for convergent validity. We can assume that the variables of the model all pass the tests of convergence and aggregation to some extent.

4.3.2. Results of the test of the research hypothesis. To test our research hypotheses, we adopted structural equation modeling using AMOS version 23 (see Fig. 1 and Table 12) H1, H2, H3, H4, H5, H6, and H7 were all supported. Overall, the model of factors influencing the effectiveness of urban community governance has withstood the test of the validity sample data, has good scientific validity and reliability, and can be fully used for the related analysis presented below.

4.3.3. Empirical results of structural equation modeling. In this study, AMOS 23.0 software was used as a tool for structural equation modeling and hypothesis testing. Its' purpose was to construct a model diagram that illustrates the factors influencing overall community governance satisfaction. Additionally, it aimed to determine the standardized coefficients of the paths and identify significant relationships among the variables, serving as an empirical basis for studying the relationships among those factors. The model comprises a total of 6 latent variables and 22 observed variables. Based on the research theory and hypotheses outlined in this paper, the path analysis diagram of the structural equation is presented below (see Fig. 1).

Firstly, among the factors that have a direct effect on the effectiveness of urban community governance, the ranked order of path coefficient size was community workforce building (0.226) more than

Table 10. Statistical results of some indicators

Item	Mean	SD	Loadings
Factor: Party leadership			
PL1 Satisfaction with the building of community party organizations	3.58	1.05	0.76
PL2 The role of party members in the area where you live	3.57	1.09	0.79
PL3 Satisfaction with the work of party organizations in the community	3.92	1.16	0.77
PL4 Party building to promote innovation in community governance	3.63	1.04	0.82
PL5 Activity in services or activities related to party organizations	3.55	1.01	0.79
Factor: Community resident self-governance			
CRS1 Satisfactory representation of community resident's representatives	3.66	1.11	0.8
CRS2 Capacity of community residents in self-organization	3.61	1.1	0.7
CRS3 Capacity of community residents in terms of political participation	3.79	1.07	0.81
Factor: Community workforce building			
CWB1 Satisfaction with the composition of the community workforce	3.73	1.26	0.947
CWB2 Community workers have adequate professional qualifications	3.69	1.18	0.843
CWB3 Work capacity of community clerks	3.92	1.2	0.849
Factor: Collaboration of social forces in community governance			
CSF1 Participation of units in the district in community building and governance	3.52	1.07	0.83
CSF2 Satisfactory participation of social organizations in community governance	3.69	1.16	0.88
CSF3 Recognition of social organizations as proactive participants in urban community governance	3.58	1.14	0.92
CSF4 Social organizations are more independent in their participation in urban community governance	3.71	1.16	0.93
Factor: Resource inputs			
RI1 Level of public financial inputs by the Government to community governance	3.53	1.11	0.78
RI2 Satisfaction with public service facilities in the community	3.4	1.19	0.76
RI3 Accessibility of community amenities	3.73	1.19	0.87
RI4 Construction and experience of using the community information platform	3.46	1.28	0.77
Factor: Overall community governance satisfaction			
OC1 Overall assessment of the current state of governance in your community	3.82	1.16	0.71
OC2 Do you feel a sense of belonging in this neighborhood	3.77	1.16	0.85
OC3 Do you care about the neighborhood	3.65	1.14	0.72

resource inputs in community governance (0.206) more than collaboration of social forces in community governance (0.198). To enhance the effectiveness of urban community governance, it is recommended that the government strengthen community workforce building, increase resource inputs in community governance, and promote the collaboration of social forces. Such comprehensive measures are expected to promote the overall improvement of urban community governance at both direct and indirect levels, and to promote the stability and development of the community (Fig. 1).

