RESEARCH IN MANAGEMENT OF TECHNOLOGY AND BUSINESS
e-ISSN: 2773-5044

RMTB

Vol. 7 No. 1 (2026) 433-458
https://publisher.uthm.edu.my/periodicals/index.php/rmtb

Application of Spatial Clustering Analysis in Identifying Patterns of Affordable Housing Construction: A Developer-Based Study in Melaka

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DOI: https://doi.org/10.30880/rmtb.2026.07.01.037

Article Info

Received: 31 March 2026
Accepted: 31 May 2026
Available online: 30 June 2026

Keywords

Affordable housing, Application, Construction, Patterns, Spatial Clustering

Abstract

Housing affordability remains a pressing challenge in Malaysia, particularly for middle-income groups, requiring more spatially informed and data-driven approaches to guide affordable housing development. Spatial clustering analysis provides critical insights into demand concentrations, spatial disparities, and location suitability; however, its use is limited by inconsistent data quality, a lack of standardisation, and insufficient integration of socio-economic factors. This study investigates the extent of spatial clustering technique use among developers, identifies key strategies to enhance their use, and examines the relationship between these two components. A quantitative correlational design was adopted, with data collected from private developers in Melaka via structured online and in-person questionnaires. The study achieved a strong response rate of 94.4% (n = 34), ensuring robust and representative findings, which were analysed using descriptive statistics and Spearman's correlation. Results indicate a high overall application level, with DBSCAN, GIS and Local Moran's I being the most widely used tools for identifying suitable locations, detecting spatial patterns and assessing inequality. Developers prioritise enhancement strategies such as land-use and zoning analysis, advanced clustering algorithms and cross-sector data sharing. Correlation analysis reveals consistently positive but varied relationships, with the strongest relationship found between the use of descriptive spatial statistics and zoning-based strategies for industrial land renewal, indicating that statistical spatial summaries play the most influential role in guiding legally and environmentally aligned redevelopment decisions. Overall, the study provides actionable insights for developers and policymakers, promoting more effective, sustainable and equitable planning of affordable housing in Malaysia through enhanced spatial clustering integration.

1. Introduction

A home is a fundamental human necessity, yet middle-class households increasingly struggle to afford housing amid rising real estate prices and rapid economic growth (Zainon *et al.,* 2017; Awang & Ling, 2024). In Malaysia, the ability to own a home depends on individual financial capacity, and low-income groups often face housing inaccessibility (Olanrewaju *et al.,* 2016; Khazanah Research Institute, 2019; Yaacob *et al*., 2024). Housing affordability is influenced by home prices and personal income, making government and private-sector interventions critical for providing affordable units (Musaddad, Maamor, & Zainol, 2023; Mat Noor, 2025; Zamri *et al.,* 2020). Affordable housing remains scarce, particularly in urban areas (Azuddin & Razak, 2021; Nexus, 2025). Spatial clustering analysis has become essential for understanding the distribution of affordable housing and guiding inclusive, sustainable urban strategies (Bhanye *et al*., 2024; Guerrero & Law, 2024; O'Neill, 2008).

Affordable housing is vital for addressing housing crises in rapidly growing urban areas, especially in emerging economies. Many initiatives, however, often overlook critical factors such as location and residents' lifestyle needs. Housing suitability is typically assessed based on site characteristics or proximity to amenities, while socioeconomic factors such as income, education, and marital status also influence affordability (Zamri *et al.,* 2020; Nasrabadi, 2024). In Malaysia, programs such as PR1MA, RUMAWIP, and Rumah Selangorku aim to meet housing demand (Tengku Adnan, 2022; Bernama, 2024). Compliance with the National Occupancy Standard ensures homes meet spatial and functional requirements. Effective, affordable housing policies are therefore essential for reducing urban overcrowding and supporting residents' quality of life.

Spatial clustering analysis in affordable housing development remains limited due to inconsistent or incomplete spatial and attribute data, which weakens clustering accuracy (Azman *et al.,* 2024; CIDB, 2019), and because existing methods often overlook non-spatial determinants such as policy incentives, land constraints, and developer preferences that significantly shape construction patterns (Jiao, Jin, & Yang, 2024). Although integrative and enhanced clustering strategies have been proposed, their performance is still constrained by the inability of traditional techniques to account for complex socio-economic factors, including zoning regulations, demographic transitions, and local economic conditions (Martínez-Rocamora *et al*., 2024; Nasrabadi *et al.,* 2024; Gu *et al.,* 2020), prompting recent research to explore how improved application levels may yield more meaningful spatial patterns (Jin *et al.,* 2024). However, no study has yet investigated the relationship between application level and enhancement strategies in spatial clustering for affordable housing, a gap driven by methodological complexity and the interdisciplinary challenge of integrating spatial analytics with developer performance metrics (Chen, Zhang, & Lu, 2015; Reid, 2023; Sohaimi *et al*., 2024)

The scope of this study focuses on the spatial analysis of affordable housing in Melaka, Malaysia, with emphasis on the spatial economics of unsold or overhang units, which remain a major concern in developing countries where affordable housing often fails to match the locational needs of intended beneficiaries (Zamri *et al*., 2020; Azman *et al.,* 2024). Melaka offers a suitable context, as the state has recorded notable progress in affordable housing development, with 48,966 Rumah Mampu Milik units involving the Melaka Housing Board, private developers, and federal agencies such as PR1MA, SPNB, and the National Housing Department. Of these, 12,464 units have been completed, 18,509 are under construction, and 17,993 are in the planning stage. The state aims to target 62,644 units by 2030, requiring approximately 4,191 new units annually (Lembaga Perumahan Negeri Melaka, 2024). This study therefore, focuses on a private housing developer in Melaka, as private sector involvement is essential to the success and sustainability of affordable housing delivery in Malaysia, yet often constrained by low profit margins, regulatory challenges, land limitations and rising construction costs (Rizal *et al.,* 2019; Urbanice Malaysia & Majlis Bandaraya Melaka Bersejarah, 2023; Ramli *et al.,* 2024). These constraints contribute to persistent gaps between supply and demand for affordable housing, defined as units designed for households below the national median income and built according to government specifications, highlighting the need for spatial clustering analysis to better understand development patterns and support more effective policy and industry strategies (CIDB, 2019; Foo, 2024).

2. Literature Review

2.1 Spatial Clustering Analysis Concept

Spatial clustering analysis examines the spatial arrangement of features or events to reveal patterns that are not readily apparent visually (Murray, 1999; Distefano, Mameli, & Poli, 2020; MGIMO University, 2024). It is widely used in fields such as epidemiology, crime mapping, environmental studies, and urban planning (Getis & Ord, 1992; Agoha *et al*., 2024). Key techniques include Moran's I for global autocorrelation, LISA for hotspot detection (Anselin, 1995), and DBSCAN for density-based grouping (Ester *et al*., 1996). Because results depend on scale and parameter choices, careful selection is essential (Lu, 2000).

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2.2 Application of Spatial Clustering Analysis for Affordable Housing Projects

Barton, Parolin, and Weilty (2005), Wu and Sharma (2012), Cellmer, Cichulska, and Belej (2012), and Azman *et al.* (2024) highlight that spatial clustering in affordable housing development helps developers identify geographic patterns of housing needs, enabling data-driven decisions. By analysing spatial data, this method identifies areas with similar socioeconomic and infrastructural characteristics, informing the strategic placement of housing projects. It enhances resource allocation, land-use efficiency, and service connectivity while identifying underserved areas and forecasting future demand to support more equitable and sustainable urban development.

