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Spatial association in students' residential apartment property characteristics around a university

Oladotun Peter Binuyo*[1], Victoria Amietsenwu Bello[1]

[1]*The Federal University of Technology, Akure, Nigeria*

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Abstract

This study aimed at examining the presence of spatial association in residential property characteristics. It considered self-contained residential apartments around a public university in Akure, Nigeria. It is a survey research where data was collected through the use of questionnaires administered to the occupants of the self-contained apartment within a 500-meter radius of the 'Southgate' axis of the university. Data collected was analyzed with the use of ArcGIS software where spatial regression was carried out as well as the Anselin Local Indicator of Spatial Association for Cluster/outlier analysis. The result of the analysis revealed that some of the property characteristics have multicollinearity which led to dropping some of them that are represented by their collinear attribute. Distance from the university was observed to have an inverse relationship with the rental prices while other property attributes have a positive influence. From the cluster/outlier analysis, it was revealed that there are significant clustering/outlying in the central and northwestern parts of the study area. The property physical attributes such as kitchen quality, bathroom quality, toilet quality, window quality, and wall quality are high in the northwestern parts where there are new and modern designs while the central part of the study area has low quality of these attributes. The results of the analysis show that the clustering/ outlying, otherwise known as spatial association, among the property attributes are not the same across a particular place and the assumption of a uniform spatial association across the area would be misleading. It is therefore recommended that analysis of real estate investment around an academic institution in Nigeria should consider the property characteristics that influence prices and also adopt spatial clustering analysis to know the specific property characteristics that are to be improved upon on the quality that should be provided to have the best prices with reference to locations. The originality of this research comes in the use of a relatively smaller study area in examining spatial associations among property characteristics. It also considers the clustering/outlying analysis of the qualities of the property characteristics with reference to specific locations which would help real estate developers and analysts on the quality of finishing that should be given to each property attribute at different locations around a university campus in Nigeria.

1. Introduction

The early adoption of the hedonic approach in real estate studies can be traced to studies such as Lancaster (1971), Griliches (1971) and Rosen (1974). There has since been its wide application in the field, especially in respect of mass appraisal for taxation and mass property valuation (Erath et al., 2009). This model allows the determination of property value, as a bundle of utilities including the property characteristics such as the quality and size, location and neighbourhood factors (Wilhelmsson et al., 2021). Wilhelmsson, et al. (2021) further emphasized that considering real estate spatial reference, real estate values vary spatially across geographic space and there has been the adoption of spatially varying models. This informs the need to ensure that spatially homogenous or heterogeneous factors should be taken into consideration when modeling real estate values as there are possibilities of submarkets which is not uncommon due to the location and neighbourhood factors, which could influence the level of development and the property characteristics (Rosen, 1974). Budziński et al. (2016) adduced that such a phenomenon is attributable to the fact that the spatial association in residential property data is linked to residential sorting, where choices of environmental goods influence people's choice of where to live which makes their preferences for the property utility-components to have high correlations. Spatial autocorrelation thereby shapes the spatial extent of the local real estate market, where the properties have similar values, dependent on special location (Li et al., 2020).

***Corresponding Author**
*(dotby2007@yahoo.com) ORCID 0000-0003-0744-4352
(opbinuyo@futa.edu.ng) ORCID 0009-0003-5571-6356

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One of the theories that create the framework of developing objective explanations for spatial association is the Alonso-Mills-Muth urban space model (Gwamna et al., 2015). It assumes that residential property renters make decisions as informed by the trade-off between property values and the cost of daily commuting where people of low-income class are closer to the CBD while the high-income class is commonly found in the suburban areas (Gwamna, et al., 2015; Kim & Kim, 2016). Properties of similar characteristics therefore develop in clusters due to the similarity of their neighborhood which could also influence their designs (Lo et al., 2022). Kim & Kim (2016) emphasized that properties within a school would have a positive correlation in their characteristics with an increase in the school qualities and high housing qualities. There could therefore be a level of homogenous development in terms of aesthetics and structures for clusters of properties within a neighbourhood that could have agglomerated around a particular homogenous function (Lo et al., 2022).

One of the utility components of the hedonic model is the structural qualities of properties, which Shen & Karimi (2015) explained to exist in homogenous groups, as a neighbourhood factor, to influence the predictability of property value models (Budziński, et al., 2016). An example of neighbourhood factors that can attract a class of people and which contributes to the nature of demand and indeed the types of residential properties developed is a university campus where students and staff are attracted, thus influencing the real estate investment nature and type in the neighbourhood.

The preferences of students to housing have not received sufficiently conclusive attention in the literature and most often in Nigeria, students have limited resources to spend which reduces their choices, thus the assumed needlessness of conducting research in that regard. Meanwhile, in an antithesis to the study of Thomsen (2007) on the preferences of students for accommodation where it was stated that there is less emphasis on the quality of the apartments because of the temporary nature of stay of students and their modal low economic status, Tavares et al. (2019) discovered the quality of apartment to be the major factor that attracts students to accommodation in the selected public universities in Portugal. An emphatic conjecture by Khozaei, et al. (2014) to accentuate the need to ensure quality housing for students was that, not only is student accommodation a place where they stay for one to four years and above of their young adult life, it is also a time of consequential phase of their lives, hence the need to make it positively contributing to the students' entire live.

The study of Park & Kim (2023) supports those residents have certain behaviors on their preferences for characteristics of residential properties which have spatial connotations. This implies that their choices have a relationship with the physical characteristics of the properties and this can be reflected in the spatial aggregation of the property characteristics and this was also established in Aluko (2011), a Nigeria study which was on a broader spectrum of analysis on neighborhood effect of location of residential properties.

While the presence of phenomena such as spatial association, spatial autocorrelation, and spatial dependence have been discovered in literature, such as Li et al. (2020), Morenikeji et al. (2017), and Park & Kim (2023), only few studies have considered similar phenomena around a university. Examples of such studies are Yunus et al. (2018) on the spatial arrangement of different off-campus student hostels around Bayero University, Kano, Nigeria, Mei et al. (2019) on travel-to-school distance as a factor of association, and Agostinelli et al. (2022) which considered access to education as a factor of the spatial association.

However, the consideration of the spatial association of qualities of housing is not readily available in the existing literature, and to emphasize the need for a study in this regard and the obvious scantiness of scholarly works on preferences for off-campus student accommodation especially where private real estate investors are involved, giving attention to the qualities of the structural characteristic of the accommodation in terms of possible spatial associations within the university environment thus creating 'micro-submarkets' would not be unnecessary.

One of the methods used in spatial analysis of local association of property data is the Local Indicator of Spatial Association (LISA) by Anselin (1995) to explore clustering spatial data and it is expressed as:

$$I = \frac{n(x_i - \bar{x}) \ \sum_i W_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})2} = Z_i \sum_j W_{ij} Z_j \quad (1)$$

where Z_i and Z_j are normalized x_i and x_j. When I_i is positive, it shows a statistically significant local clustering of the data where there is a similarity in the value of the local space and it could be when high values cluster or when low values cluster. When I_i is negative, it shows significant outliers, where there is clustering of low values around high data or high values around low data.

To further the LISA of Anselin (1995), the study of Basu & Thibodeau (1998) is one of the earliest geostatistical methods applied in examining the presence of associations among spatial data in a particular location. The approach of the study was to model the covariance matrix within the referenced location, denoted by $s_i = (x_i, y_i)$ and $s_j = (x_j, y_j)$, to which the Generalized Least Squares can be applied

$$y = X\beta + \varepsilon \quad (2)$$

This gives room for the use of local parameter estimation where the weighted least squares method of weighting matrix is applied to locations and diagonal matrices of w_ij is measured by the distance locations ith and jth and the local parameters for each other are given as $\beta(x_i, y_i)$

$$\hat{\beta}(x_i, y_i) = (X^T W_{(i)} X)^{-1} \cdot X^T W_{(i)} y \quad (3)$$

For each of the locations,

$$\hat{y_i} = x_i \cdot \beta(x_i, y_i) \quad (4)$$

For the residuals at all locations (x_i, y_i)

$$\varepsilon_i = y_i - \widehat{y_i} = y_i - x_i \cdot \beta(x_i, y_i) \quad (5)$$

The application of local statistics in real estate values/prices in Nigeria is scanty and examining the property characteristics that influence students' choice of residential accommodation around a university campus has not received a local examination which informs this research. Existing literature has not extensively researched the clustering of property characteristics in influencing property values, especially with reference to residential properties around a university campus. This study, therefore, aims at using self-contained apartments occupied by students around a university in a developing country, to examine the spatial clustering and association of property physical attributes around the University. In this, the study uses a smaller geographic space in the examination of spatial clustering contrary to the convention of using a large study area when analyzing spatial association and property submarkets as observed in some existing studies.

2. Literature review

2.1. Student housing preferences

According to Khozaei, et al. (2014) student housing is such that provides accommodation for students during their time in the school and Ghani (2018) expressed that student accommodation provides the basis for the interaction between the students and their environment in determining their happiness, productivity and success while in school. Dizaj & Khanghahi (2022) affirmed that student housing is important in university students' lives after their education, as it serves the purpose of being their home for the time, they are in school which makes it necessary for it to meet the needs of the students while also responding to their social lives. Dizaj & Khanghahi (2022) therefore stated that student housing is expected to be properly planned as it has a direct impact on their behaviour, leadership traits, citizenship, academic performance, social and psychological attributes and sense of solidarity.

In the same light as the opinion of Dizaj & Khanghahi (2022), Najib & Abidin (2011), maintained that student accommodation should be provided by higher institutions so as to enhance their intellectual abilities but in some cases especially in developing countries there is inadequate accommodation for students by the Institutions. Therefore, Yunus et al. (2018) consented that many students in situations where there is inadequate accommodation on campus are constrained to seeking off-campus accommodation mostly within the proximity of the university.