Secondly, among the factors that have an indirect effect on the effectiveness of urban community

Table 11. CR and AVE of the Model

Construct	AVE	CR
Party leadership	0.62	0.89
Community resident self-governance	0.6	0.82
Community workforce building	0.78	0.91
Collaboration of social forces	0.79	0.94
Resource inputs	0.63	0.87
Overall community governance satisfaction	0.58	0.8

Table 12. Hypothesis testing and path coefficient

Research hypothesis	Reject/Accept	β	Std.Err	p-value
H1 PL–RI	Accept	0.491	0.037	$P < 0.001$
H2 PL–CWB	Accept	0.585	0.046	$P < 0.001$
H3 PL–CRS	Accept	0.738	0.039	$P < 0.001$
H4 CRS–CSF	Accept	0.432	0.032	$P < 0.001$
H5 CSF–OC	Accept	0.198	0.027	$P < 0.001$
H6 RI–OC	Accept	0.206	0.03	$P < 0.001$
H7 CWB–OC	Accept	0.226	0.021	$P < 0.001$

governance, the ranked order of the size of the path coefficients was party leadership of community governance (0.738) had the greatest impact on community residents self-governance, followed by community workforce building (0.585) and resource inputs of community (0.491), and lastly, community resident's self-governance (0.432) had the least impact on the collaboration of social forces. This shows that the leading role of the government plays a crucial role in the indirect influence, and that by guiding community resident's self-governance, strengthening the construction of community social workers and investing in resources, the government is able to effectively promote the coordinated governance of social forces.

Overall, to improve the effectiveness of urban community governance, it is necessary to focus on strengthening community workforce building, increasing the resources inputs of community governance, and prompting the Government to play a greater role in party leadership of community governance. This will directly improve the effectiveness of community governance, while indirectly influencing the self-governance of community residents and the collaboration of social forces through the leading role of the Government, thus comprehensively promoting the progress of urban community governance.

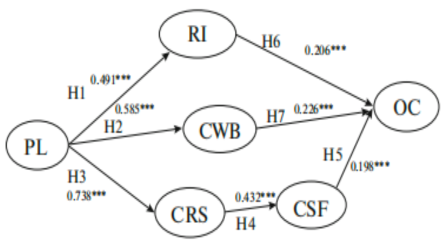

Fig. 1. Proposed Research Model and the models normalized path coefficients.

5. DISCUSSION

By analyzing the structural equation modeling of key factors in urban communities in Guangxi, the effects of multiple factors in community governance on resident satisfaction were revealed.

Firstly, the impact of party leadership on community governance has an indirect and significant effect on resident satisfaction through the resources input of community, the community workforce building and community resident self-governance. This emphasizes the central role of party leadership in community governance, which improves the effectiveness of urban community governance through substantial resources input in community, through policies and guidelines that influence the training, deployment and effectiveness of social workers, and resident's access to self-governance through participation in the decision-making process and in the management of community affairs. In the future, it can be expected that party leadership will be more refined and professionalized, with greater emphasis on communication and interaction with community residents to ensure that policy decisions are more responsive to the actual needs of the community.

Secondly, collaboration of social forces has a positive impact on resident satisfaction. This suggests that promoting the participation of social parties is an effective way to enhance resident satisfaction. Community cohesion and governance effectiveness can be enhanced by strengthening cooperation among different stakeholders and promoting resident's participation in self-governance. The role of collaboration of social forces in community governance will become more prominent. In the future, more social organizations, enterprises and individuals can be expected to participate in community governance, forming a more diversified and open governance pattern. At the same time, the deepening of the collaboration mechanism will also promote the effectiveness of community governance.

Lastly, urban community building is still dominated by the investment of hardware resources. Community governance resource input occupies a central position and directly plays a positive role in the effect of urban community governance, indicating that China's urban community construction relies more on resource input, and is more inclined to hardware resource input in terms of infrastructure, the main reason being that there are still short boards in the current residential community such as insufficient reasonable scale, insufficient equipment, insufficient space for public activities, and insufficient coverage of property service management, and there is still a certain gap between the standards of complete residential community and the standard of urban community. The main reason for this is that the current living communities are still shortcomings in terms of size, equipment, public activity space, and property service and management coverage, and are still far from being complete living communities. Resource allocation will be more accurately aligned with the needs of community governance, so as to avoid waste and mismatch of resources. At the same time, how to effectively mobilize and utilize social resources will also become the focus of future research and practice.