2.2.1 Using Geographic Information System (GIS)

Spatial clustering analysis, combined with GIS, enhances affordable housing mapping by evaluating concentrations relative to neighbourhood features, transportation, and job access (Zhong *et al.,* 2017). GIS integrates demographic, land-use, infrastructure, and socioeconomic data, enabling clustering algorithms to reveal spatial inequality and underserved areas (Zhang et al., 2009; Ahasan *et al.,* 2022; Maurya & Kumar, 2024; Rashid & Che Haron, 2024; Haripavan, Dey, & Chandana, 2025). This integration helps identify overconcentration or shortages of affordable housing and supports scenario modelling to assess impacts on access to services, guiding equitable and efficient housing planning (Kementerian Perumahan dan Kerajaan Tempatan, 2020; Vardopoulos *et al*., 2023; Malaker & Meng, 2024; Attah *et al.,* 2024).

2.2.2 Employing Fine-Grained Spatial Clustering Techniques

Recent improvements in spatial clustering have shown that analysing housing density within precise radial distances reveals that inexpensive and public housing generally has little effect on nearby property values. This fine-grained approach captures local impacts missed by aggregated data, consistently disproving misconceptions and supporting evidence-based decisions on affordable housing placement (Khazanah Research Institute, 2015; Cheung *et al*., 2022; Levine & Yavo, 2024; Nelson *et al.,* 2024; Alkan-Gökler, 2025).

2.2.3 Identifying Hotspots Through Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

Spatial clustering analysis is critical for targeting affordable housing interventions by identifying areas with concentrated low-income populations (Katz *et al.,* 2003). DBSCAN are utilised to detect and map "hot spots" of affordability stress, providing the necessary spatial precision for policy development (Civera *et al.*, 2023; Anselin, 1995). DBSCAN is particularly effective in urban settings because it accurately identifies dense clusters and spatial outliers without needing predefined parameters, optimising resource allocation for high-stress areas (Falkowski, 2009; Ram *et al.,* 2009; Tu *et al.,* 2022; Colbert, Chuang, & Sila-Nowicka, 2024; Götze, 2024).

2.2.4 Monitoring Gentrification and Displacement Risks

Spatial clustering analysis is an effective tool for detecting early indicators of gentrification, such as rapid increases in property values and demographic shifts (Smith *et al*., 2024; Mitchell *et al.,* 2025). By dynamically tracking these spatial patterns, planners can identify vulnerable communities at risk of displacement and implement timely interventions (Doraizo, 2022). Integrating this monitoring into urban planning enhances the capacity to balance urban growth with social equity, enabling more informed and proactive responses to neighbourhood change (Zuk *et al*., 2018; Cao *et al.,* 2024; Levine & Yavo, 2024; Suárez *et al.,* 2025; Zhang, 2025).

2.2.5 Using Spatial Statistics Descriptive

The geographic dispersion of affordable low-income housing, while suggesting progress, often shifts residents to peripheral areas lacking amenities, risking the prolongation of poverty and requiring closer attention to resource access (Liu & Shatford, 2019). Spatial statistics and clustering analysis are vital tools for identifying patterns in housing distribution and demographics, enabling developers to detect underserved areas (Azman *et al*., 2024; Zur'ain, Tarmidi, & Adi, 2020; Akinsulire *et al.*, 2024). These analyses support the strategic placement of units based on access to services, transportation, and socioeconomic conditions, fostering equitable urban development (Maliene, Howe, & Malys, 2008; World Green Building Council, 2023; Azlan *et al.*, 2025).

2.2.6 Using Local Moran's Statistics

The Local Moran's I Statistic provides crucial insights into affordable housing development by identifying hotspots (high concentrations) and cold spots (areas of scarcity). This technique converts spatial data into actionable intelligence, allowing developers to detect demand patterns and gaps (Tiefelsdorf & Boots, 1997; Fan & Myint, 2014; Tepanosyan *et al.,* 2019; Mohd Sairi, Burhan, & Mohd Safian, 2021; Lee, 2025). This spatial understanding aids strategic planning, resource allocation, and zoning, ultimately supporting more equitable urban growth

2.2.7 Spatial Autocorrelation Method

Spatial autocorrelation measures the degree to which affordable housing unit values are clustered, dispersed, or random across an area (Mohd Sairi, Burhan, & Mohd Safian, 2021). This is essential for developers, as clustering may signal demand or segregation risk, while dispersed patterns affect service planning (Wang *et al.,* 2017; Roy *et al.,* 2024; Chege, 2024). Spatial autocorrelation thus supports data-driven decisions to optimise site selection and promote equitable housing distribution aligned with spatial realities (Bagheri & Shaykh-Baygloo, 2021; Zhang *et al.,* 2024; Kpeebi & Evans, 2025).

2.1.1 2.2.8 Guiding Site Selection for New Housing Projects

Spatial clustering analysis is vital for strategically placing affordable housing. By assessing proximity to key urban amenities (jobs, transit, schools), developers ensure well-connected sites that promote residents' social and economic mobility (Grant, 2010; Hu & Wang, 2019; Ismail *et al*., 2023; Wang *et al.,* 2023; Azman *et al*., 2024). This approach prevents poverty concentration and supports equitable, sustainable urban planning (Samat, Abdul Rashid, & Elhadary, 2018; Kisiała & Rącka, 2021; Affandi *et al*., 2025; Gachanja & Yang, 2025; Nguyen, 2005; Yang *et al*., 2024; Economic Planning Unit, 2024; Andrade *et al.,* 2025; Ng, Shari, & Hassan, 2025).

2.3 Strategies to Enhance the Application of Spatial Clustering Analysis for Affordable Housing Projects

Spatial clustering analysis has been widely applied in housing projects to identify market segmentation, optimise land use, and assess affordability patterns. However, limitations in current frameworks necessitate strategic enhancements to improve accuracy and applicability in urban planning. Therefore, strategies to enhance the application of spatial clustering analysis in affordable housing projects in Malaysia aim to improve housing placement efficiency and address socio-spatial inequalities.

2.3.1Integrating Multi-Source Spatial Data for Enhanced Accuracy

Enhancing spatial clustering effectiveness requires integrating diverse spatial datasets (demographics, land use, transit, housing trends) to capture the complex links between socioeconomic factors and location (Elhorst, 2010; Batty, 2013; Chen *et al*., 2015; Azman *et al*., 2024; Jang & Park, 2025). Utilising high-resolution data enhances the detection of subtle disparities, enabling timely and targeted interventions to anticipate and address future affordability issues (Goodchild, 2007; Elwood *et al.,* 2012; Haffner & Hulse, 2019; Ren *et al.,* 2024).

2.3.2 Employing Advanced Clustering Algorithms

Advanced methods such as DBSCAN, K-means, and spatiotemporal clustering significantly enhance the analytical power of spatial clustering in affordable housing research, particularly in complex urban environments where spatial patterns are often fragmented and influenced by dynamic factors. DBSCAN excels at identifying clusters of varying shapes and densities within noisy urban data, making it a valuable tool for uncovering meaningful patterns that traditional methods might miss (Ester *et al.,* 1996; Chen *et al.,* 2016; Kapacu *et al.,* 2024).

