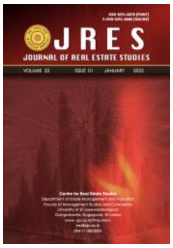

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Analysing the Impact of Guest Preferences on Airbnb Pricing Across Submarkets in Dar es Salaam, Tanzania

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ABSTRACT

The rapid proliferation of Airbnb accommodations has revolutionized the hospitality sector, providing travelers with diverse options while empowering property owners to tap into a dynamic rental market. This study explores the nuanced impact of guest preferences on Airbnb pricing across distinct submarkets in Dar es Salaam, Tanzania. Drawing insights from consumer surveys and linear regression models based on OLS for 141 guests in five wards of Dar es Salaam, it was noted that there was a price reduction effect of accommodation accessibility (-0.48, sig. 0.01) in low submarkets but such effect was insignificant in the high submarket. Building design was also negative on price and statistically significant (-2.85, sig. 0.01). When building design was assessed in the high-submarket, a sign reversal of the price effect was noted though not statistically significant. The study suggests for significant price effect reversal in relation to number of visits and neighbourhood quality. Visitations exhibits a normal downward sloping demand (-0.03, sig. 0.05) in the high submarket and it is an abnormal demand (0.07, sig. 0.001) in the low-submarket while improving neighbourhood quality reduces price (abnormal) in the high-submarket (-2.76, sig. 0.001) and turns out to be normal in the low-submarket (0.71, sig. 0.001). These findings contribute to the global discourse on platform-based rental markets by highlighting the critical role of localized consumer behavior in emerging economies. It provides actionable insights for hosts, policymakers, and platform managers aiming to optimize pricing strategies and enhance market efficiency by improving neighbourhood quality only when necessary and encouraging formalized Airbnb across submarkets. By shedding light on the unique Airbnb dynamics in submarkets of a rapidly urbanizing African city, this study enriches the literature on peer-to-peer accommodation services in underexplored regions.

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1. INTRODUCTION

Unlike traditional hospitality services, such as hotels and guesthouses, Airbnb offers a peer-to-peer (P2P) lodging model where individuals can rent their homes or apartments to short-term guests (Ramos-

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Henriquez & Morini-Marrero, 2025). Since its inception in 2008, Airbnb has grown exponentially and is now a global phenomenon, operating in over 191 countries and revolutionizing how travelers book accommodations (Volgger, et al., 2019). It has provided consumers with diverse lodging options and introduced flexibility in pricing, locations, and services (Contu, et al., 2023). The rise of Airbnb as a disruptive innovation has brought about a shift in the hospitality landscape, compelling scholars, practitioners, and policymakers to explore its implications and the factors driving its popularity (Bashir & Verma, 2016).

The sharing economy is characterized by decentralized access to goods and services, often facilitated by digital platforms (Marti-Ochoa, et al., 2024). Airbnb's business model aligns with this trend, allowing individuals to share their homes with strangers for a fee (Chang & Li, 2021). This model contrasts with traditional accommodations like hotels, which rely on institutional ownership and standardized service offerings (Quattrone, et al., 2022). The growth of Airbnb has posed challenges to the hotel industry by providing consumers with a more personalized, cost-effective, and flexible lodging option (Guttentag, 2015). According to Guttentag et al. (2017), cost savings, the opportunity to live like a local, and unique lodging experiences are among the top reasons why travelers opt for P2P accommodation. Barbosa (2020) found that online reviews played a crucial role in boosting customer satisfaction with Airbnb stays, as they provided transparency and trust, factors often missing in hotel bookings.

P2P accommodation rental market, particularly Airbnb, has experienced rapid growth due to factors such as the rise of customized travel experiences and the flexibility offered by Airbnb (Birinci, et al., 2018; Contu, et al., 2023). Hansen et al. (2018) suggest that Airbnb listings offer unique value propositions, such as access to local culture and community, which cannot be matched by conventional hotels. Cohen et al., (2023) highlight the convenience of short-term rentals in residential neighbourhoods, which allow guests to feel more connected to their surroundings. Montali (2017) emphasized that the Airbnb platform has facilitated the transformation of residential properties into viable short-term rentals, allowing local hosts to tap into the global travel market.