Owing to the need for seeking off-campus accommodation by such students, different designs have emerged to cater for their specific needs at the time in school. The minimalist perspective for design has however affected the quality of designs of student accommodation by some of the private real estate investors through the use of inferior materials of design (Dizaj & Khanghahi, 2021). Meanwhile, in the view of Nijënstein et al. (2015), differences in taste bring about varying housing preferences that are reflected in the quality of materials of construction and designs, where the taste of students in a university might have been motivated by factors that are consistent with their purpose of being in school, which is to pursue a level of education that makes their preferences different from other categories of housing consumers. Moreover, housing preferences could often serve as the basis for measuring housing satisfaction derivable by students which could also vary by individuals.

The study of Khzaei et al. (2014) on the preferences of students on the design of their halls of residence revealed that students have preferences for accommodation of suite-style and single rooms. Along this line of research, the study of Nijënstein et al. (2015) discovered that factors that determine the decision of students as regards accommodation are travel time to the university, size of the room, sharing the kitchen with other students and the aesthetics of the housing, The study of Verhetsel et al. (2017) on the preferences of Belgian students as regards housing showed more preference for the size of the property, and rent payable before they make their choice which constraints them to prefer studio flat that provides privacy to the student. The finding of Verhetsel et al. (2017) was also confirmed in a study by Yunus, et al. (2018) carried out in Kano, Nigeria where privacy was emphasized as an important factor considered by students in making their housing choices.

As regards off-campus accommodation, the study of Edwards (2019) adopted a quantitative research approach to the preferences of students of a University in Cape Town, South Africa and discovered that their choices of housing are dependent on the presence of Wi-Fi, round-the-clock security and the presence of computer lab in the building. Noraini et al. (2017) however emphasized the need to conduct location-specific research as students' housing preferences could vary based on the location and other peculiar factors with respect to different areas. To this end, the study of Zubairu et al. (2018) in Nigeria discovered that distance from the school is the major preference by the students in choosing housing in the study area.

There are few studies that directly considered the finishing of the housing accommodation as part of the factors motivating the choices of students (Chiwuzie, et al., 2019; Bello & Binuyo, 2020). While there is evidence of preferences for aesthetics, the individual housing structural qualities have not been thoroughly examined in the available literature and the possibility of spatial association of these structural qualities around a university environment is conspicuously scanty in available literature, hence a need to start filling this gap.

The Nigerian situation is such that there is low funding for university education, which has implications on the availability of adequate dormitories for the students on campus, leading to the involvement of private developers to build student hostels, majorly off campus (Edwards, 2019).

2.2. Physical Property Characteristics/Attributes

In terms of accommodation qualities, Khzaei et al. (2014) stated that student housing is often configured such that toilets and bathrooms are used by one, two, three or four students and the rooms are designed such as to provide sleeping and study spaces. These relate to the structural or physical characteristics of the properties and generally in Nigeria, Chiwuzie, et al., (2019) expressed that structural attributes that affect the demand and values of residential properties are the number of living rooms, bedrooms, type and quality of floor finishes, perimeter fencing, interior and exterior decoration, number and quality of toilet and bathrooms, size of both bedrooms and living rooms, which also forms the basis for the attributes considered by students when making residential choice in the country.

Meanwhile, the characteristics mentioned in Chiwuzie, et al., (2019) define the quality of life of the people who live within a particular housing, making households in Nigeria particularly give preference to the aforementioned housing characteristics when choosing residential accommodation. Studies like Buys et al. (2005), Sitar & Krajnc (2008), Anthony (2012) and Okorie (2015) also established that structural attributes determine the demand and price paid for residential accommodation. The structural qualities considered in the study of housing and neighbourhood characteristics by Jiboye (2014) are building outlook, features of floors, windows, wall finishes, ceiling type, type of wall, and roof. Other facilities considered in the study of Jiboye (2014) are privacy, lighting, kitchen, toilet and bathroom.

The study of Amole (2009) on four universities in Nigeria discovered that the property characteristics considered by students before choosing an off-campus hostel are the number of people to be staying in a bedroom, the sharing size of the kitchen, sharing size of the bathroom, the floor on which the accommodation is located, presence of balcony and where to study. Sodiya, et al. (2016) however established that there are a few research works on the influence on building finishes like the use of aluminum roofs, glazed windows, floor tiles, security floors, and UPVC ceilings on rental values of properties unlike other infrastructure like, access to road, types of toilet and bathroom, electricity and water supply which is one of the motivations of this study to consider the influence of some of the former property characteristics mentioned in Sodiya, et al. (2016) on rental prices of residential accommodation around a university in Nigeria.

2.3. Spatial Autocorrelation of property characteristics

Spatial autocorrelation stems from the classical Tobler's (1969) first law of geography which states that everything is related to everything else but near things are more related than distant things, which establishes relationships among things that are within a geographic space as they influence one another. Studies such as Can (1990), Kim & Shin (2016) have suggested the presence of spatial autocorrelation in the prices of properties, where there are spatial interrelationships among properties within a particular location. Some of the variables that constitute spatial autocorrelation are crime rate (Collins et al., 2006), population density (Hong & Shen, 2013; Morenikeji, et al., 2017) which could influence the values and prices of house. Kim & Kim (2016) further stated that one of the factors that are responsible for spatial autocorrelation in property values is accessibility in terms of roads within the neighbourhood. Neighbourhood characteristics could also be the factor of attraction, while the time and nature of real estate investment could influence the structural attributes and values of properties within a confined location. The mode of real estate development in Nigeria which is majorly through individual ownership, with a large percentage through equity finance except in large-scale development where a large percentage of the funds is through debt financing.

Most often, real estate development by individuals is gradual and incremental, with funds inflow to the project. This also makes people of similar socioeconomic status to be found within a defined location and this is reflected in the type, attributes and nature of the properties in the area, where property development concentrates in different aggregates of locations within a particular area (Collins et al., 2006; Sipan et al, 2018). It is therefore not unusual to have undeveloped or less developed portions within a developed area that is proximate to a particular development attracting neighborhood factor. In most of such instances, values of properties within the confinement of each congregate of developments often correlate spatially (Sipan, et al., 2018).

In a developing country like Nigeria where funds are scarce for property development and there are no effective structures for housing provision and development, people often resort to self-help, which makes the morphology of properties to be similar within defined areas in terms of quality and standard. This might also be explained by existing urban theories like the classical Burgess theory and the Alonso-Mills-Muth theory although spatial autocorrelation considers what happens in different segregates of the city. These make properties in proximity have similarity in their structural attributes which could also be related to similarity in the time of development and the socio-economic status of the population of the people in the area, leading to spatial autocorrelation in the values of the properties that could disappear with distance (Clapp et al., 2002). This phenomenon is emphasized in Lin et al. (2014) and Barreca et al. (2018) that found spatial autocorrelations in the demographic and socio-economic characteristics of different ethnic groups.

Therefore, several factors can be responsible for spatial autocorrelation in a housing area and in the light of this study, considering real estate development and investment in Nigeria that is still evolving and majorly through equity finance, coupled with unguided development due to ineffective urban planning and development tools, it is not impossible to have different submarkets within a relatively small geographical space, in proximity to a neighbourhood factor.

Sipan, et al., (2018) conducted a study on the spatiotemporal neighbourhood-level house price index. It developed a standalone GIS statistical application of

Geographically Weighted Regression (GWR) for the analysis and the result shows a visual variation of house price based on neighbourhood, which was used in developing the price index. Lo, et al., (2022) examined the factors that affect spatial autocorrelation in residential properties considering both the vertical and horizontal dimensions of spatial autocorrelation. The spatial autoregressive hedonic model was used to analyze data from open market transactions. The result of the analysis linked market liquidity and market volatility with spatial autocorrelation in housing prices for properties within the same building in terms of vertical autocorrelation and that market liquidity increases vertical spatial autocorrelation.

2.4. Submarkets in real estate data

Song et al. (2021) observed that the factor of heterogeneity brings about segments of housing submarkets that are defined by different locations, neighborhoods and physical structures. This engenders more accurate property valuations and aids the formulation of strategy for policymaking in terms of household demand and housing market structure (Xiao et al. 2020). Following the study of Goodman & Thibodeau (1998), Song et al. (2021) submarkets housing market analysis helps in establishing the geographical boundaries of submarkets where properties of the same characteristics are bounded together. Can (1990) earlier differentiated the factors that constitute neighbourhood effects to be accessibility, physical environment, social, economic and demographic context and public-service provision. However, Can (1990) did not explicitly consider how a major neighbourhood function like academic or administrative can contribute to the values of surrounding properties, thus creating a separate housing market. Within this market, there is a likelihood of different submarkets which could be created by the factors considered in Can (1998).

It is also possible that the housing submarket would be categorized in terms of structural attributes. Cox & Hurtubia (2020) found that the structural attributes categorization could be in terms of the size of the properties, age of the properties, and number of bedrooms. This could also be in terms of accessibility to the housing neighbourhood considering the central business district or road accessibility which could influence housing location choices thus creating subgroups of housing markets, necessary for decision-making and a factor for real estate investors to consider (Can, 1990; Cox & Hurtubia, 2020).

Song et al. (2021) constructed segmented rental housing indices in Beijing, China using the hedonic model and clustering analysis was used to identify the submarkets in the study area. The findings of the study revealed that housing submarkets are distributed along administrative boundaries and there was identified rental housing spatial heterogeneity within the study area. Sipan, et al. (2017) retorted that neighbourhood which is an important definition of location shows spatial differentials with localized property markets within a restricted geographic space. This could get into micro-level value differentials up to streets and layouts, thus creating submarkets.