2.3.3 Machine Learning Techniques

Integrating machine learning into spatial clustering enhances urban design by enabling dynamic, real-time adaptation to changing market conditions (Reades, De Souza, & Hubbard, 2018; Ohakawa *et al.,* 2024; Rane *et al.,* 2024; Zhang *et al.,* 2024). Models such as self-organising maps continuously update cluster boundaries, thereby improving prediction accuracy for gentrification and shortages (Li, Dragicevic & Castro, 2020). This adaptability supports robust decision-making and equitable resource targeting in evolving urban landscapes.

2.3.4 Linking Clustering Outputs to Equity-Focused Policy Design

Jang & Park (2025) emphasise that to ensure the equitable distribution of affordable housing, spatial clustering analysis must be integrated with equity-focused policymaking. By identifying spatial injustices, such as resource gaps and housing segregation, policymakers can design targeted interventions, including inclusionary zoning, rent control, and community land trusts (Chapple & Loukaitou Sideris, 2019; Talen, 2008).

2.3.5 Enhancing Visualisation Tools for Public and Stakeholder Engagement

Effective visualisation is crucial for conveying complex spatial clustering results in formats that are accessible to non-technical stakeholders (Addepalli *et al.,* 2023). Tools such as heat maps and interactive GIS dashboards clarify housing dynamics, promote inclusivity, and strengthen participatory planning processes (MacEachren *et al.,* 2005; Goodchild, 2007; Brown & Kyttä, 2014). Enhancing visual communication fosters more inclusive and well-informed urban development strategies

2.3.6 Integrating Temporal Analysis for Monitoring Change Over Time

Incorporating temporal dimensions into spatial clustering enables developers to track the dynamic evolution of affordability, gentrification, and displacement. Time-series analysis identifies long-term trends and emerging hotspots, crucial for designing adaptive and responsive housing policies (Zuk *et al.,* 2018; Liu *et al.,* 2016). This dynamic foresight enables the development of proactive strategies to anticipate future market shifts, thereby fostering sustainable and equitable urban development (Perić *et al*., 2022).

2.3.7 Encouraging Cross-Sector Collaboration/Data Sharing

Effective affordable housing requires multidisciplinary collaboration and data sharing among government, developers, and community groups (Economic Planning Unit, 2015; Azman *et al*., 2024). Integrating diverse datasets through spatial clustering enables informed, context-sensitive site selection (Anselin, 1995; Brail, 2008). Data-sharing frameworks promote transparency and facilitate iterative decision-making (Kitchin, 2014; Rodes *et al.,* 2007), thereby enhancing resource allocation and aligning initiatives with long-term resilience and social equity (CIDB, 2019; Jeske, Hagbert, & Engström, 2024; Nguyen, 2005).

2.3.8 Land Use and Zoning Analysis

For legislators, zoning and land use analysis are essential tools for balancing housing needs with sustainable growth by considering transit and infrastructure (Azman *et al.,* 2024). Brownfield sites offer valuable opportunities for urban regeneration, helping curb sprawl and revitalise neglected areas (De Sousa, 2006). Developing affordable housing on these sites aligns with efficient land use and environmental goals (Dixon *et al.,* 2007). Integrating these factors supports the development of sustainable, inclusive, and strategically located affordable housing.

2.3.9 Using Multi-Objective Programming

Multi-objective programming balances the societal benefits of affordable housing with concerns about spatial equity and concentrated disadvantage (Johnson, 2007; Chan & Adabre, 2019; Zhong *et al.,* 2019; Bhanye *et al.,* 2024). Early models guided site selection based on factors such as travel distances and rent disparities (Zhong *et al.,* 2017). The approach evolved to use net social benefit functions to analyse trade-offs, such as income disparities and subsidy needs (Murdoch & Sandler, 1997). Recent advances have monetised improvements in neighbourhood quality and addressed the complex balance among equity, cost, and social outcomes (Lens, 2014).

2.4 Relationship Between Application and Strategies to Enhance the Application of Spatial Clustering Analysis Affordable Housing Projects

Spatial clustering analysis offers crucial insights into geographic housing disparities by utilising tools such as Moran's I and LISA to identify underserved areas and inform evidence-based interventions (Zhang & Du, 2020;

Sun *et al*., 2021). Its effectiveness increases when supported by high-resolution and real-time geospatial data, satellite imagery, open-source platforms, mobile surveys, and AI or machine learning methods, including DBSCAN and K-means, which reveal complex spatial patterns often missed by traditional datasets (Kang *et al.,* 2018; Feng *et al.,* 2023). Participatory GIS further strengthens clustering outcomes by integrating qualitative spatial knowledge and community validation to enhance transparency and social relevance (Goodchild & Glennon, 2020; Ahmed *et al*., 2019).

The relationship between clustering application and enhancement strategies becomes evident when analyses are updated over time and complemented with community-based inputs, ensuring that spatial patterns accurately reflect evolving urban conditions (Zhao *et al.,* 2021; Azman *et al.,* 2024; Fang *et al.,* 2025). This relationship is further reinforced when clustering is embedded within multi-scalar policy frameworks that promote data interoperability, stakeholder training, and the translation of spatial insights into municipal, regional, and national housing actions (Debrunner & Hartmann, 2020; Wu *et al.*, 2025; Huang, Bibri, & Keel, 2025). Ethical considerations also shape this relationship, as inclusive and transparent enhancement strategies prevent algorithmic bias and support fair outcomes for marginalised communities (Rodero-Cosano *et al.,* 2022; Liu & Lv, 2024; Mendler *et al*., 2025; Debnath, 2021; Pilan, Costa & Cailo, 2023; Yang & Yi, 2024). Overall, the effectiveness of spatial clustering in affordable housing depends on the integration of robust data, advanced analytical techniques, community participation and supportive policy structures to ensure accurate, legitimate and equitable housing interventions

3. Research Methodology

3.1 Research Design

This quantitative study employed structured questionnaires administered online and face-to-face across affordable housing projects in Melaka. The data were analysed using SPSS to determine means and relationships, ensuring the validity of the findings. This approach enabled the study to generate reliable empirical evidence that supports a clearer understanding of developers' spatial clustering practices.

3.3 Procedure of Research

In the first stage, researchers identify key issues and problems in the field of study. Based on the current situation, research goals are established. The second stage involves a literature review to ensure a comprehensive understanding of the research topic. Information is gathered from books, journals, and articles and is supported by strong evidence. This topic presents a detailed review focusing on the application-level use of spatial clustering analysis, the strategies developers use to improve its application, and the relationship between application levels and enhancement strategies in affordable housing construction projects. The third stage focuses on data collection to achieve the research objectives. This study uses both primary and secondary data. Primary data is collected through questionnaires distributed to developer companies in Melaka, either face-to-face or online. The collected data is analysed using SPSS. Secondary data, primarily from previous studies and scholarly publications, is extensively used in the literature review to support and strengthen the research framework. In the fourth stage, data from primary sources is analysed using SPSS. Statistical analyses, such as percentages, means, and correlations, are used to examine relationships between application levels and enhancement strategies. The results are presented using tables, graphs, and pie charts, with both descriptive and inferential statistics applied to summarise data and test hypotheses. The final stage involves reporting the findings and drawing conclusions based on data analysis. Identified patterns, trends, and relationships form the basis of the conclusions, providing a comprehensive understanding of the study and contributing to future research and practical applications.