P2P accommodation preferences via the Airbnb platform are associated with price elasticity of demand, property quality (cleanliness, amenities, overall appeal), and location attributes (safety, accessibility and proximity to attractions) (Suárez-Vega & Hernández, 2020; Teubner, et al., 2017; Karubi, 2024). Chang & Li, (2021) observed that Airbnb accommodation prices respond negatively to proximity to railway station, airport and tourist attraction while it is positive for proximity to subway. Gunter & Önder, (2018) observed that Airbnb demand tend to be elastic in response to many of its determinants with the exception of listing price, distance and response time which featured a negative (-) sign. Neighbourhood quality attributes such as cleanliness and location tend to have a positive effect on prices (Jiang, et al., 2022; Chen & Xie, 2017; Kakar, et al., 2016). Dar es Salaam, as the business capital of Tanzania, is home to a growing urban population, an increasing number of expatriates, and a booming tourism sector. the property characteristics of Airbnb rentals in Dar es Salaam vary widely, from luxury beachside villas in Masaki to modest apartments in Kinondoni. Despite the city's flourishing P2P accommodation market, the determinants of Airbnb prices and the associated interactions across submarket remain understudied with limited explanations on the penetration of Airbnb in traditional hotels dominated submarkets. The central research question guiding this study is: ***What is the effect of guests' preference for Airbnb on the prices paid by guests in Dar es Salaam submarkets and to what extend do these submarkets prices affect one another?*** The study assesses variation in Airbnb accommodation across submarkets in relation to the overall level of Airbnb price in selected submarket.

2. LITERATURE REVIEW

2.1. Price responsiveness of Airbnb demand

Affordability is perhaps one of the most widely cited reasons for choosing Airbnb. Studies by Abraham (2018) and Guttentag et al., (2017) demonstrate that Airbnb's competitive pricing structure appeals to budget-conscious travelers. Airbnb rentals often offer more space at a lower price compared to alternative accommodation such as Hotel rooms, which is a strong incentive for families, groups, or long-term visitors (Gunter & Önder, 2018; Contu, et al., 2023). Cohen et al. (2023), underscores the impact of price-sensitive travelers on the growing preference for Airbnb.

According to Guttentag et al., (2017) and Zhang et al., (2018), Airbnb has gained significant traction due to its price competitiveness, particularly for relatively longer stays than their hotel short stay counterpart; authenticity and uniqueness of co-created experiences and household amenities. Gunter & Önder, (2018) suggest that the number of guests i.e., "visitation" tend to be negative on Airbnb uptake suggesting for a negative effect on price as well. However, Perez-Sanchez, et al., (2018) observed that the increased number of visitors had a positive effect on prices, suggesting that cheaper Airbnb locations may not necessarily attract more visitors.

Airbnb's flexibility in offering entire homes, private rooms, or shared spaces allows for a range of price points, appealing to budget-conscious travelers (Guttentag & Smith, 2017; Wang & Nicolau, 2017). Airbnb's price variability especially when comparing entire homes to private rooms often provides travelers with more cost-effective options compared to traditional hotels. Zervas, et. al., (2017) argue that Airbnb's lower pricing, especially for large groups or extended stays, is one of its most significant competitive advantages over hotel accommodations.

Despite the notable price advantages mentioned above, some studies present contradictory views. Guttentag et al. (2017) argue that Airbnb rentals are not always the cheapest option, particularly in high-demand urban areas where short-term rentals can command premium prices. In these contexts, hotels may offer competitive rates, especially when factoring in last-minute deals or off-season pricing. This introduces an interesting dimension to the price debate, as affordability fluctuates based on market conditions, location, and duration of stay. Ntongani, (2024) observed that Airbnb rentals often operate at a lower cost than traditional hotels in urban centers like Dar es Salaam. However, these properties can be more expensive than long-term residential rentals.