2.5. Spatial analysis with the Geographic Information System (GIS)

GIS comprises tools that are used in the collection, storage, retrieval, transformation, manipulation and display of spatial data from the real-world phenomenon for a particular purpose (Burrough & McDonnell, 1998). More than a combination of software and hardware, it is a process that uses data with geo-references and can handle issues of spatial manipulation and analysis which could be helpful in decision-making (Sipan et al., 2018). Unwin (1996) established that GIS can manipulate spatial data with the use of deterministic functions like spatial buffering, queries, overlays and the ability to carry out map algebra and this differentiates it from other database management systems. Can (1990) also maintained that the GIS enhances the management of geographic data by taking advantage of the location information to support spatial statistical and econometric analysis. Can (1990) further stated that there is a level of neighbourhood effect in the spatial data especially in real estate and it is dependent on spatial location which the GIS can analyze.

One of the recent developments in the application of GIS in real estate spatial analysis is the modeling of geographical constructs in real estate prices and the factors that contribute to the values of real estate. This has been discussed in Sipan et al. (2018) to explain property value changes within a given geographical space across neighborhoods thus creating submarkets of micro-level property prices are. When this is neglected, however, it could constitute misleading predictions at the local level for real estate investment decision-making and discountenance the possible effects of the heterogeneous nature of property characteristics. Hamid et al., (2012) expressed that there has been a rapid development in GIS with capabilities and support that are applicable to property-related spatial analysis

Spatial data analysis examines the distribution of such data and explains the process that produced the distribution, which assists in finding patterns in the data and would provide meaningful relation to the domain of knowledge (Unwin, 1996). GIS gives the opportunity for the use of a large geographic data set, the assumption that such global spatial analysis can be applied to smaller geographic data sets is unrealistic because it would be established on a faulty foundation of spatial homogeneity, which is inconsistent with location-specific characteristics of property data. This necessitates the use of local spatial statistics, where individual data in relation to a particular location is compared to other values in neighboring locations. Moreover, Zhang et al. (2015) maintained that the characterization of heterogeneity and spatial features of data is achievable through the use of GIS, where prices can be placed on a property to develop empirical models.

3. Study area and reconnaissance survey

The immediate neighbourhood of the Federal University of Technology, Akure is considered as the study area for this research. The Federal University of Technology Akure, is owned by the Federal Government of Nigeria. It is located in a medium-sized city in the southwestern part of Nigeria and the number of undergraduate students in the university is fifteen thousand five hundred and thirty-three (15,533) where only one thousand nine hundred and twenty-three (1,923) bed spaces are available in the hotels provided on-campus for student accommodation (FUTA, Giant Strides, 2016). This shows a huge bed-space deficit of thirteen thousand six hundred and ten (13,610) for off-campus accommodation provided by private real estate investors and owners. The accommodation deficit keeps growing with an increasing number of students admitted into the university every year as the study of Bello & Adebisi (2014) had earlier revealed on ten thousand six hundred and thirty-three (10,633) students in the university in the year 2013. Therefore, most of the students live in the 'Northgate', 'Southgate' and 'Westgate' axes of the university in off-campus hostels provided by private real estate developers.

There are few commercial properties in the study area. While some of them are being converted to residential properties, others provide retail and support functions to the residential accommodation for the students and other owner-occupied houses. The trend of development in recent times in the area is such that commercial and old-fashioned residential properties are being converted to self-contained (Studio) apartments, especially within a 500-meter radius of the university. This radius is also in tandem with the buffer established in Koster & Rouwendal (2012) on the impact of mixed land uses on residential properties. This radius is also adopted in this research in delineating the distance-decaying boundary of the impact of the university on neighboring residential properties occupied by students.

Most students prefer the self-contained (studio) apartment to other design types because it gives them a sense of privacy where they are able to make individual academic plans, with access to personal conveniences and a kitchen. Meanwhile, in order to minimize the cost of securing the accommodation due to the dwindling economic condition of the country, some of the students engage the idea of having one or two roommates, with whom they share the accommodation and the cost of securing it. Notwithstanding the affordability factor that brought about the roommate idea, most students would not want to be too far from the university and the number of available off-campus accommodations would not accommodate the growing student population if each unit of the apartment is occupied by only one student.

There are different layouts with different classes of roads running through the study area and the distance influences the amount which students are willing to commit to secure the apartment. Also, the quality of finishing of the apartment, the number of units in the building and the quality of the environment determine the desirability for the students and the rent passing in different locations. Most of the off-campus private residents are in the 'Southgate' axis of the university which is adopted in this study, and development of self-contained residential apartments started close to this 'Southgate' which continues to extend outwards with new and modern development found as one moves away from the 'Southgate', notwithstanding pockets of redevelopment activities at different part close to it.

A reconnaissance survey was carried out in the study area to analyze the perception of the students on the quality of different physical attributes of self-contained apartments. The physical qualities of the property thus assessed are kitchen quality, bathroom quality, toilet quality, wall finishing, floor finishing, window quality, and door quality. Other factors assessed are the quality of the environment and the number of floors of the building. After a delineation of the study area, where a 500-meter radius from the 'Southgate' axis of the university was measured on Google Earth software, a physical count was adopted in determining the total number of self-contained residential properties in the study area. The result of the physical count revealed that there are Two hundred and Seven self-contained buildings which is within the total census and all the properties that are the target population are considered in eliciting data.

Different observed designs and quality of the various attributes of self-contained apartments were included in the reconnaissance survey questionnaire where the respondents gave their preference in terms of quality and desirability in their accommodation. The data was elicited from the respondents using a Likert scale on the desirability of such quality and subsequently analyzed using a weighted mean score for the weighted average analysis of the responses from the respondents. The results of the analysis of how the students rate the presence of the physical attribute qualities presence in their apartments are presented in Table 1.

Table1. Results of a reconnaissance survey of factors influencing self-contained rental prices

Physical Attributes	5	4	3	2	1	Mean Score	Mean Score Ratio
Kitchen Quality							
Washing sink with tap	137	47	11	0	0	4.65	0.93
Floor tiled	133	46	12	4	0	4.58	0.92
Wall tiled	124	55	12	4	0	4.53	0.91
worktop	112	47	4	16	16	4.14	0.83
Water heater	31	4	0	43	117	1.92	0.38

Table1. (Continued)

Physical Attributes	5	4	3	2	1	Mean Score	Mean Score Ratio
Bathroom Quality							
Flowing tap	138	47	4	8	0	4.59	0.92
Shower	86	101	8	0	0	4.40	0.88
Floor tiled	116	63	0	8	8	4.39	0.88
Wall tiled	89	72	8	19	7	4.11	0.82
Shower tray	8	67	114	3	3	3.38	0.68
Water Heater	30	54	7	68	36	3.13	0.63
Jacuzzi	24	18	32	66	55	2.44	0.49
Toilet quality							
Floor tiled	100	79	8	8	0	4.39	0.88
Wall tiled	68	95	16	16	0	4.10	0.82
Special WC	189	54	24	24	12	3.86	0.77
WC	22	129	32	12	0	3.83	0.77
Wall quality							
Emulsion painting	75	83	12	11	8	4.15	0.83
Texcote painting	8	8	44	81	44	2.21	0.44
cement rendered	0	16	4	58	117	1.58	0.32
Floor quality							
Ceramic tile	91	88	8	8	0	4.34	0.87
PVC tiles	0	0	48	80	67	1.90	0.38
Cement creed	4	4	7	88	92	1.67	0.33
Window quality							
Aluminum glazed sliding window	68	55	60	12	0	3.92	0.78
Aluminum glazed casement window (swing)	23	120	40	8	4	3.77	0.75
Louvre blades	4	4	84	99	4	2.51	0.50
Door quality							
Imported steel door	106	77	8	4	0	4.47	0.89
Metal door	95	95	4	0	0	4.46	0.89
Panel door	4	4	54	117	16	2.30	0.46
Flush door	4	0	48	86	57	2.02	0.40

3.1. Measure of property characteristics

PCM = C_1 * Mean Ratio C_1 + C_2 * Mean Ratio C_2+,…, C_n* Mean ratio C_n

where PCM is the property characteristics measure which is the value contributed by a particular property characteristic as indicated by each respondent. C_1 , …, C_n are the features of the property characteristics. The mean ratio is determined from the ratio of the weighted mean score from the responses from the reconnaissance survey on the desirability of each property characteristic in the study area to the maximum weighted mean score from the ordinal scale adopted.

4. Method of data analysis

One of the preliminary data analyses conducted was to examine the presence of spatial association among the property characteristics that were identified to influence rental values of self-contained apartments in the study area. For this analysis, the Local Indicator of Spatial Association (LISA) which performs the Cluster/outlier analysis on each of the property characteristics was conducted. Multicollinearity test was however carried out among the variables to prevent overinflation of results that could arise from statistically significant spatial association among variables that give the same explanation. In this instance, where there is discovered statistically significant multicollinearity among variables, one of the variables is chosen to also explain the contribution of other variables within the association. In carrying out multiple regression analysis of spatial data, there is a need to examine the presence of collinearity among the independent variables. According to Shrestha (2020), collinearity shows where two variables are in perfect combination in their contribution to the dependent variable and this becomes multicollinearity when several independent variables have this significant correlation. The implication of the inter-correlation is a skewed result as an outcome of redundancy in the variables. Apart from correlation coefficients and eigenvalue methods indicated by Shrestha (2020) in detecting collinearity among the independent variables, the Variance Inflation Factor (VIF) suggested in Belsley (1991) has also been considered a method for detecting multicollinearity. VIF is used in measuring how much variance of the coefficients of the regression is inflated due to correlation among the variables. VIF is given as:

$$\frac{1}{1-R^2} = \frac{1}{Tolerance}. \qquad (6)$$

After the collinearity test, the resulting variables are then regressed against the annual rent collected of the property.