3.3 Sampling

Sampling involved selecting a subset of data from a larger population to draw efficient and meaningful conclusions (McCombes, 2019). The techniques were categorised as either non-probability (non-random) or probability (where each element had an equal chance of selection) (Alvi, 2016). The chosen method significantly influenced the validity, reliability, and generalizability of the findings, as a properly designed sampling process minimised bias and strengthened the overall credibility of the results (Berndt, 2020; Taherdoost, 2004).

This study targets a private housing developer in Melaka, chosen for its strategic growth context (New Straits Times, 2024; Devan, 2025). Developers' insights are vital because they influence housing distribution and challenges (Majid et al., 2023; Khairi et al., 2021), informing the assessment of spatial clustering to optimise site selection (Bank Negara Malaysia, 2017; Azman *et al.,* 2024).

Melaka, Malaysia, is an ideal case study that aligns with the study's objective. The state's substantial RMM unit targets (62,644 by 2030) and collaborative environment support longitudinal analysis of how developers enhance spatial clustering applications (Lembaga Perumahan Negeri Melaka, 2024; Resilience Unit of Melaka, 2019). The population is Melaka's active, affordable housing developers. Given 38 active companies, the required sample size is 36 respondents (Krejcie & Morgan, 1970). This sample ensures reliability and generalizability regarding developer commitment to policy implementation.

3.4 Research Methodology

This study employed a quantitative approach that aligned with its research goals. A structured questionnaire served as the primary data collection tool, enabling the efficient, systematic collection of reliable participant opinions and perspectives to achieve a comprehensive understanding of the research topic. Regarding questionnaire design, the questionnaire was divided into three clear sections:

Section A: Demographic Background
Section B: The Level of Application of Spatial Clustering Analysis in the Patterns of Affordable Housing Construction Projects by Developers.
Section C: The Main Strategies Developers Use to Enhance the Application of Spatial Clustering Analysis in the Patterns of Affordable Housing Construction Projects.

The survey used two types of five-point Likert scales to measure developer attitudes. A frequency scale (Never–Always) was applied to assess the Application Level (Objective 1), while a standard agreement scale (Strongly Disagree–Strongly Agree) was used to measure Enhancement Strategies (Objective 2), effectively capturing variations in opinion (Allen & Seaman, 2007).

3.5 Pilot Study

A pilot study (encompassing 5 respondents) was conducted to assess feasibility, refine research tools and logistics, and minimise potential errors (Hulley *et al.,* 2013). This preliminary investigation helps estimate data variability and enhance the validity and reliability of the main study's findings (Teijlingen & Hundley, 2001). Reliability analysis ensures the collection of consistent and accurate data (Nunnally & Bernstein, 1994). Cronbach's Alpha (α) is the measure of internal consistency (Salkind, 2007). In this study, the reliability analysis yielded a Cronbach's Alpha of 0.913, indicating very strong internal consistency and confirming that the questionnaire is highly reliable, as per Bond's (2015) interpretation scale.

Table 1 *Reliability Test*

Number of Questions	Number of Respondents	Alpha Cronbach's Value
120	5	0.913

3.6 Distribution of Questionnaire

The questionnaire was primarily distributed via social media platforms, including WhatsApp, Telegram, Twitter, Facebook, and email, to maximise reach and engagement. This approach enabled quick and easy access to a broad audience, thereby improving response rates and facilitating real-time feedback. Additionally, face-to-face distribution was used to ensure thorough data collection. Combining online and in-person methods helped achieve a more representative and diverse sample.

3.7 Data Analysis

Data collected via a Likert-scale questionnaire were analysed using SPSS to ensure accuracy and reliability. The results were presented using tables, graphs, and pie charts to clearly highlight trends and patterns, thereby enhancing the depth and clarity of the analysis.

3.7.1 Descriptive Analysis

The researcher used frequency analysis to examine data from Sections A (demographics), B (application level of spatial clustering), and C (strategies to enhance spatial clustering). Frequency analysis, a descriptive technique, counts response occurrences and computes means and percentages using SPSS, aiding interpretation and inference

3.7.2 Mean Analysis

Mean analysis was applied to summarise quantitative data clearly and accurately, enabling effective interpretation for both Objective 1 (the application level of spatial clustering analysis) and Objective 2 (the main strategies). In this study, mean scores were interpreted using three categories: Low (1.00–2.33: Not agree/Very poor/Never), Medium (2.34–3.67: Agree/Satisfied/Sometimes), and High (3.68–5.00: Strongly agree/Fully satisfied/Always), as recommended by Ibrahim (2013). This classification provided a consistent basis for evaluating developers' level of application and strategic practices in spatial clustering analysis.

3.7.3 Correlation Analysis

In this study, the analysis focuses on two types of variables: the dependent variable (DV) and the independent variable (IV). Since the data showed a $P < 0.05$, Spearman's correlation analysis was applied. The p-value was also used to determine whether to accept the null hypothesis (H_0) or the alternative hypothesis (H_1). Correlation methods were used to assess the direction and strength of relationships between variables. The correlation coefficient (r), which ranges from -1 to +1, specifically gauges the linear association between continuous variables, where +1 indicates a perfect positive correlation, -1 a perfect negative correlation, and 0 indicates no correlation (Field, 2013; Gravetter & Wallnau, 2014).

3.7.4 Normality Test

Normality tests were essential because valid survey instruments must meet the criteria of validity, reliability, and normality. In this study, the Shapiro-Wilk and Kolmogorov-Smirnov tests showed $p = 0.03 < 0.05$ for all items, confirming that the data were non-normal. Therefore, non-parametric analysis, such as Spearman's correlation, was employed (Field, 2018; Pallant, 2020; Noor & Fuzi, 2025).

3.7.5 Spearman's Correlation

Spearman's correlation was used as a nonparametric test to assess the direction and strength of a monotonic relationship between two variables based on ranked values. This method was appropriate because it does not require assumptions of normality or linearity and is well-suited for ordinal, skewed, or non-linear data (Field, 2018; Pallant, 2020). (Refer to Appendix)

4. Data Analysis

4.1 Analysis of Questionnaire

A total of 34 valid responses were obtained from the 36 registered developers in Melaka who participated, resulting in an exceptional response rate of 94.4%, which validates the reliability and suitability of the sample for evaluating spatial clustering in affordable housing (Johanson & Brooks, 2010; Kaliyadan & Kulkarni, 2019; Holtom, Baruch & Aguinis, 2022; Pallant, 2020).

4.1.1 Section A: Demographic Background

Table 2 shows that the demographic data collected confirm the sample's credibility: the majority are male (58.8%, n = 20) and in their productive years (30–49 years: 52.9%, n = 18). Racially, the sample is primarily Malay (67.6%, n = 23), followed by Chinese (20%, n = 7) and Indian (11.8%, n = 4). Most hold a bachelor's degree (61.8%) and have moderate industry experience (6–10 years, 44.1%, n = 15). The largest job categories are Architects (32.4%) and Engineers (26.5%), demonstrating that the respondents hold decision-making and technical roles directly relevant to spatial planning and project implementation.