2.2. Location and neighbourhood quality effect on price

Airbnb's appeal is also driven by its unique property features and personalized hospitality provided by hosts. Guttentag et al. (2017) emphasize that Airbnb properties often offer distinct features, such as homes with historical significance, unique architectural styles, or scenic locations, which attract travelers seeking non-traditional experiences. These amenities form part of neighbourhood and location characteristics which are expected to have a positive effect on Airbnb prices (Toader, et al., 2022; Jiang, et al., 2022; Suárez-Vega & Hernández, 2020; Chang & Li, 2021). This sense of uniqueness and local flavor is less common in standardized hotel settings, where uniformity and consistency are prioritized (Medina-Hernandez, et al., 2024). Geographical proximity is a crucial factor in the lodging decision-making process. Proximity to essential services especially in the CBD has emerged as another critical determinants of Airbnb prices (Toader, et al., 2022; Medina-Hernandez, et al., 2024; Perez-Sanchez, et al., 2018). For Airbnb guests, proximity to key attractions, work areas, or family homes can significantly influence their Airbnb accommodation choices (Kim & Lee, 2018; Toader, et al., 2022; Jiang, et al., 2022).

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2.4. Airbnb space size and quality effect on price

The Airbnb accommodation services space is often listed to include room type, number of bathrooms, number of bedrooms and other facilities such as car parking, swimming pool, and wireless Internet (Perez-Sanchez, et al., 2018). Magno, et al. (2018) observed that the price of entire homes/apartments is on average 39.86 per cent higher than the price of private or shared rooms. Quang, et al. (2024) findings suggest that guests achieve satisfaction from host families' attitudes and language abilities, high-quality facilities in the bedrooms and grounds, authentic cuisine, a peaceful location, the availability of complementary services, and affordable prices. Suárez-Vega & Hernández, (2020) revealed that the price increases due to an additional bathroom varied between 12.7 and 27.5%, with an average of 20.1%. The effect of these quantity/size-related factors on Airbnb is generally expected to be positive (Toader, et al., 2022; Gibbs, et al., 2018; Wang & Nicolau, 2017; Chang & Li, 2021).

2.5. Personal experience and willingness to pay

The level of personal interaction and service flexibility that hosts provide can significantly enhance the Airbnb experience (Asaad, et al., 2019; Medina-Hernandez, et al., 2024). In contrast, the personalized interactions between Airbnb hosts and guests can create a sense of home away from home (Medina-Hernandez, et al., 2024). In this regard, Airbnb listings often provide a more intimate experience, with hosts offering insights into local culture, restaurants, and activities that are not typically part of the service package in hotels (Agapitou, et al., 2020; Medina-Hernandez, et al., 2024; Perez-Sanchez, et al., 2018). Hotel-like hospitality services in Airbnb accommodation such as free breakfast have been associated with negative impact on prices (Gibbs, et al., 2018; Wang & Nicolau, 2017). Yobesia, et al. (2024) observed that a positive effect on "whether the facility provided a buffet breakfast" (B = .22) in Kenya. Despite of the positive experiences accorded to Airbnb; prices may also respond to some dissatisfactions since hosts are not professionals in the hospitality industry and hence their treatment of guests may significantly deviate from similar accommodation such as Hotels (Chen & Tussyadiah, 2021). Medina-Hernandez, et al., (2024) observed that Airbnb had the highest percentage of negative feelings which they associated to the expectations in terms of compensation of what they pay i.e., the "destination image".