The Local Indicator of Spatial Association is given as:

$$l_i = \frac{z_i - \bar{Z}}{\sigma^2} = \sum_{j=1}^{n} j \neq i \left[W_{ij}(Z_j - \bar{Z})\right] \qquad (7)$$

Where is the mean value of $\bar{Z}$ ith the sample number of n; Z_i is the value of the variable at location i; zj is the value at other locations (where $j \neq i$); σ^2 is the variance of Z; and W_{ij} is a distance weighting between Z_i and ; Z_j, which can be defined as the inverse of the distance. The weight W_{ij} can also be determined using a distance band: samples within a distance band are given the same weight while those outside the distance band are given the weight of 0.

To measure the relationship between the selected independent variables (property characteristics and dependent variables (rental prices), the multiple regression model is adopted which is given as;

$$RV = b_0(i) + b_1(i)KQ + b_2(i)BQ + b_3(i)TQ + b_4(i)DQ + b_6(i)WQ + b_7(i)FF + b_8(i)WF + b_9(i)DFUTA + e \qquad (8)$$

where RV = rental Value, KQ = Kitchen quality; BQ = Bathroom Quality; TQ= Toilet Quality; DQ = Door Quality; FF = Floor finishes; WQ = Window Quality; WF = Wall Finishing; DFUTA = Distance from FUTA; e = error term; I = ith observation.

Table 2. Calibration of variables

Variable	Scale	Measurement	Category
Rental Price	Interval	Actual Price in ₦	Dependent
Distance from FUTA	Interval	Actual distance in meters	Independent
Location	Interval	Longitude and latitude (x and y)	Independent
Kitchen quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Washing sink with tap	Binary converted to Scale using equation 1	1 = Present 0 = Absent	Independent
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
worktop	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Water heater	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Bathroom quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Flowing tap	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower tray	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Water Heater	Binary converted to Scale using equation 1	1 = Present 0 = Absent	

Table 2. (Continued)

Variable	Scale	Measurement	Category
Bathroom quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Flowing tap	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower tray	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Water Heater	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Jacuzzi	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Toilet quality (multiplied by the mean ratio from reconnaissance survey on each characteristic)			Independent
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Special WC	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
WC	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Door quality (multiplied by the mean ratio from reconnaissance survey on each characteristics)			Independent
Imported steel door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Metal door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Panel door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Flush door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Floor quality (multiplied by the mean ratio from reconnaissance survey on each characteristics)			Independent
Ceramic tile	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
PVC tiles	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Cement creed	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Window quality (multiplied by the mean ratio from reconnaissance survey on each characteristics)			Independent
Aluminum glazed sliding window	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Aluminum glazed casement window (swing)	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Louvre blades	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Emulsion painting	Binary converted to Scale using equation 1		
Texcote painting	Binary converted to Scale using equation 1		
cement rendered	Binary converted to Scale using equation 1		

5. Data Analysis, result presentation and discussion

5.1. Questionnaire administration and retrieval

From a reconnaissance survey where the physical count of the self-contained (studio) apartments was done, in 2022, there were 207 of such residential apartments within a 500-meter radius off the Southgate axis of the Institution. Each of the self-contained apartments was physically administered the questionnaire, where the coordinates of the properties were also taken to enhance the spatial analysis.

The result of the questionnaire administration is shown on Table 3. The result indicates that 94.2% of the total number of self-contained properties that were administered gave sufficient responses that are usable for the analysis in this study, which is a high percentage and could be relied upon for generalization to the entire population of self-contained properties in the study area.

Table 3. Questionnaire administration and retrieval

Total Number of questionnaires administered	207 (100%)
Total Number of questionnaires retrieved	195 (94.2%)

Within the radius of 500 meters from the 'Southgate' axis of the University, the self-enumeration done to show that there are two hundred and seven (207) self-contained residential buildings and all these buildings were administered questionnaire where one questionnaire was assigned to each building to provide data that shows the quality of the self-contained apartment, rent paid per annum and the distance from the 'Southgate' is determined with the aid of the coordinates taken at the survey beacon location of each building. As the difference between the administered and the properly retrieved questionnaire is not high, it gives more reliability and accuracy to the model.

Table 4. Collinearity Test

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	10362.928	10227.313		1.013	.312		
KITCHEN_QU	413.679	3235.370	.007	.128	.898	.440	2.271
BATHROOM_Q	8992.874	2883.057	.194	3.119	.002	.299	3.339
TOILET_QUA	13189.800	2562.945	.303	5.146	.000	.333	3.003
WINDOW_QUA	13242.707	3053.649	.267	4.337	.000	.305	3.284
DOOR_QUALI	4965.551	3431.783	.070	1.447	.150	.487	2.054
WALL_FINIS	10986.165	3406.534	.170	3.225	.001	.415	2.411
FLOOR_FINI	2581.114	3979.255	.031	.649	.517	.510	1.959
DISTANCEFR	-15.038	10.995	-.053	-1.368	.173	.755	1.324

The VIF analysis was carried out using SPSS and the result shows that there is no multicollinearity among the variables in their relationship with the rental prices, and this suggests the possibility of relying on the result for the rental price estimates in the study area. However, this analysis was carried out without recourse to spatial reference of property data but with an assumption of global uniformity. This was proved using spatial multiple regression analysis, using the spatial analyst tools of ArcMap with the ordinary least square function. However, this analysis was not possible to run on ArcMap due to spatial multicollinearity meanwhile non-spatial regression analysis had a misleading result which indicated that there was no collinearity among the variables from the VIF results.

Therefore, to further identify the variables with high multicollinearity that prevented the spatial regression analysis on ArcMap, the pairwise scatter plot was used to observe the variables' relationships with respect to the locations of each property. From the scatter plots, there was observed a positive spatial correlation in the following pairs: window quality and door quality', 'floor quality and wall quality', and 'bathroom quality and toilet quality. Therefore, one variable from each of the spatially inter-correlated pairs was selected and used to perform the spatial regression on ArcMap with the ordinary least square tool.

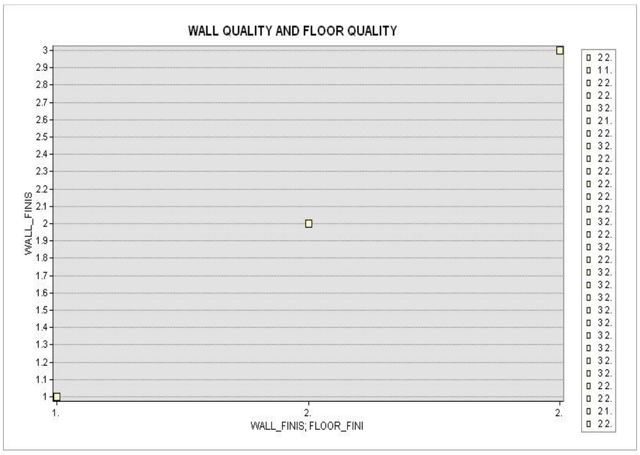

Figure 1. Scatter plot of wall quality and floor quality

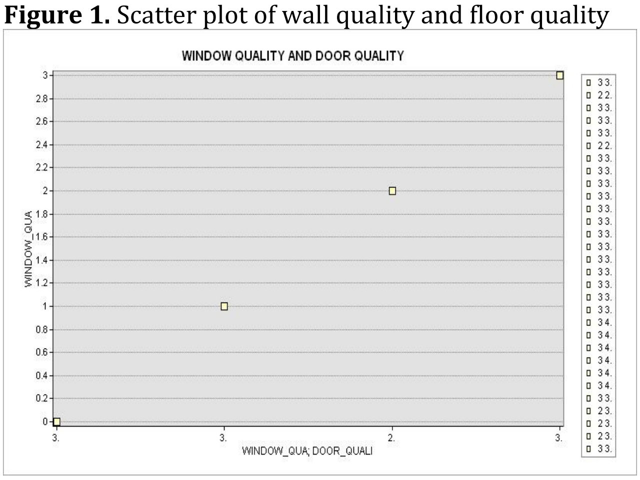

Figure 2. Scatter plot of window quality and door quality

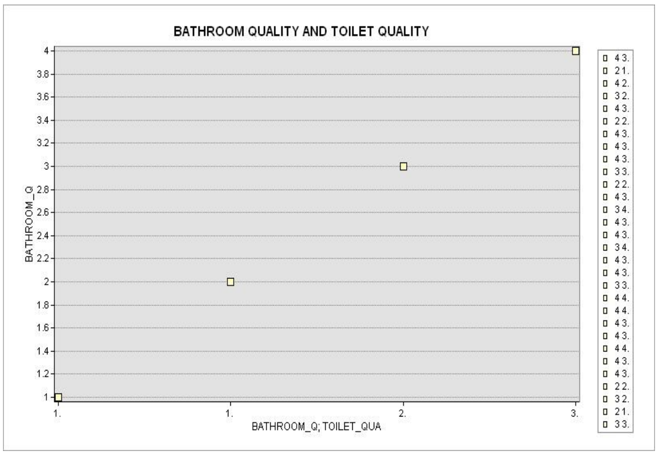

Figure 3. Scatter plot of bathroom quality and toilet quality

5.2. Spatial ordinary least square regression on ArcMap

The Ordinary Least Square Regression was carried out to examine the relationship between the rent paid by the occupiers (students) of the properties and the property characteristics (without spatial collinearity) that were discovered from literature to influence rents of residential apartments occupied by students in Nigeria, taking the peculiarity of FUTA into consideration.