Table 2 *Demographic Background*

No.	Respondent Background	Frequency	Percentange(%)
01	Gender		
	Male	20	58.8
	Female	14	41.2
02	Age		
	Between 18-19 years old	1	2.9
	Between 20-29 years old	14	41.2
	Between 30-49 years old	18	52.9

	Between 50-59 years old	1	2.9
	60 years old and above	-	-
03	Race		
	Malay	23	67.6
	Indian	4	11.8
	Chinese	7	20
04	Highest Qualification		
	Primary/ Secondary	1	2.9
	Diploma	3	8.8
	Bachelor	21	61.8
	Master/ Ph. D	9	26.5
05	Years of Active in the industry		
	1 -5 years	11	32.4
	6-10 years	15	44.1
	11-20 years	7	20.6
	21 and above	1	2.9
06	Position of Respondent		
	Project Planner	8	23.5
	Project Manager	4	11.8
	Engineer	9	26.5
	Architect	11	32.4
	Quantity Surveyor	1	2.9
	Others	1	2.9

4.1.2 Section B: Level of Application of Spatial Clustering Analysis in the Patterns of Affordable Housing Construction Projects by Developers

The findings in Table 3 shows that Melaka developers apply spatial clustering analysis at a high level, with mean scores across all components ranging between 3.7 and 4.1, indicating strong agreement and widespread use of spatial tools for affordable housing planning. GIS recorded the highest mean (4.059) for identifying suitable locations, while fine-grained clustering and DBSCAN were also frequently used to assess price impacts (3.882), uncover hidden spatial patterns (3.765), and select prime housing sites (3.912). Monitoring methods and spatial descriptive statistics similarly showed high utilisation for identifying vulnerable communities (3.735), locating key areas (3.824), and planning better housing placement (4.000). Local Moran's I and spatial autocorrelation showed strong mean values (up to 4.059), supporting equitable spatial decisions, hotspot detection, and data-driven planning. Overall, developers consistently rely on spatial clustering techniques to guide site selection, reduce segregation, and improve connectivity in affordable housing development.
exists.

Table 3 *Objective 1 result*

Application	Mean	Level	Ranking
Using a Geographical Information System (GIS)	3.956	High	**1**
1. Map the location of the housing.	3.853	Medium	4
2. Choose the best locations.	4.059	High	1
3. Analyse different types of data on the platform.	3.912	High	3
4. Identify the areas.	4.000	High	2
Using Fine-Grained Spatial Clustering Techniques	3.775	High	**5**
1. Measure housing density-based house proximity.	3.676	Medium	3
2. Uncover hidden patterns beyond borders.	3.765	High	2
3. Check nearby impact prices.	3.882	High	1
Identifying Hotspots Through Density-Based Spatial Clustering of Applications with Noise (DBSCAN)	3.765	High	**6**
1. Find communities dense with low-income households.	3.559	Medium	6
2. Decide on a suitable location.	3.912	High	1

3. Identify connected areas.	3.676	Medium	4
4. Separate dense clusters.	3.647	Medium	5
5. Show the concentration areas of locations.	3.883	High	3
6. Pick prime locations for new homes.	3.912	High	1
Monitoring Gentrification and Displacement Risks	3.729	High	**8**
1. Spot initial neighbourhood change indicators.	3.500	Medium	5
2. Reduce displacement risks.	3.676	Medium	4
3. Identify vulnerable communities.	3.735	High	3
4. Locate places.	3.824	High	2
5. Map zones for rent stabilisation measures.	3.912	High	1
Using Spatial Statistics Descriptive	3.835	High	**2**
1. Find many low-income houses.	3.735	High	3
2. Describe housing using statistics.	3.971	High	2
3. Describe transport using statistics.	3.735	High	3
4. Describe service using statistics.	3.735	High	3
5. Plan housing in better places.	4.000	High	1
Using Local Moran's I Statistic	3.805	High	**4**
1. Offer valuable insights.	3.324	Medium	7
2. Identify specific areas needing improvement.	3.500	Medium	6
3. Assist design in suitable location.	3.882	High	4
4. Locate housing near employment hubs.	3.971	High	2
5. Detect spatial cluster.	3.824	High	5
6. Build inclusive neighbourhoods.	3.971	High	2
7. Identify hotspots for community development.	3.912	High	3
8. Support equitable using spatial data	4.059	High	1
Using Spatial Autocorrelation Method	3.828	High	**3**
1. Show clustering.	3.471	Medium	6
2. Show dispersion.	3.676	Medium	5
3. Show randomness.	3.676	Medium	5
4. Detect patterns.	3.912	High	4
5. Interpret patterns.	4.029	High	2
6. Support better planning.	3.971	High	3
7. Support data-driven decisions.	4.059	High	1
Guiding Site Selection for New Housing Projects	3.753		**7**
1. Select strategic location.	3.618	Medium	5
2. Connect housing developments	3.706	High	3
3. Avoid isolation.	3.647	Medium	4
4. Reduces poverty concentration.	3.824	High	2
5. Reduces poverty segregation.	3.971	High	1

Overall, the study reveals that the application level of spatial clustering analysis among developers is high, with DBSCAN, GIS, and Local Moran's I being the most widely applied techniques for identifying suitable locations, detecting demand patterns, and assessing spatial inequalities. These findings correspond with past studies, where DBSCAN supports suitability analysis (Azman Shah *et al.*, 2024), GIS enhances spatial interpretation and site selection (Zhang *et al.*, 2009; Ahasan *et al.*, 2022; Rashid & Che Haron, 2024; Haripavan *et al.*, 2025), and Local Moran's I effectively identifies high-need and underserved clusters (KPKT, 2020; Attah *et al.*, 2024), confirming that developer practices are aligned with established empirical evidence and international best practices.

4.1.3 Section C: The Main Strategies Used to Enhance the Application of Spatial Clustering Analysis in the Patterns of Affordable Housing Construction Projects.

Table 4 indicates that a total of nine spatial clustering strategies were assessed, all achieving a 'high' agreement level (3.684-3.827). The highest-ranked strategy is 'Encouraging Cross-Sector Collaboration/Data Sharing' with a mean of 3.827, followed closely by 'Land Use and Zoning Analysis' with a mean of 3.824. Other top strategies include 'Integrating Multi-Source Spatial Data with a mean 3.788, 'Enhancing Visualisation Tools' with a mean 3.784, and 'Using Multi-Objective Programming' with a mean 3.772. The lowest-ranked yet still highly agreedupon strategies are 'Machine Learning Technique' (mean = 3.686) and 'Linking Clustering Outputs to Equity-Focused Policy Design' (mean = 3.684).