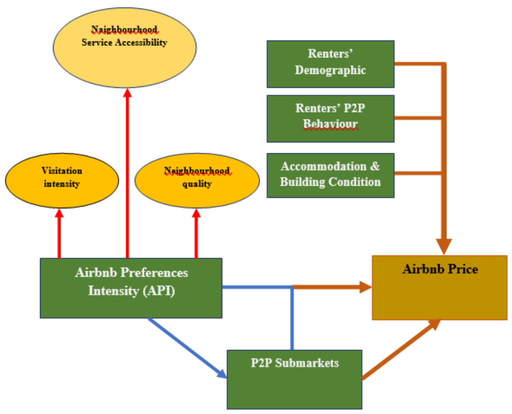
2.6. Demographic effect on Airbnb price

Mao & Liu (2017) note that changes in household demographics, such as age, income levels and marital status, significantly impact preferences for short-term rentals which could influence price. For instance, Millennials and Generation Z, particularly those aged between 21 and 47, have been found to prefer Airbnb over traditional accommodations due to their affinity for technology, flexibility, and unique experiences (Contu, et al., 2023; Agapitou, et al., 2020). In Africa, Bananda & Nwagwu (2021) suggest that the continent presents significant growth potential for Airbnb, driven by tech-savvy Millennials looking for flexible and cost-effective travel accommodations. Mao & Liu (2017) found that while younger travelers, particularly Millennials, value unique experiences, older guests and business travelers prioritize reliability and predictability. Traditional hotels, known for their standardized services, tend to attract this demographic clusters due to the guaranteed consistency in amenities, cleanliness, and customer service (Medina-Hernandez, et al., 2024). Iglesias (2022) conducted research in China and found that women, particularly those belonging to Generation Y, were more likely to choose Airbnb over hotels. This aligns with findings by Guttentag et al. (2017), who observed that women tend to spend more time browsing Airbnb options compared to men. Having a child in the family is associated with relatively lower price when compared to having non (Chang & Li, 2021) thus signaling that larger families could prefer Airbnb as a cost saving strategy. Despite the strong and significance of demographic factor on preferences, the effect of Gender, marital status, and sexual orientation on price has been reported to be insignificant (Chen & Xie, 2017; Kakar, et al., 2016). Kim & Lee (2018) challenge the notion that age and gender are significant determinants of Airbnb preferences. Their findings suggest that preferences for short-term rentals or hotels can vary widely within the same age group depending on specific travel needs. For instance, some travelers prioritize access to amenities like fitness centers or concierge services amenities commonly found in hotels but often lacking in Airbnb rentals (Gibbs, et al., 2018).

Conceptual Framework

The flexibility of geographical location in Airbnb listings provides an edge over other short-term accommodation, which are typically concentrated in more touristic or commercial areas (Jiang, et al., 2022; Contu, et al., 2023). The importance of personalized hospitality is further highlighted by Tussyadiah & Zach (2015), who argue that Airbnb's appeal lies in its ability to offer a localized and immersive experience. Travelers often enjoy the opportunity to interact with hosts, receive personalized recommendations, and feel connected to the community (Medina-Hernandez, et al., 2024). Figure 1 shows a conceptualization of the localization of factors that shape Airbnb prices and potential interaction through submarkets, the cost of hotel stays can be high in central areas such as Masaki and Mikocheni thus Airbnb can offer a more affordable alternative in these HIGH submarkets.

Figure 1: Conceptual Framework for Airbnb Pricing and Guest Preferences in Dar es Salaam Submarkets



Given the potential for HIGH and LOW submarkets in the city and the fact that Airbnb can have STRONG or WEAK preferences, four hypotheses have been formulated as summarized in Table 1. In HIGH submarkets, Airbnb could be attractive but expensive as they mingle with many of the Hotels in the city. As such, there could be neighbourhood interactions such that the STRONG Airbnb preferences in the HIGH submarket is translated into higher rents in LOW submarkets in the vicinity such as in Kinondoni, as renters drift away from high to low submarkets (complementary effect). Complementarities may exist in cases where STRONG preferences in HIGH submarkets is not accommodatable through affordable Airbnb accommodation thus drifting visitors to nearby affordable accommodation. Kinondoni being a relatively MID submarket compared to Sinza and Mwenge could also exert a similar complementary effect. If the HIGH submarket is associated with relatively affordable (low) Airbnb accommodation prices, one would expect more uptake for its Airbnb with negative consequences in nearby submarket.

Table 1: Summary of hypotheses on Airbnb preferences and pricing effects across submarkets

		AIRBNB PREFERENCES	
		WEAK	**STRONG**
NEIGHBOURHOOD/SUBMARKET	LOW	**PRICE NEUTRAL EFFECT** H1: **WEAK** Airbnb preferences among guests in **LOW** submarket **will internalize all** price changes leading to neutral effect in other submarkets	**PRICE COMPLEMENTARY EFFECT** H2: The **LOW submarkets prices with STRONG** Airbnb preference among guests respond positively to nearby HIGH submarkets preference changes leading to price Complementary effect [prices increase (+)]
	HIGH	**PRICE SUBSTITUTION EFFECT** H3: **HIGH submarket** prices with WEAK Airbnb preference respond negatively to nearby **WEAK preference** guests in nearby **LOW** submarkets leading to a price Substitution effect (-).	**PRICE COMPETITIVE EFFECT** H4: The **HIGH** submarket prices facing **STRONG** preference among Airbnb guests leads to **competitive Airbnb prices** in nearby **LOW** submarket (as guests attempt maintain their preferences at relatively low price).