Table 5. Spatial Ordinary least square Regression results

Variable	Coefficient(a)	Std. Error	t-Statistics	Probability (b)	Robust_SE	Robust_t	Robust_Pr (b)	VIF
Intercept	21596.78	8355.68	2.5847	0.0105*	8008.01	2.6969	0.0076*	-
DISTANCEFROM FUTA	-14.93	10.57	-1.4121	0.1596	10.64	-1.4029	0.01623*	1.2294
KITCHEN_QU	1065.62	3193.43	0.3337	0.7390	3581.11	0.2976	0.7664	2.2209
BATHROOM_Q	12013.97	2421.56	4.9612	0.0000*	2560.53	4.6920	0.0000*	2.3650
TOILET_QUA	13351.51	2515.53	5.3076	0.0000*	2126.17	6.2796	0.0000*	2.9041
WINDOW_QUA	12571.32	2904.15	4.3287	0.0000*	3116.11	4.0343	0.0001*	2.9816
WALL_FINIS	12003.87	3336.57	3.5977	0.0004*	3127.09	3.8387	0.0001*	2.3220

Input Features: SELF-CONTAINED PROPERTI	Dependent Variable: RENT
Number of Observations: 195	Akaike's Information Criterion (AICc) [d]: 4408.956469
Multiple R-Squared [d]: 0.783890	Adjusted R-Squared [d]: 0.776993
Joint F-Statistic [e]: 113.654857	Prob(>F), (6,188) degrees of freedom: 0.000000*
Joint Wald Statistic [e]: 1521.338543	Prob(>chi-squared), (6) degrees of freedom: 0.000000*
Koenker (BP) Statistic [f]: 20.161757	Prob(>chi-squared), (6) degrees of freedom: 0.002592*
Jarque-Bera Statistic [g]: 10.623622	Prob(>chi-squared), (2) degrees of freedom: 0.004933*

Property characteristics that are therefore responsible for the determination of rental prices of self-contained residential properties around the university are Distance (-14.93, p< 0.016), Bathroom quality (1065.62, P< .050), Toilet quality (13351.51, p <0.050), window quality (12571.32, p <.050) and wall finishing (12003.87, p <.050). the coefficient of kitchen quality was not significant for the prediction.

The result on Table 5 shows the self-contained residential property attributes that do not have global spatial autocorrelation which are used in modeling the relationship between rental prices and the implicit contribution of each of the property characteristics. The result shows that out of the six predictors (independent variables), only kitchen quality does not have a statistically significant contribution using a 95% confidence level. The result further shows that Distance from FUTA has a negative effect which indicates that the rental prices of the self-contained apartment reduce with distance away from the university.

Meanwhile, other property characteristics like bathroom quality, toilet quality, window quality and wall quality have statistically significant positive implicit contributions to the rents paid by the occupants who are mostly students of the university. However, this result does not indicate the spatial reference of the contribution of each of the property characteristics which could be skewed to different locations severally across the property characteristics. This is therefore examined through the use of the Local Indicator of Spatial Association (LISA).

To examine the possibility of spatial patterns in the impact of the property characteristics that form the independent variables, the Local Indicator of Spatial Association (LISA) was assessed using the ArcGIS 10.2© software.

Table 6. LISA analysis results

Property Characteristics	HH significant spatial clustering (p<.050)	LH significant spatial clustering (p<.050)	HL significant spatial clustering (p<.050)	LL significant spatial clustering (p<.050)	Total Significant spatial clustering points	Percentage significant
Kitchen Quality	21 spatial locations (31.3%)	8 spatial location (11.9%)	3 spatial locations (4.5%)	37 spatial locations (55.2%)	67 spatial locations	**34.4%**
Window Quality	19 spatial locations (28.8%)	4 spatial locations (6.1%)	8 spatial locations (12.1%)	35 spatial locations (53%)	66 spatial locations	**33.8%**
Wall Quality	22 spatial locations (41.5%)	2 spatial locations (3.8%)	0 spatial location	29 spatial location (54.7%)	53 spatial locations	**27.2%**
Bathroom Quality	29 spatial location (58%)	5 spatial locations (10%)	1 spatial location (2%)	15 spatial locations (30%)	50 spatial locations	**25.6%**
Toilet Quality	7 spatial locations (14.9%)	3 spatial locations (6.4%)	8 spatial locations (17%)	29 spatial locations (61.7%)	47 spatial locations	**24.1%**

An analysis on the local spatial association was carried out using the Anselin Local Moran's I spatial model at a p-value of 0.050. This is to identify spatial points on the Gaussian field where properties within the neighbourhood using adaptive kernel bandwidth, exhibit statistically significant clustering in the property characteristics which are the independent variables that determine the annual rental price of the self-contained apartment in the study area. The spatial associations observed in the study are:

i. where a high-quality spatial point is surrounded by high qualities of the property physical attribute denoted by HH.
ii. Where a low-quality spatial point is surrounded by high quality of the property physical attribute denoted by LH.
iii. where high high-quality spatial point is surrounded by low quality of the property physical attribute
iv. where low quality spatial point is denoted by low quality of the property physical attribute.

5.3. Kitchen quality Local Spatial Association

From this analysis, it was shown that 64 spatial locations which is 34.4% of the 195 spatial points of the study area have significant spatial association in the kitchen quality. It shows that spatial locations where there is low quality of kitchen quality are surrounded by low kitchen quality have the highest spatial location. This shows that the quality of the kitchens of most of the self-contained apartments in the study area is low. Meanwhile, 31.3% of this significant kitchen quality spatial location has high kitchen qualities that are surrounded by high-quality kitchen qualities. This result can be explained by the fact that most of the property owners and developers in the study area used similar materials for their kitchens, which are significantly low or high. Those of low quality often have a wash hand basin and water while those of high quality have, in addition to the features of the low quality, wall and floor tiles, cooker unit, kitchen cabinet and water heater. Results of the interpolated p-value of the spatial association are shown on Figure 4 where the statistically significant spatial association is observed in the central part of the study area close to the south gate as well as the northwestern part of the University. Statistically significant spatial associations are also observed in the southwestern part. There are local points where low kitchen quality is surrounded by properties with low kitchen quality, which could be responsible for the spatial association in the central part of the study area where residential development started. The significant spatial association in the farther northwest and southwest parts could be due to new residential development and those experiencing redevelopment where newer kitchen facilities are installed and such properties are also surrounded by others that have high kitchen-quality installations.

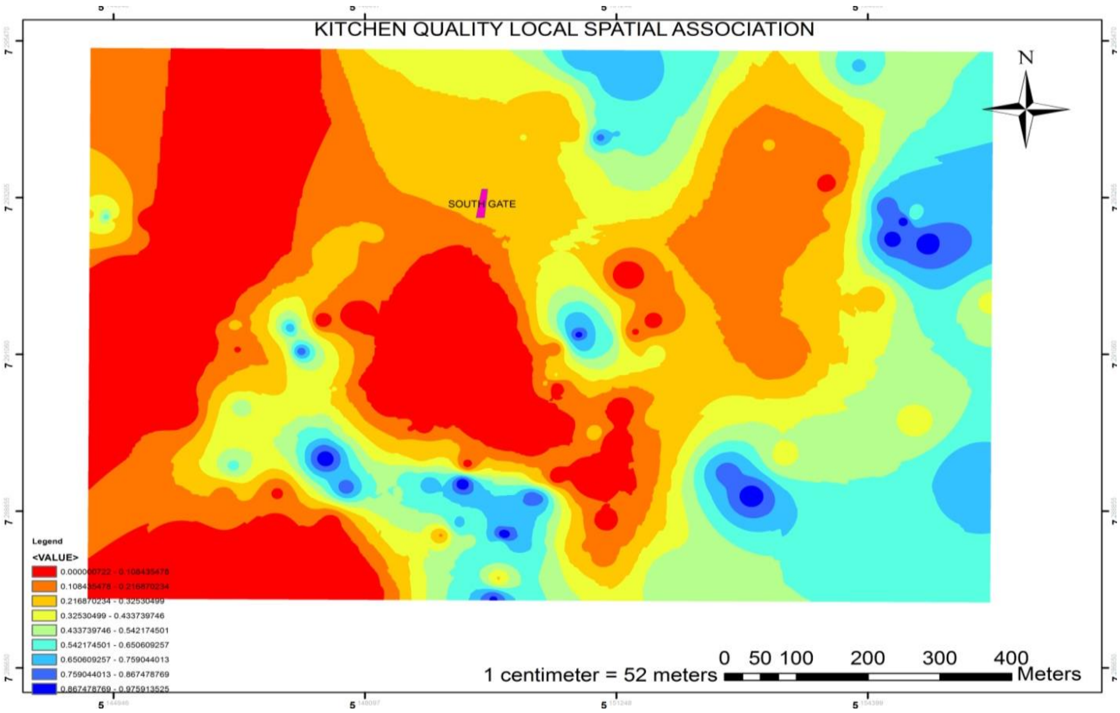

Figure 4. Map of the interpolated p-value of the kitchen quality

5.4. Window quality local spatial association

For the window quality, there are 66 spatial locations which represent 33.8% of the 195 points that have significance, where low window qualities are surrounded by other self-contained residential properties with low window quality as well. Similar to what was observed in the kitchen quality, the LL spatial association is followed by spatial points where high window-quality self-contained properties are surrounded by others with high window quality. From the desirability perspectives obtained in a reconnaissance survey, low window quality is those with louver blades and without antiburglary bars while those of high quality are windows of glazed aluminum with anti-burglary bars and adequate illumination and lightning. Similar to the kitchen quality, the map in Figure 5 shows that the statistically significant 66 spatial points that have spatial association are in the central and northwestern parts of the study area, where a similar explanation as regards the trends of development for the kitchen quality applies to the window quality which could be explained for door quality. However, a significant association does not exist for window/door quality in the southwestern part which suggests that there is no spatial association in the distribution of window/door quality in this axis of the study area.