6. CONCLUSIONS

Based on the analysis of the structural equation modeling of key factors in urban communities in Guangxi, the future of urban community governance is expected to evolve towards greater specialization, refinement, and socialization.

Firstly, as the significant role of party leadership in community governance is increasingly recognized, and its indirect impact on resident satisfaction through the allocation of community resources, community workforce building of a community, and community resident self-governance is acknowledged, it is foreseeable that party leadership will prioritize communication and interaction with community residents to ensure that policy decisions are more responsive to community needs.

Secondly, the collaboration of social forces is anticipated to have a positive influence on resident satisfaction, indicating that fostering the participation of various societal actors is an effective means of enhancing resident satisfaction. In the future, an increasing number of social organizations, businesses and individuals are expected to engage in community governance, leading to a more diverse and inclusive governance framework. Furthermore, deepening collaboration mechanisms will enhance the effectiveness of community governance.

Lastly, urban community development is currently heavily reliant on investment in physical infrastructure. However, future resource allocation is likely to align more precisely with the needs of community governance, thereby reducing resource wastage and mismatch. Effectively mobilizing and utilizing social resources will also emerge as a focal point for future research and practice.

In conclusions, the future trajectory of urban community governance will involve greater specialization, refinement, and socialization in policy guidance, societal involvement, and resource allocation, thus driving sustained improvement in urban community governance and the stable development of communities.

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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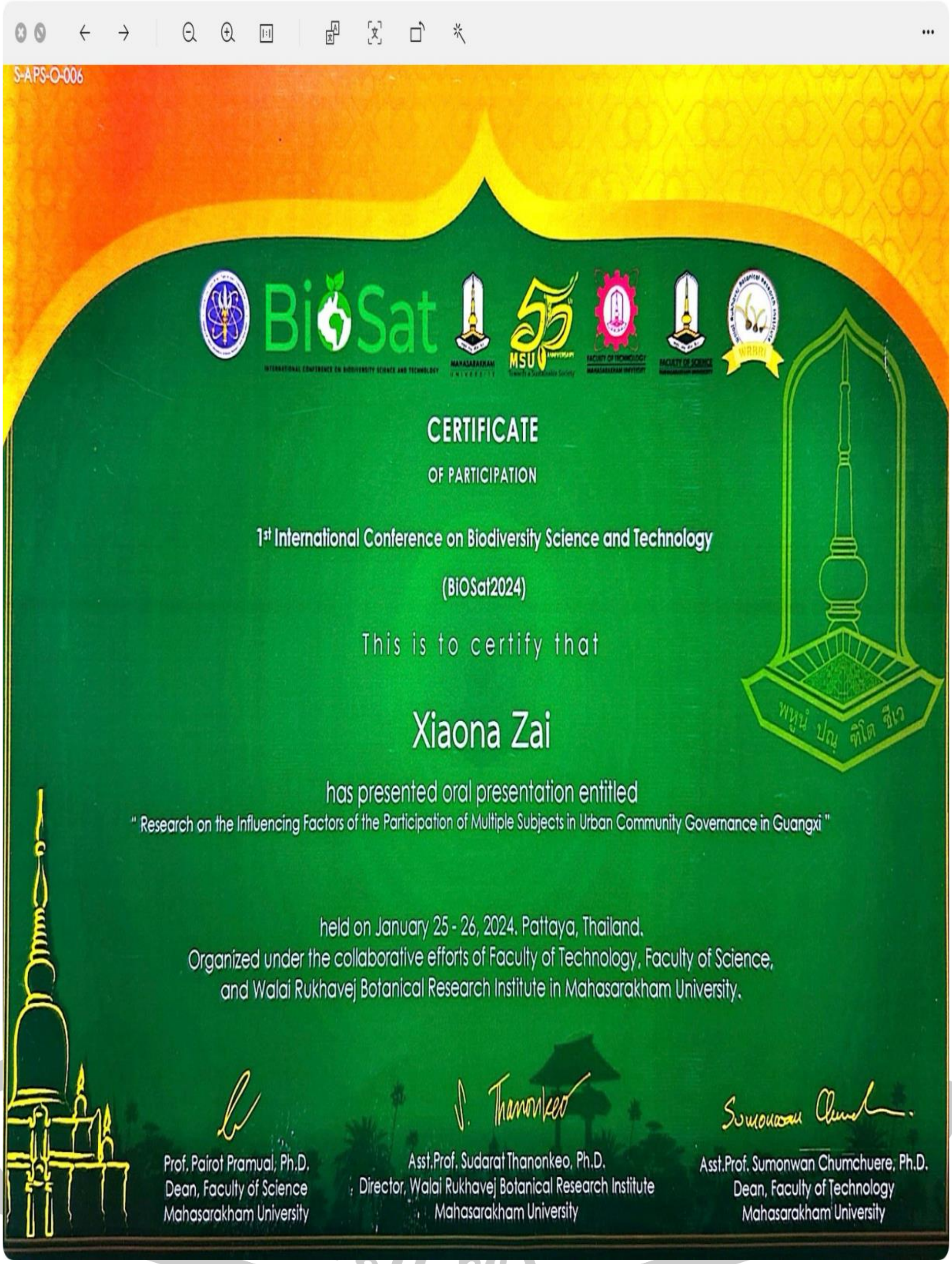
C.2 BioSat 2024 Conference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C.3 ICAS 2024 Conference