Table 4 *Objective 2 Result*

Strategy	Mean	Level	Ranking
Integrating Multi-Source Spatial Data for Enhanced Accuracy	**3.788**	**High**	**3**
1. Enhance the precision.	3.706	High	4
2. Improve the use.	3.974	High	1
3. Highlight small-scale inequalities unnoticed.	3.824	High	3
4. Highlight small-scale patterns unnoticed.	3.706	High	4
5. Identify regions facing increasing challenges.	3.912	High	2
Employing Advanced Clustering Algorithms	**3.765**	**High**	**6**
1. Enhance the detection of complex urban housing.	3.647	Medium	4
2. Identify clusters with different shapes.	3.588	Medium	5
3. Identify clusters with different sizes.	3.765	High	3
4. Identify clusters with different densities.	3.794	High	2
5. Monitor housing stress changes for planning.	4.029	High	1
Machine Learning Technique	**3.686**	**High**	**8**
1. Adapt urban design.	3.500	Medium	5
2. Modify cluster boundaries dynamically.	3.647	Medium	4
3. Improve forecast accuracy.	3.647	Medium	4
4. Provide more robust decision-making.	3.765	High	2
5. Ensure the decisions are well-informed.	3.676	Medium	3
6. Target high-risk areas using machine learning.	3.882	High	1
Linking Clustering Outputs to Equity-Focused Policy Design	**3.684**	**Medium**	**9**
1. Enable the development of equitable housing policies.	3.559	Medium	4
2. Identify areas with housing inequality.	3.676	Medium	3
3. Reduce inequality.	3.706	High	2
4. Support inclusive growth.	3.794	High	1
Enhancing Visualisation Tools for Public and Stakeholder Engagement	**3.784**	**High**	**4**
1. Visualise complex housing data with heat maps.	3.647	Medium	4
2. Visualise complex housing data with 3D models.	3.853	High	1
3. Engage communities in housing plans.	3.794	High	2
4. Include non-experts.	3.853	High	1
5. Promote transparency in urban planning decisions.	3.765	High	3
6. Support inclusivity in the planning process.	3.794	High	2
Integrating Temporal Analysis for Monitoring Change Over Time	**3.699**	**Medium**	**7**
1. Track changes over time.	3.559	Medium	3
2. Spot long-term trends early.	3.676	Medium	2
3. Identify new problem areas early.	3.618	Medium	4
4. Encourage early action to prevent displacement.	3.941	High	1
Encouraging Cross-Sector Collaboration/Data Sharing	**3.827**	**High**	**1**
1. Enhance planning by uniting diverse expertise.	3.706	High	7
2. Increase the quality of spatial data.	3.735	High	6
3. Increase the accuracy of spatial data.	3.794	High	5
4. Enhance spatial clustering for housing decisions.	3.853	High	4
5. Share data in real-time through open platforms.	3.706	High	7
6. Enable responsive strategies.	3.912	High	2
7. Enable fair strategies.	3.882	High	3
8. Enable sustainable strategies.	4.029	High	1
Land Use and Zoning Analysis	**3.824**	**High**	**2**
1. Identify suitable locations.	3.735	High	4
2. Encourage sustainable growth via brownfield reuse.	3.735	High	4
3. Promote efficient land use.	3.735	High	4
4. Promote renewal of outdated industrial areas.	3.765	High	3

5.	Comply with environmental standards	3.824	High	2
6.	Comply with legal standards	4.147	High	1
Using Multi-Objective Programming		**3.772**	**High**	**5**
1.	Balance with fairness impact.	3.471	Medium	5
2.	Balance with community impact.	3.735	High	4
3.	Optimise housing sites balancing multiple factors.	3.706	High	6
4.	Balance housing policy goals.	3.706	High	6
5.	Assess income long-term.	3.794	High	3
6.	Assess property long-term.	3.882	High	2
7.	Assess neighborhood long-term.	3.882	High	2
8.	Make housing decision environmentally sustainable.	4.00	High	1

Findings indicate that land-use and zoning analysis is the most important strategy, as it ensures legal compliance and supports brownfield redevelopment to enhance land efficiency, environmental sustainability, and urban resilience (De Sousa, 2006; Dixon *et al*., 2007). Advanced clustering algorithms are also highly prioritised because they align with spatial–temporal models that detect changing housing stress patterns and provide deeper analytical insights (Shekhar *et al.,* 2011; Yuan *et al.,* 2004; Huang *et al.,* 2016; Li *et al*., 2022; Bittencourt *et al.,* 2024). Additionally, cross-sector collaboration and data sharing are crucial, as partnerships among government agencies, researchers, private developers, and communities improve data quality, support evidence-based decisions, and strengthen planning outcomes (Economic Planning Unit, 2015; Azman *et al*., 2024; Nguyen, 2005; Kitchin, 2014; Rodes *et al.,* 2007). Collectively, these three top-ranked strategies establish a robust, data-driven framework that enhances the effectiveness and sustainability of spatial clustering applications in affordable housing development.

4.1.4 Section D: Strength of the Relationship Between the Level of Application of Spatial Clustering Analysis with the Main Strategies Developers Use

The analysis in this study used the Spearman correlation to examine relationships among the variables. The focus was limited to the top three ranked mean variables from Objectives 1 and 2 to ensure methodological robustness, as higher-mean variables represent the most stable, meaningful, and behaviorally significant response patterns. This makes them the most appropriate for Spearman correlation and helps reduce analytical noise, aligning with the recommendations of Pallant (2020), Hair *et al.* (2019), and Creswell and Creswell (2023).

The correlation analysis shows that all identified relationships are positive, thereby supporting hypothesis H1. The strongest correlation occurs between Spatial Statistics Descriptive (Plan Housing in Better Places) and Land Use and Zoning Analysis (Promote Renewal of Outdated Industrial Areas), with $r = 0.712$ ($p = 0.01$). Three moderate correlations also emerge: GIS (Choose the Best Location) with Land Use and Zoning Analysis (Comply with Legal Standards) ($r = 0.628$, $p = 0.01$), Spatial Statistics Descriptive (Plan Housing in Better Places) with Land Use and Zoning Analysis (Comply with Environmental Standards) ($r = 0.622$, $p = 0.01$), and GIS (Choose the Best Location) with Multi-Source Data Integration (Highlight Small-Scale Inequalities) ($r = 0.610$, $p = 0.01$). Several weak but significant correlations are also noted, including GIS (Identify the Areas) with Multi-Source Data Integration ($r = 0.492$, $p = 0.03$), Spatial Statistics Descriptive with Cross-Sector Collaboration ($r = 0.481$, $p = 0.04$), and GIS (Choose the Best Location) with Cross-Sector Collaboration ($r = 0.475$, $p = 0.005$). Very weak correlations, such as Spatial Autocorrelation (Support Better Planning) with Cross-Sector Collaboration ($r = 0.268$, $p = 0.125$), remain positive despite low strength. Overall, the appendix indicates that although correlation magnitudes differ, all relationships are positive and aligned with the expected direction of H1.

The heatmap in Figure 1 shows that most correlations between developers' spatial clustering applications and enhancement strategies fall within weak to moderate ranges, indicating that integration is developing but not yet fully established. The strongest relationship is observed between Spatial Statistics Descriptive and Zoning Analysis ($r = 0.712$), highlighting the strong support that statistical tools provide for zoning-related decisions. GIS applications exhibit moderate alignment with strategies that enhance spatial precision and reveal small-scale inequalities, while autocorrelation methods demonstrate moderate connections with data-sharing and accuracy-oriented strategies, underscoring the importance of reliable, high-quality spatial data. Strategies focused on fairness, equity, and community impacts display consistently weak correlations, suggesting limited practical adoption. Overall, the heatmap reflects a maturing yet still evolving system in which developers are beginning to align technical spatial tools with planning strategies; however, greater capacity-building and collaboration are required to strengthen their effectiveness.