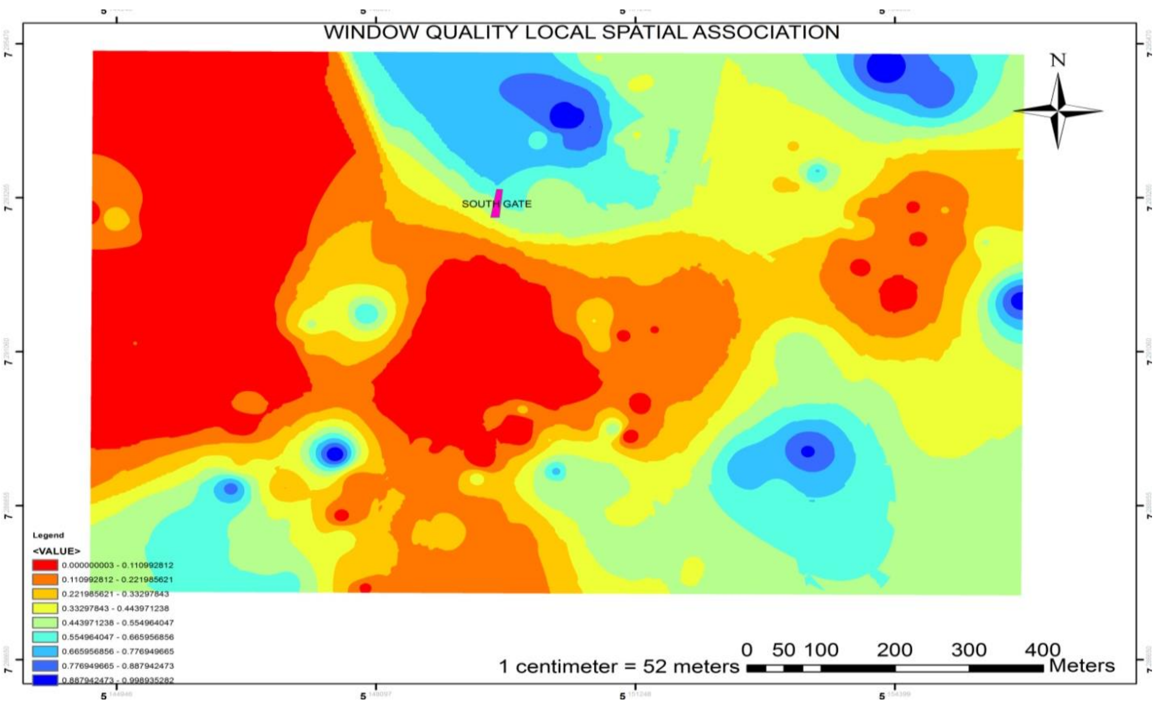

Figure 5. Map of the interpolated p-value of the window quality

5.5. Wall-quality local spatial association

Similar to the pattern of local spatial associations observed in both kitchen quality and window quality, wall quality has the highest spatial association in points where low wall quality is surrounded by other self-contained residential apartments with low wall quality. No spatial association was observed in the HL clustering/outlier but 22 locations exhibited significant local spatial association of high wall quality being surrounded by high wall quality self-contained residential apartments in the study area. In total, 27.2% of the 195 spatial locations showed significant spatial association in the wall quality. The visual display of significant association among wall quality of the self-contained apartment in the study area shows that the 27.2% spatial points that have the significant association are distributed across the central, western and southwestern parts of the study area. This means that there are low wall qualities that are surrounded by other properties with low wall qualities especially in the central parts of the study area while the farther western and southwestern parts where there are significant spatial associations are of spatial locations where high wall quality are surrounded by other high wall qualities self-contained residential properties.

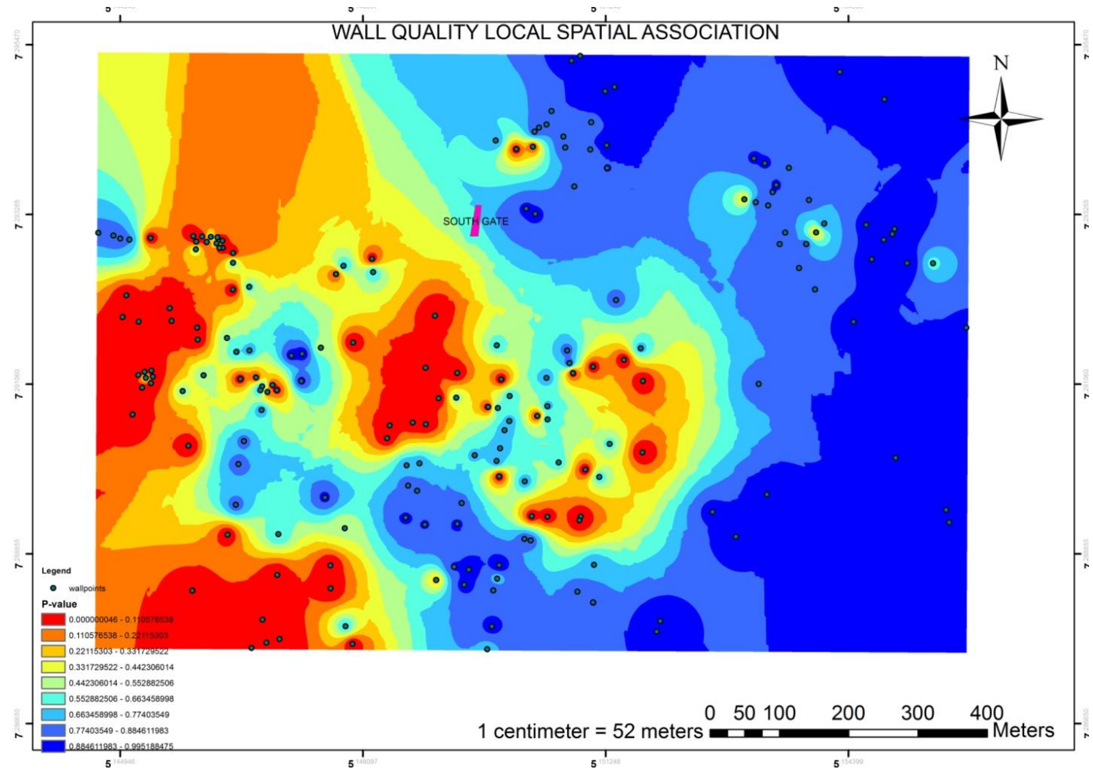

Figure 6. Map of the interpolated p-value of the wall quality

5.6. Bathroom Quality Local Spatial Association

Unlike the kitchen quality, window quality and wall quality, bathroom quality showed higher spatial associations in locations where higher bathroom quality is surrounded by other self-contained residential properties with high bathroom quality with 29 points out of the 50 significant locations in the bathroom quality. This was followed by 15 locations where low bathroom quality is surrounded by other self-contained residential properties that have low bathroom quality. The result further shows that out of the 25.5% of locations that have significant spatial locations, 58% are points where high bathroom qualities are surrounded by other self-contained apartments with high bathroom qualities. Most of the statistically significant spatial points of the bathroom quality are found in the central part, transcending the northwestern part. A similar trend of discussion along the line of stages of development could be responsible for the pattern of the spatial association where lower bathroom quality is closer to the south gate than the farther northwestern part where there are new developments of higher bathroom quality with spatial clustering.

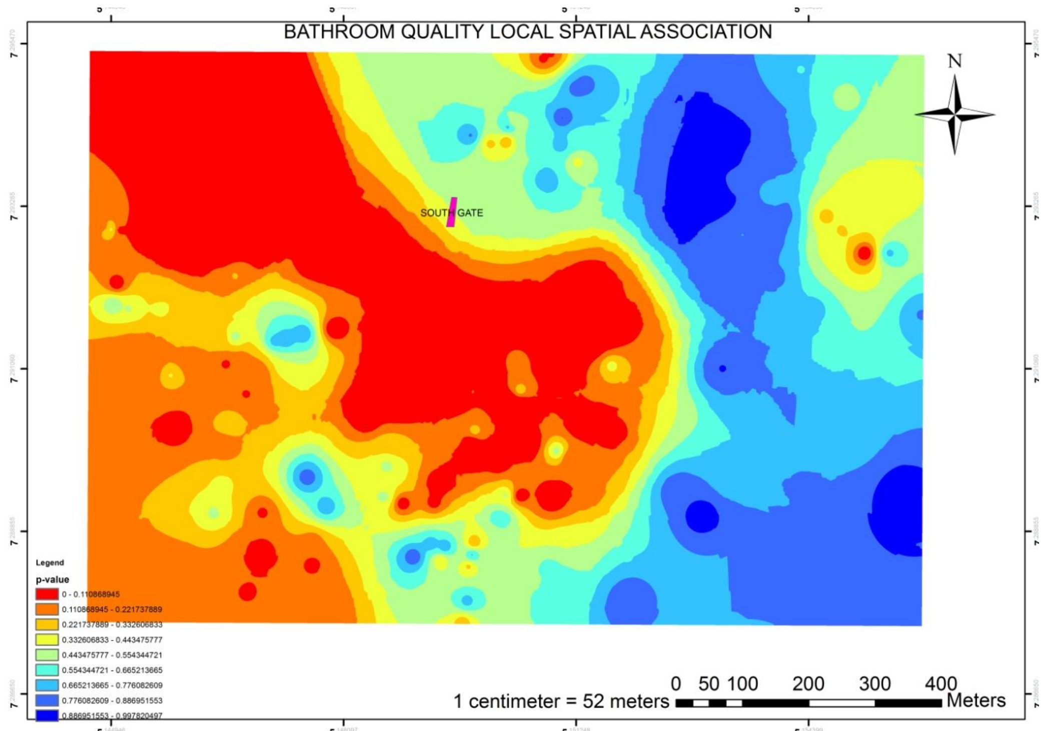

Figure 7. Map of the interpolated p-value of the bathroom quality

5.7. Toilet quality Local Spatial Association

The condition of the toilet qualities in the self-contained properties showed the least spatial association where only 24.1% of the 195 spatial locations exhibited spatial association. Most of these significant spatial associations (61.7%) are observed in points where low-quality toilet facilities are surrounded by other self-contained residential properties that have similar low toilet quality toilet facilities. This was followed by locations that have high-quality toilet facilities surrounded by low-quality toilet facilities. From the map in Figure 8, significant spatial associations in toilet quality are majorly concentrated in the northwestern part of the study area where the number of spatial associations shows that there are significant self-contained properties with low toilet quality surrounded by other self-contained properties that have low toilet quality and this might be connected to the quality of toilet facilities used by property owners and developers, which is the basic and old designs of water closest (WC) installation, with a significant association in the western and northwestern parts of the study area.