NB: The price effect depends on both preferences and submarket characteristics with strong and competitive prices being expected at the interaction between High-submarket and Strong Airbnb preferences

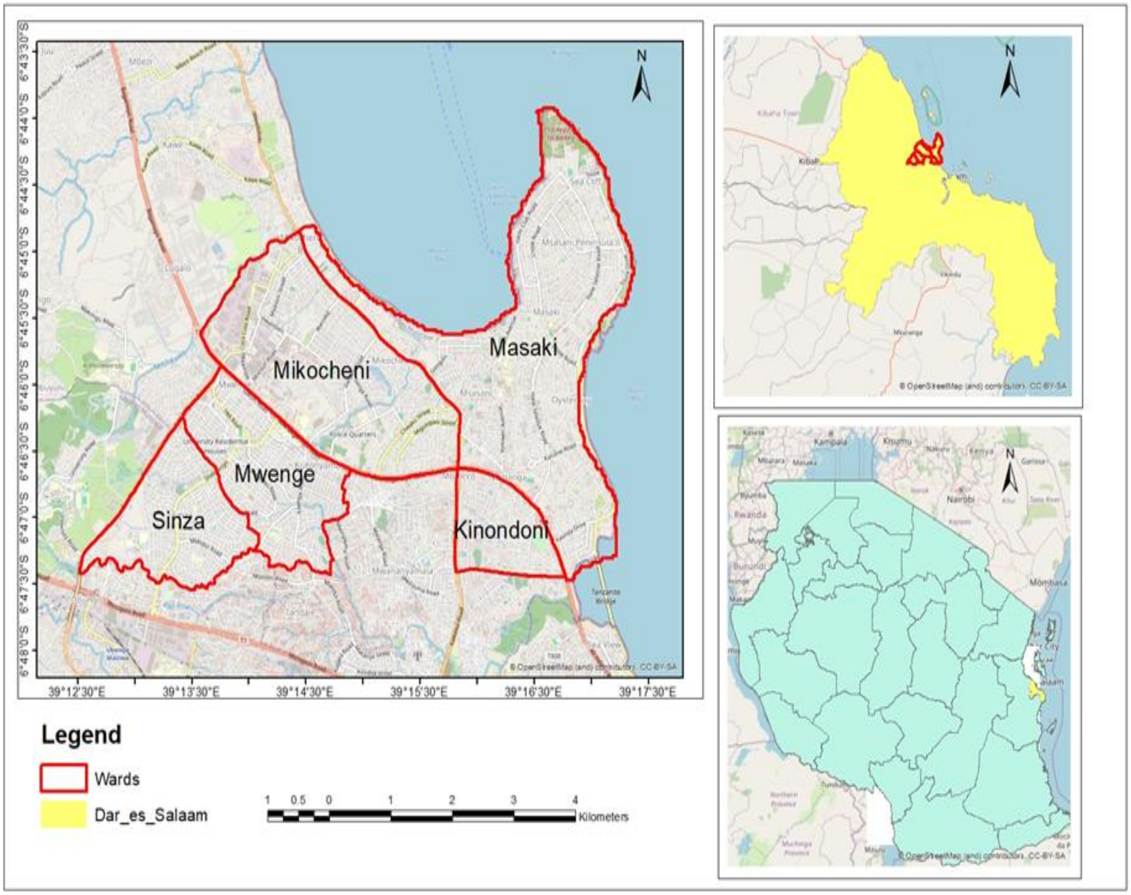
It is also possible to experience the neutral effect if WEAK Airbnb preference is associated with LOW submarket since the LOW neighbourhood is less attractive from outsiders' point of view, the weaker preferences for Airbnb accommodation will be translated into lower local rental prices and is unlikely to be transferred elsewhere. If these low submarkets are associated with HIGH Airbnb preferences, they can have a price reducing effect to nearby HIGH submarkets that experiences WEAK Airbnb preferences among rental customers of HIGH submarkets who may shift to LOW submarket in as long as they do not have STRONG Airbnb accommodation preferences. Thus, Airbnb preferences exert a substitution effect on nearby high submarket with WEAK preferences if such nearby submarket with LOW preferences exists or similar LOW submarkets with WEAK preferences. If they do not exist, internal price competition within LOW submarkets may ensue, leading to downward price spiral in a competitive manner.