			Strategies developers use to enhance the application of spatial clustering analysis in the patterns of affordable housing construction projects.								
			Data Sharing			Zoning Analysis			Enhanced Accurancy		
			ESS	ERS	EFS	CLS	CES	PRO	ITU	IRF	HSS
Level of application of spatial clustering analysis in the patterns of affordable housing construction projects by developers.	GIS	BL	0.265	0.487	0.475	0.628	0.573	0.397	0.525	0.501	0.61
		DT	0.338	0.356	0.537	0.503	0.418	0.369	0.351	0.451	0.421
		ITA	0.416	0.373	0.256	0.46	0.417	0.323	0.352	0.343	0.492
	Statistic Descriptive	PH	0.558	0.524	0.706	0.532	0.622	0.712	0.437	0.359	0.592
		DH	0.335	0.481	0.583	0.604	0.536	0.527	0.588	0.547	0.602
		LI	0.173	0.154	0.231	0.362	0.308	0.35	0.314	0.369	0.334
	Autocorrelation Method	DD	0.33	0.215	0.389	0.538	0.455	0.504	0.31	0.36	0.567
		IP	0.271	0.271	0.415	0.435	0.305	0.333	0.394	0.322	0.596
		BP	0.135	0.268	0.367	0.32	0.262	0.24	0.378	0.402	0.509

Very Weak   Weak   Moderate   Strong

Figure 1 *Heatmap Relationship (Objective 3 result)*

Objective 3 successfully analysed the relationship between the application of spatial clustering and enhancement strategies among private developers in Melaka, confirming that the variables exhibit a range of connections (related or unrelated). The strongest positive relationship (H1 Strong) was found between the application of Spatial Statistics Descriptive (*Plan Housing in Better Places*) and the strategy of Land Use and Zoning Analysis (*Promote Renewal of Outdated Industrial Areas*), a finding that aligns with research emphasizing the integration of spatial analysis in land use planning and brownfield redevelopment (De Sousa, 2006; Dixon et al., 2007; Boots, 2003). Conversely, the analysis identified the lowest relevance (Very Weak) between the Spatial Autocorrelation Method (*Support Better Planning*) and the strategy of Encouraging Cross-Sector Collaboration/Data Sharing (*Enable Responsive Strategies* or *Enable Sustainable Strategies*), leading to very weak support for both H1 and H0, which suggests these two constructs are minimally related in current developer practices.

5. Conclusion

This study successfully achieved all three research objectives by evaluating the level of spatial clustering application, identifying key enhancement strategies, and examining their relationships in affordable housing development in Melaka. The findings indicate a high level of application among developers, with GIS, DBSCAN, and Local Moran's I being the most widely utilised tools, while land-use zoning analysis, advanced clustering algorithms, and cross-sector data sharing emerge as the most influential strategies. Hypothesis testing confirms that H1 is achieved, demonstrating a significant relationship between spatial clustering applications and enhancement strategies, with varying strengths of association. Stronger relationships are observed between descriptive spatial statistics and zoning analysis, supporting effective land optimisation and redevelopment planning. In contrast, moderate to weaker linkages reflect constraints related to data integration, digital readiness, and organisational capacity. Based on the ranked strength of these relationships, this study develops a relationship framework (Figure 2) that prioritises empirically supported application–strategy pairings and provides practical guidance for developers and policymakers to enhance data-driven, sustainable, and equitable affordable housing development in Malaysia.

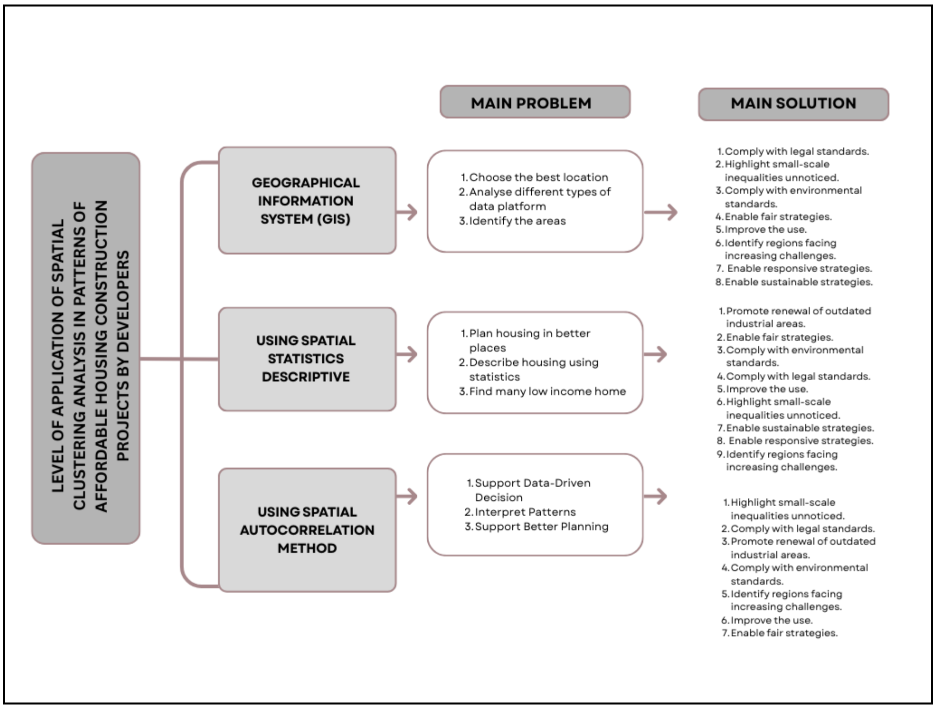

Figure 2 *Relationship framework between the Level of Application of Spatial Clustering Analysis and the Main Strategies Developers*

Acknowledgement

The author would like to thank the Faculty of Technology Management and Business and Universiti Tun Hussein Onn Malaysia for its support.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Nurin Alyaa Syafiqah Zamri, Rozlin Zainal, Hamidun Mohd Noh;* ***data collection:*** *Nurin Alyaa Syafiqah Zamri;* ***analysis and interpretation of results: Nurin Alyaa Syafiqah Zamri, Rozlin Zainal; draft manuscript preparation:*** *Nurin Alyaa Syafiqah Zamri, Rozlin Zainal. All authors reviewed the results and approved the final version of the manuscript.*

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Appendix: Correlation Analysis

Main Problems	Main Solutions	Correlation Coefficient Value, r	Significant level P	Relationship Strength	Level of the relationship	Hypothesis	Ranking
1) Using a Geographical Information System (GIS) -Choose the best locations	**1) Encouraging Cross-Sector Collaboration / Data Sharing** -Enable sustainable strategies. - Enable responsive strategies. - Enable fair strategies.	0.265 0.487 0.475	0.129 0.003 0.005	Very weak Weak Weak	Positive Positive Positive	H0 H1 H1	- 28 30
	2) Land Use and Zoning Analysis - Comply with legal standards. - Comply with environmental standards. - Promote renewal of outdated industrial areas.	0.628 0.573 0.397	-0.01 -0.01 0.20	Moderate Moderate Weak	Positive Positive Positive	H1 H1 H0	3 12 -
	3) Integrating Multi-Source Spatial Data for Enhanced Accuracy - Improve the use. - Identify regions facing increasing challenges. -Highlight small-scale inequalities unnoticed.	0.525 0.501 0.610	0.001 0.03 -0.01	Moderate Moderate Moderate	Positive Positive Positive	H1 H1 H1	21 26 5
1) Using a Geographical Information System (GIS) - Analyse different types of data platform	**1) Encouraging Cross- Sector Collaboration / Data Sharing** -Enable sustainable strategies. - Enable responsive strategies. - Enable fair strategies.	0.338 0.356 0.537	0.51 0.39 0.001	Weak Weak Moderate	Positive Positive Positive	H0 H0 H1	- - 17
	2) Land Use and Zoning Analysis - Comply with legal standards. - Comply with environmental standards. - Promote renewal of outdated industrial areas	0.503 0.418 0.369	0.02 0.14 0.32	Moderate Weak Weak	Positive Positive Positive	H1 H0 H0	25 - -
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy - Improve the use. - Identify regions facing increasing challenges. -Highlight small-scale inequalities unnoticed.	0.351 0.451 0.421	0.42 0.07 0.013	Weak Weak Weak	Positive Positive Positive	H0 H0 H1	- - 34
1) Using a Geographical Information System (GIS) - Identify the areas	**1) Encouraging Cross- Sector Collaboration / Data Sharing** -Enable sustainable strategies. - Enable responsive strategies. - Enable fair strategies.	0.416 0.373 0.256	0.014 0.30 0.143	Weak Weak Very Weak	Positive Positive Positive	H1 H0 H0	36 - -
	2) Land Use and Zoning Analysis - Comply with legal standards. - Comply with environmental standards. - Promote renewal of outdated industrial areas.	0.460 0.417 0.323	0.006 0.014 0.063	Weak Weak Weak	Positive Positive Positive	H1 H1 H0	31 35 -
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						