Abstracts: ICAS2024

A Study on Factors Influencing Residential Satisfaction i Multi-Ethnic Urban Communities in Guangxi: A Hybrid Approach Based on SEM and ANN

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Abstract

With the advancement of globalization, industrialization, and urbanization, Guang as a multi-ethnic region, has seen an increasingly diverse ethnic composition in i urban communities. Multi-ethnic communities have become important carriers for ad dressing urban ethnic issues and promoting harmonious ethnic relations. This stud conducted an in-depth analysis of multi-ethnic communities in Guangxi using a com bination of questionnaire surveys, in-depth interviews, field observations, structura equation modeling (SEM), and artificial neural networks (ANN). The SEM analysi results showed that the participation of community social organizations, communit development and services, and residents' awareness of participation had a signifi cant positive impact on residential satisfaction, while the influence of community so cial networks was not significant. The ANN analysis further revealed that the factor influencing residential satisfaction in Guangxi's multi-ethnic urban communities, i descending order of strength, are: community development and services, residents awareness of participation, participation of community social organizations, and com munity social networks. Based on these findings, this paper proposes strategic recom mendations to improve residential satisfaction in Guangxi's multi-ethnic communities including strengthening the construction of community social organizations, alignin community services with residents' needs, enhancing residents' awareness and capacity for participation, and building a collaborative governance mechanism involving multiple parties. These strategies aim to promote the harmonious and stable development of multi-ethnic communities and enhance overall residential satisfaction

Keywords: Multi-Ethnic Urban Communities,Residential Satisfaction,ANN,SEM

C.4 The 2nd manuscript


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C.5 The 3rd manuscript

Integrating Structural Equation Modeling and Machine Learning for Urban Community Governance Analysis

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Abstract

Urban community governance is essential for social cohesion and sustainable development. This study combines Structural Equation Modeling (SEM) with machine learning methods, including ANN, XGBoost, and LightGBM, to analyze key governance factors.Using survey data from 1,216 valid responses in Guangxi, SEM examines causal relationships, while machine learning evaluates factor importance. Results show Community Integration Satisfaction (CI) is the most critical driver of harmonized community development (HCD), followed by Resident Satisfaction (RS) and Resource Inputs (RI).Machine learning models validate SEM findings, with ANN capturing nonlinear relationships, and XGBoost and LightGBM ranking governance factors. Party Leadership (PL), Community Resident Self-Governance (CRS), Collaboration of Social Forces (CSF), and Workforce Building (CWB) show relatively lower importance.The study concludes that fostering community integration, resident satisfaction, and resource investment is key to governance effectiveness. Integrating SEM and machine learning provides a comprehensive approach for optimizing urban community governance strategies.

Keywords: Urban Community Governance, Structural Equation Modeling (SEM), Artificial Neural Networks (ANN), XGBoost, LightGBM

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