3. RESEARCH METHODS

This research focused on five Wards within Kinondoni Municipality namely Sinza, Mwenge, Mikocheni, Kinondoni, and Masaki, as illustrated in **Figure 2**. For the purpose of this study, we use neighbourhood defined through political boundaries called Wards as submarkets kernels. These wards are however combined based on proximity to major features (road) to come up with only three submarkets. Despite the rigidity of political boundaries in spillover effect studies, we still believe that the Airbnb industry at its nascent stage can be studied from discrete building units. The selected neighbourhoods like Masaki and Mikocheni are popular destination for visitors for different reasons. Masaki, for instance, is known for its upscale residences and close proximity to the ocean, making it an attractive option for high-end tourists/visitors thus can be classified as HIGH submarkets. On the other hand, Kinondoni, Mwenge and Sinza offer more affordable accommodation close to the central business districts thus can be considered LOW submarkets. Knondoni can also be sought as a MID submarket given its close proximity to Masaki, a HIGH submarket.

To gather a representative sample of Airbnb guests and hosts, the study employed a combination of purposive and snowball sampling techniques. The initial phase utilized purposive sampling to target key neighbourhoods these neighbourhoods or rather subawards were specifically chosen due to their popularity among Airbnb users and their relevance to the study's objectives. The Sample Size was not predetermined as the actual population of the Airbnb properties is yet to be established throughout the study area. To distribute the questionnaire, we started with an unknown population with a rule of thumb sample size of 50 respondents per cluster-subward (250), However the actual respondents were obtained through the snowballing techniques for which a large sample is unlikely thus yielding 144 usable questionnaires. Snowballing usage has questionable usage in quantitative research in the main document when it comes to diversity in the sample (Kirchherr & Charles, 2018). To address this shortcoming, we enhanced sample diversity using submarkets as data collection kernels although were did not have a mechanism for terminating the sample. The only option was to ignore out of submarket references. As a results of this procedure, the final results are expected to be relevant within submarkets, but replicability and generalization should be inferred with a caveat. Snowball sampling was introduced as an effective method for reaching out to the respective guests at

Figure 2: Map of Study Areas: Wards in Kinondoni Municipality



somehow lower cost.

The survey design incorporated a combination of structured and closed-ended questions. Both self-administered and researcher-administered questionnaires were used, providing flexibility for respondents who were geographically dispersed across the five wards of Kinondoni Municipality. Google Forms was utilized for respondents who could not be reached in person, allowing them to complete the questionnaire at their convenience. The description of respondents is provided in Table 2. A central feature of the survey involved the use of five-point Likert scale items, which assessed preferences and perceptions regarding several dimensions of Airbnb services as summarized in Table 3. Notably, around 41 of the renters were observed in the LOW submarket (18 from Sinza and 23 from Mwenge), A total of 29 renters are from MID Submarket (Kinondoni), and 71 were observed from the HIGH submarket (41 were from Mikocheni and 30 from Masaki subward). Sinza had the least number of respondents, followed by Mwenge which had 23 respondents.

Table 2: Distribution of Airbnb Preferences and Demographics Across Submarkets

	Airbnb preference in different location			**Total**
	LOW Submarket	**MID Submarket**	**HIGH Submarket**	
Birth year category				
1946-1964	0	1	0	**1**
1965-1976	6	3	9	**18**
1977-2003	35	25	62	**122**
Gender category				
Female	14	10	42	**66**
Male	27	19	29	**75**
Marital status category				**0**
Single	22	19	37	**78**
Married	19	10	34	**63**
Permanent residency category				
Outside Dar es salaam	19	16	41	**76**
Dar es salaam	22	13	30	**65**
Family size category				
Father, mother and one child	9	5	16	**30**
Single parent family	28	21	46	**95**
Father, mother and children	4	2	9	**15**
Extended family	0	1	0	**1**
Employment status category				
Unemployed	2	0	3	**5**
Employed	22	18	38	**78**