	- Improve the use.	0.352	0.41	Weak	Positive	H0	-
	- Identify regions facing increasing challenges.	0.343	0.047	Weak	Positive	H1	46
	-Highlight small-scale inequalities unnoticed.	0.492	0.03	Weak	Positive	H1	27
1) Using Spatial Statistics Descriptive	**1) Encouraging Cross- Sector Collaboration / Data Sharing**						
- Plan housing in better places	-Enable sustainable strategies.	0.558	-0.01	Moderate	Positive	H1	14
	- Enable responsive strategies.	0.524	0.01	Moderate	Positive	H1	22
	- Enable fair strategies.	0.706	-0.01	Moderate	Positive	H1	2
	2) Land Use and Zoning Analysis						
	- Comply with legal standards.	0.532	0.001	Moderate	Positive	H1	19
	- Comply with environmental standards.	0.622	-0.01	Moderate	Positive	H1	4
	- Promote renewal of outdated industrial areas.	0.712	-0.01	Strong	Positive	H1	1
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						
	- Improve the use.	0.437	0.010	Weak	Positive	H1	33
	- Identify regions facing increasing challenges.	0.359	0.037	Weak	Positive	H1	44
	-Highlight small-scale inequalities unnoticed.	0.592	-0.01	Moderate	Positive	H1	10
2) Using Spatial Statistics Descriptive	**1) Encouraging Cross- Sector Collaboration / Data Sharing**						
- Describe housing using statistics	-Enable sustainable strategies.	0.335	0.53	Weak	Positive	H0	-
	- Enable responsive strategies.	0.481	0.04	Weak	Positive	H1	29
	- Enable fair strategies.	0.583	-0.01	Moderate	Positive	H1	11
	2) Land Use and Zoning Analysis						
	- Comply with legal standards.	0.604	-0.01	Moderate	Positive	H1	6
	- Comply with environmental standards.	0.536	0.01	Moderate	Positive	H1	18
	- Promote renewal of outdated industrial areas.	0.527	0.01	Moderate	Positive	H1	20
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						
	- Improve the use.	0.588	-0.01	Moderate	Positive	H1	9
	- Identify regions facing increasing challenges.	0.547	-0.01	Moderate	Positive	H1	15
	-Highlight small	0.602	-0.01	Moderate	Positive	H1	7
1) Using Spatial Statistics Descriptive	**1) Encouraging Cross- Sector Collaboration / Data Sharing**						
- Find many low-income home	-Enable sustainable strategies.	0.173	0.329	Very Weak	Positive	H0	-
	- Enable responsive strategies.	0.154	0.386	Very Weak	Positive	H0	-
	- Enable fair strategies.	0.231	0.189	Very Weak	Positive	H0	-
	2) Land Use and Zoning Analysis						
	- Comply with legal standards.	0.362	0.035	Weak	Positive	H1	42
	- Comply with environmental standards.	0.308	0.076	Weak	Positive	H0	-
	- Promote renewal of outdated industrial areas.	0.350	0.042	Weak	Positive	H1	45
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						
	- Improve the use.	0.314	0.70	Weak	Positive	H0	-
	- Identify regions facing increasing challenges.	0.369	0.32	Weak	Positive	H0	-
	-Highlight small-scale inequalities unnoticed	0.334	0.54	Weak	Positive	H0	-

1) Using Spatial Autocorrelation Method - Support Data Driven Decisions	**1) Encouraging Cross- Sector Collaboration / Data Sharing**						
	-Enable sustainable strategies.	0.330	0.057	Weak	Positive	H0	-
	- Enable responsive strategies.	0.215	0.223	Very Weak	Positive	H0	-
	- Enable fair strategies.	0.389	0.23	Weak	Positive	H0	-
	2) Land Use and Zoning Analysis						
	- Comply with legal standards.	0.538	0.001	Moderate	Positive	H1	16
	- Comply with environmental standards.	0.455	0.007	Weak	Positive	H1	32
	- Promote renewal of outdated industrial areas.	0.504	0.002	Weak	Positive	H1	24
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						
	- Improve the use.	0.310	0.074	Weak	Positive	H0	-
	- Identify regions facing increasing challenges.	0.360	0.037	Weak	Positive	H1	43
	-Highlight small-scale inequalities unnoticed.	0.567	-0.01	Moderate	Positive	H1	13
1) Using Spatial Autocorrelation Method - Interpret Patterns	**1) Encouraging Cross- Sector Collaboration / Data Sharing**						
	-Enable sustainable strategies.	0.271	0.121	Very Weak	Positive	H0	-
	- Enable responsive strategies.	0.271	0.218	Very Weak	Positive	H0	-
	- Enable fair strategies.	0.415	0.015	Weak	Positive	H1	37
	2) Land Use and Zoning Analysis						
	- Comply with legal standards.	0.435	0.10	Weak	Positive	H0	-
	- Comply with environmental standards.	0.305	0.79	Very Weak	Positive	H0	-
	- Promote renewal of outdated industrial areas.	0.333	0.054	Weak	Positive	H0	-
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						
	- Improve the use.	0.394	0.021	Weak	Positive	H1	39
	- Identify regions facing increasing challenges.	0.322	0.064	Weak	Positive	H0	-
	-Highlight small-scale inequalities unnoticed.	0.596	-0.01	Moderate	Positive	H1	8
1) Using Spatial Autocorrelation Method - Support better planning	**1) Encouraging Cross- Sector Collaboration / Data Sharing**						
	-Enable sustainable strategies.	0.135	0.446	Very Weak	Positive	H0	-
	- Enable responsive strategies.	0.268	0.125	Very Weak	Positive	H0	-
	- Enable fair strategies.	0.367	0.033	Weak	Positive	H1	41
	2) Land Use and Zoning Analysis						
	- Comply with legal standards.	0.320	0.65	Weak	Positive	H0	-
	- Comply with environmental standards.	0.262	0.134	Very Weak	Positive	H0	-
	- Promote renewal of outdated industrial areas.	0.240	0.171	Very Weak	Positive	H0	-
	3) Integrating Multi-Source Spatial Data for Enhanced Accurancy						
	- Improve the use.	0.378	0.028	Weak	Positive	H1	40
	- Identify regions facing increasing challenges.	0.402	0.018	Weak	Positive	H1	38
	-Highlight small-scale inequalities unnoticed.	0.509	0.002	Moderate	Positive	H1	23

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