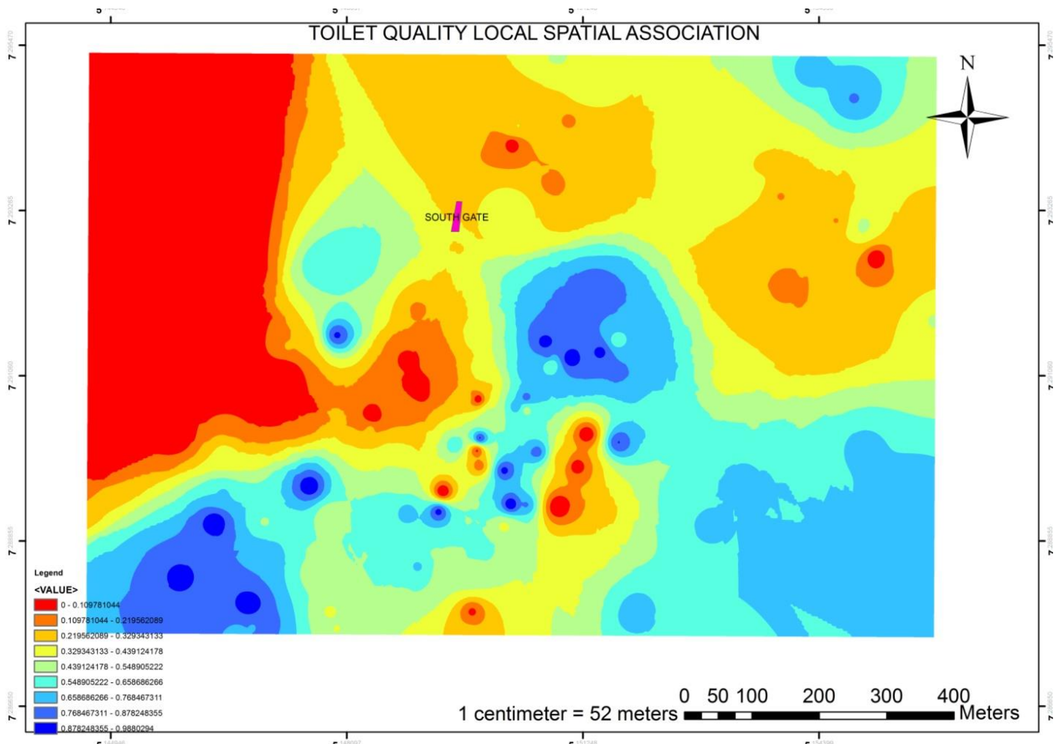

Figure 8. Map of the interpolated p-value of the toilet quality

6. Conclusion

Considering the preference of students for off-campus accommodation, there are basic attributes that attract accommodation interests and influence the price paid for residential apartments by the students who seek the accommodation. For the Federal University of Technology, Akure (FUTA), the most prominent factor that influences rental prices of off-campus accommodation is the distance from the University as discovered in the study of Adebisi & Bello (2017) and Bello & Binuyo (2020). The influence of this factor on the values with distance of the accommodation from the University was further reinforced with the result of this study where it was discovered that the rental prices paid by the students decrease with distance from the university as observed from the statistically significant negative relationship that exists between the two variables. There are other factors that attract students to the self-contained apartments which are the physical attributes of the property. In line with the studies of Anthony (2012) and Okorie (2015), the results of the analysis show that the physical attributes of the property that influence rental prices paid by the students include qualities of the kitchen, toilet, bathroom, wall, floor, window and door.

There are multicollinearities among some of the physical attributes which indicates that respondents gave similar responses to such attributes, and it was not possible to compute regression analysis with them to avoid overinflation of results. This suggests that in computing relationships between dependent and independent variables for property values or prices, it is necessary to examine if there are some variables that exhibit collinearity.

However, due to the spatial reference of property value, it is imperative to examine the possibility of spatial relationship among the attributes, to confirm the findings of Can (1990), and Li et al. (2020) that property attributes often have spatial association. The use of the Local Indicator of Spatial Association (LISA) of Anselin (1995) provided an opportunity for examining the clustering and by implication, outliers of each of the property characteristics which are better appreciated through the visual display of ArcGIS-analyzed maps. The result of this analysis on each of the property attributes shows that there are significant clustering and outliers in some parts of the study area. From the maps of the results, the central part, northwestern part and southwestern part of the Southgate axis reveal spatial associations where there are high-quality attributes clustering around high-quality attributes and other areas where there is low-quality clustering for each of the attributes. These results are linkable to evidence from the development trends of self-contained properties in the study area, where there is low-quality clustering in areas where development started and high-quality clustering in newer areas. This confirms that there is a need to examine the spatial distribution of attributes and characteristics when modeling property prices as the specific locations where the spatial association or autocorrelation exist might be different.

7. Recommendations

From the results of the analysis of this study, it is necessary for real estate property value/price researchers to examine the possibility of multicollinearity among the property characteristics used in modeling to avoid over-bloated results. Meanwhile, in an extension of the existing knowledge on spatial autocorrelation where large study areas are often considered, the results of this study show that there is a possibility of spatial clustering even within a small geographic space. The identification of this spatial clustering would reveal parts of the study area that have significant spatial clustering and where such does not exist. Having this knowledge would help developers with the specific property characteristics (attributes) that need to be improved to positively influence property values with reference to specific locations in the study area. It is also recommended that university off-campus real estate investment analysts conduct their analysis beyond the scope of profitability to specific details of the properties that need to be put in place to enhance the values depending on the location of the investment.

Author Contributions

The contributions of the authors to the article are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

References

Agostinelli, F., Luflade, M., & Martellini, P. (2024). *On the spatial determinants of educational access* (No. w32246). National Bureau of Economic Research.

Aluko, O. (2011). The effects of location and neighbourhood attributes on housing values in metropolitan Lagos. *Ethiopian Journal of Environmental Studies and Management*, 4(2), 69-82. https:/doi.org/10.4314/ejesm.v4i2.8

Amole, D. (2009). Residential satisfaction in students' housing. *Journal of Environmental Psychology,* 29(1), 76-85. https://doi.org/10.1016/j.jenvp.2008.05.006

Anselin, L. (1995). Local indicators of spatial association-LISA. *Geographical analysis*, 27(2), 93-115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anthony, O. A. (2012). Examination of the determinants of housing values in urban Ghana and Implications for Policy Makers. *Journal of African Real Estate Research,* 2(1),58-85.

Barreca, A., Curto, R., & Rolando, D. (2018). Housing vulnerability and property prices: Spatial analyses in the Turin real estate market. *Sustainability*, 10(9), 3068. https://doi.org/10.3390/su10093068

Basu, S., & Thibodeau, T. G. (1998). Analysis of spatial autocorrelation in house prices. *The Journal of Real Estate Finance and Economics*, 17, 61-85. https://doi.org/10.1023/A:1007703229507

Bello, V. A., & Binuyo, O. P. (2020). Geospatial Techniques for Rental Value Determinantion. *Journal of Propety Research & Construction,* 4(1), 26 – 45.

Belsley, D. A. (1991). A guide to using the collinearity diagnostics. *Computer Science in Economics and Management,* 4(1), 33-50. https://doi.org/10.1007/BF00426854

Budziński, W., Campbell, D., Czajkowski, M., Demšar, U., & Hanley, N. (2016). *Using geographically weighted choice models to account for spatial heterogeneity of preferences.* Working Paper-Faculty of Economic Sciences, University of Warsaw, (WP17/208).

Burrough, P. A., & McDonnell, R. A. (2015). *Principles of geographical information systems.* Oxford University Press.

Buys, L., Barnett, K., Miller, E., & Hopkinson, C. (2005). Smart housing and social sustainability: learning from the residents of Queensland's research house. *International Journal of Emerging Technologies and Society*, 3(1), 44-57.

Can, A. (1990). The measurement of neighborhood dynamics in urban house prices. *Economic geography*, 66(3), 254-272. https://doi.org/10.2307/143400

Chiwuzie, A., Dabara, D. I., Adenipekun, T. M., Prince, E. M., & Ajiboye, B. O. (2019). Tenant's demand for structural attributes in residential properties: The case of Ede, Nigeria.

Clapp, J. M., Kim, H. J., & Gelfand, A. E. (2002). Predicting spatial patterns of house prices using LPR and Bayesian smoothing. *Real Estate Economics*, 30(4), 505-532. https://doi.org/10.1111/1540-6229.00048

Collins, K., Babyak, C., & Molone, J. (2006). Treatment of spatial autocorrelation in geocoded crime data. In *Proceedings of the American Statistical Association Section on Survey Research Methods*, 2864-2871.

Cox, T., & Hurtubia, R. (2020). Subdividing the sprawl: Endogenous segmentation of housing submarkets in expansion areas of Santiago, Chile. *Environment and Planning B: Urban Analytics and City Science*, 48(7), 1770-1786. https://doi.org/10.1177/2399808320947728

Dizaj, M., & Khanghahi, T. (2022). Students' residential preferences: a case study is dormitories of University of Mohaghegh Ardabili. *Journal of Asian Architecture and Building Engineering*, 21(4), 1348-1363. https://doi.org/10.1080/13467581.2021.1941987

Edwards, S. (2019). Student preferences for accommodation at a Cape Town University: an application of the stated preference approach [Doctoral dissertation, Cape Peninsula University of Technology].

Erath, A., Löchl, M., & Axhausen, K. W. (2009). Graph-theoretical analysis of the Swiss road and railway networks over time. *Networks and Spatial Economics,* 9, 379-400. https://doi.org/10.1007/s11067-008-9074-7

FUTA Giant strides. (2016). *A publication of the Federal University of Technology*. Akure.

Ghani, Z. A. (2018). Higher education institutions students housing provision for off–campus living in Malaysia [Doctoral dissertation, Universiti Tun Hussein Onn Malaysia].

Goodman, A. C., & Thibodeau, T. G. (1998). Housing market segmentation. *Journal of housing economics,* 7(2), 121-143. https://doi.org/10.1006/jhec.1998.0229

Griliches, Z. (1971). *Price indexes and quality change*. Harvard University Press.

Lancaster, K. (1971). *Theories of consumer choice from economics: a critical review. National Science Foundation, Directorate for Research Applications, RANN (Hrsg.), Selected aspect of consumer behavior. A summary from the perspective of different disciplines*, 11-31.

Gwamna, E. S., Wan Yusoff, W. Z., & Ismail, M. F. (2015). Determinants of land use and property value. *Advanced science letters*, 21(5), 1150-1153. https://doi.org/10.1166/asl.2015.6065

Hamid, A. M. I., Sipan, I., & Ismail, S. (2012), *Geographic information system and spatial analysis of real estate.* Universiti Teknologi Malaysia Press.

Hong, J., & Shen, Q. (2013). Residential density and transportation emissions: Examining the connection by addressing spatial autocorrelation and self-selection. *Transportation Research Part D: Transport and Environment*, 22, 75-79. https://doi.org/10.1016/j.trd.2013.03.006

Jiboye, A. D. (2014). Significance of house-type as a determinant of residential quality in Osogbo, Southwest Nigeria. *Frontiers of Architectural Research*, 3(1), 20-27. https://doi.org/10.1016/j.foar.2013.11.006

Khozaei, F., Hassan, A. S., Al Kodmany, K., & Aarab, Y. (2014). Examination of student housing preferences, their similarities and differences. *Facilities*, 32(11/12), 709-722. https://doi.org/10.1108/F-08-2012-0061

Kim, B., & Kim, T. (2016). A study on estimation of land value using spatial statistics: Focusing on real transaction land prices in Korea. *Sustainability*, 8(3), 203. https://doi.org/10.3390/su8030203

Kim, D., & Shin, Y. H. (2016). Spatial autocorrelation potentially indicates the degree of changes in the predictive power of environmental factors for plant diversity. *Ecological indicators*, 60, 1130-1141. https://doi.org/10.1016/j.ecolind.2015.09.021

Koster, H. R., & Rouwendal, J. (2012). The impact of mixed land use on residential property values. *Journal of regional science*, 52(5), 733-761. https://doi.org/10.1111/j.1467-9787.2012.00776.x

Lo, D., Chau, K. W., Wong, S. K., McCord, M., & Haran, M. (2022). Factors affecting spatial autocorrelation in residential property prices. *Land*, 11(6), 931. https://doi.org/10.3390/land11060931

Li, C., Wu, K., & Gao, X. (2020). Manufacturing industry agglomeration and spatial clustering: Evidence from Hebei Province, China. *Environment, Development and Sustainability*, 22(4), 2941-2965. https://doi.org/10.1007/s10668-019-00328-1

Lin, W. S., Tou, J. C., Lin, S. Y., & Yeh, M. Y. (2014). Effects of socioeconomic factors on regional housing prices in the USA. *International Journal of Housing Markets* *and Analysis*, 7(1), 30-41. https://doi.org/10.1108/IJHMA-11-2012-0056

Mei, D., Xiu, C., Feng, X., & Wei, Y. (2019). Study of the school–residence spatial relationship and the characteristics of travel-to-school distance in Shenyang. *Sustainability*, 11(16), 4432. https://doi.org/10.3390/su11164432

Morenikeji, W., Umaru, E., Pai, H., Jiya, S., Idowu, O., & Adeleye, B. M. (2017). Spatial analysis of housing quality in Nigeria. *International Journal of Sustainable Built Environment*, 6(2), 309-316. https://doi.org/10.1016/j.ijsbe.2017.03.008

Najib, N., & Abidin, N. (2011). Student residential satisfaction in research universities. *Journal of Facilities management*, 9(3), 200-212. https://doi.org/10.1108/14725961111148108

Nijënstein, S., Haans, A., Kemperman, A. D., & Borgers, A. W. (2015). Beyond demographics: human value orientation as a predictor of heterogeneity in student housing preferences*. Journal of Housing and the Built Environment*, 30, 199-217. https://doi.org/10.1007/s10901-014-9402-9

Noraini, M., Sanusi, S., Elham, J., Sukor, Z., & Halim, K. (2017). Factors affecting production of biogas from organic solid waste via anaerobic digestion process: A review. *Solid state science and technology*, 25(1), 29-39.

Okorie, A. (2015). Housing infrastructural facilities as determinants of rental values of residential properties in Osogbo, Osun State Nigeria. *Journal of Research in Business Economics and Management (JBREM),* 1(1), 7-14.

Park, G. R., & Kim, J. (2023). Trajectories of life satisfaction before and after homeownership: The role of housing affordability stress. *Journal of Happiness Studies,* 24(1), 397-408. https://doi.org/10.1007/s10902-022-00601-7

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1), 34-55. https://doi.org/10.1086/260169

Shen, Y., & Karimi, K. (2015). Understanding the roles of urban configuration on spatial heterogeneity and submarket regionalisation of house price pattern in a mix-scale hedonic model: the case of Shanghai, China. *In SSS 2015-10th International Space Syntax Symposium*, Space Syntax Laboratory, The Bartlett School of Architecture, UCL.

Shrestha, N. (2020). Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistic*s, 8(2), 39-42. https://doi.org/10.12691/ajams-8-2-1

Sipan, I., Mar Iman, A. H., & Razali, M. N. (2018). Spatial–temporal neighbourhood-level house price index. *International Journal of Housing Markets and Analysis*, 11(2), 386-411. https://doi.org/10.1108/IJHMA-03-2017-0027

Sitar, M., & Krajnc, K. (2008). Sustainable housing renewal. *American Journal of Applied Sciences*, 5(10), 61-66.

Sodiya, A. K., Oyedeji, O. J., & Bello, I. K. (2016). Examination of tenants perceptions of finishes and facilities in residential properties of public housing estates in Abeokuta Metropolis. *Pearl Journal of Management, Social Science and Humanities*, 2(2), 25-32.

Song, Z., Wilhelmsson, M., & Yang, Z. (2022). Constructing segmented rental housing indices: evidence from Beijing, China. *Property Management*, 40(3), 409-436. https://doi.org/10.1108/PM-07-2021-0052

Tavares, F. O., Pacheco, L. D., & Almeida, L. G. (2019). Preferences in university residences: A confirmatory study. *African Journal of Hospitality, Tourism and Leisure,* 8(2), 1-10.

Thomsen, J. (2007). Home experiences in student housing: about temporary homes and institutional character. *Journal of Youth Studies*. 10(5), 577-596. https://doi.org/10.1080/13676260701582062

Tobler, W. R. (1969). Geographical filters and their inverses. *Geographical Analysis*, 1(3), 234-253.

Unwin, D. J. (1996). GIS, spatial analysis and spatial statistics. *Progress in Human Geography*, 20(4), 540-551. https://doi.org/10.1177/030913259602000408

Yunus, S., Yusuf, Y. A, Ilah, S. K. & Yakubu, M. D. (2018). Spatial Analysis of Off-Campus Student Housing Around the New Campus of Bayero University, Kano, Nigeria. *Savanna*, 24(2), 358-371.

Verhetsel, A., Kessels, R., Zijlstra, T., & Van Bavel, M. (2017). Housing preferences among students: collective housing versus individual accommodations? A stated preference study in Antwerp (Belgium). *Journal of Housing and the Built Environment*, 32, 449-470. https://doi.org/10.1007/s10901-016-9522-5

Wilhelmsson, M., Ceccato, V., & Gerell, M. (2022). What effect does gun-related violence have on the attractiveness of a residential area? The case of Stockholm, Sweden. *Journal of European Real Estate Research,* 15(1), 39-57. https://doi.org/10.1108/JERER-03-2021-0015

Xiao, Y., Hui, E. C., & Wen, H. (2020). The housing market impacts of human activities in public spaces: The case of the square dancing. *Urban forestry & urban greening,* 54, 126769. https://doi.org/10.1016/j.ufug.2020.126769

Zhang, Z., Tan, S., & Tang, W. (2015). A GIS-based spatial analysis of housing price and road density in proximity to urban lakes in Wuhan City, China. *Chinese Geographical Science*, 25, 775-790. https://doi.org/10.1007/s11769-015-0788-4

Zubairu, G. A., Sulaiman, N., & Mohammed, M. I. (2018). Student Housing a Resilient Housing Rental Market: Case of Federal Polytechnic Neighbourhood Bauchi, Nigeria. *Traektoriâ Nauki= Path of Science*, 4(3), 4008-4017.