	Airbnb preference in different location			**Total**
	LOW Submarket	**MID Submarket**	**HIGH Submarket**	
Self employed	17	11	30	**58**
Monthly income				
LOW/500K-3M	33	21	35	**89**
MID/3M-9M	7	7	29	**43**
HIGH/9M-20	1	1	7	**9**
Daily expenditure category				
LOW/20K-100K	20	16	12	**48**
MID/100K-400K	20	11	50	**81**
HIGH/400K-5M	1	2	9	**12**
Occupation category				
Profession	9	10	20	**39**
Business	5	1	20	**26**
Other	27	18	31	**76**
Total	**41**	**29**	**71**	**141**

Source: Author's compilation, 2024

Table 3: Variables and Measurement Indicators for Airbnb Pricing Analysis

S/N	Abbreviation	Description	Measurement
A	**Dependent Variables**		
A.1	LnLP	Natural log of Airbnb price in LOW submarkets (Sinza & Mwenge)	Scale
A.2	LnMP	Natural log of Airbnb price in MID Submarket (Kinondoni)	-do-
A.3	LnHP	Natural log of Airbnb price in HIGH submarkets (Mikocheni & Masaki)	-do-

S/N	Abbreviation	Description	Measurement
B	**Location and Neighbourhood Preferences (LNP)**		
B.1	KIN	Airbnb most preferred location Kinondoni	Dummy {1, if Kinondoni, 0 if otherwise}
B.2	MIK	Airbnb most preferred location Mikocheni	Dummy {1, if Mikocheni, 0 if otherwise}
B.3	MWE	Airbnb most preferred location Mwenge	Dummy {1, if Kinondoni, 0 if otherwise}
B.4	MAS	Airbnb most preferred location Masaki	Dummy {1, if Masaki, 0 if otherwise}
B.5	SIN	Airbnb most preferred location Sinza	Dummy {1, if Sinza, 0 if otherwise}
B.6	APLI	Airbnb most preferred location intensity	Index computed as per equation 1
B.7	PRE_LOW	Preference in low submarket	Dummy {1, if the renter's Airbnb visitation are dominated in either Masaki or Mikocheni Subwards, 0 if otherwise}
B.8	PRE_MID	Preference in middle submarket	Dummy {1, if the renter's Airbnb visitation are dominated in Kinondoni Subwards, 0 if otherwise}
B.9	PRE_HIGH	Preference in high submarket	Dummy {1, if the renter's Airbnb visitation are dominated in either Sinza or Mwenge Subwards, 0 if otherwise}
B.10	PRE_VHIGH	Preference in very high submarket	Dummy {1, if the renter's Airbnb visitation are dominated in either Sinza or Mwenge Subwards, 0 if otherwise}
B.11	NQI	Neighbourhood Quality Index	Index computed as per equation 1
B12	NSLI	Neighbourhood Service Location Index	Index computed as per equation 1
C	**Renters AirBnB Behaviour (RAB)**		
C.1	Low_spender	Pro-visitation renters	Dummy {1, if Airbnb spending falls in the lowest

S/N	Abbreviation	Description	Measurement
			quartile, 0 if otherwise}
C.2	Middle_spender	Pro-finance renters	Dummy {1, if Airbnb spending falls in the second lowest quartile, 0 if otherwise}
C.3	High_spender	Pro-accessibility renters	Dummy {1, if Airbnb spending falls in the second highest quartile, 0 if otherwise}
C.4	Vhigh_spender	Total number of Airbnb visits	Dummy {1, if Airbnb spending falls in the highest quartile, 0 if otherwise}
C.5	VISIT	Total Airbnb visits in 2 years	Number
D	**Accommodation & Building Condition (HBC)**		
D.1	AAI	Accommodation Accessibility Index	Index computed as per equation 1
D.2	API	Accommodation Proximity Index	-do-
D.3	ASAI	Accommodation Service Availability Index	-do-
D.4	IAI	Internal Amenities Index	-do-
D.5	ASSI	Accommodation Services Space Index	-do-
D.6	ASAI	Accommodation Space Adequacy Index	-do-
D.7	BDUI	Building Design Uniqueness Index	-do-
D.8	BQI	Building Quality Index	-do-
D.9	PCI	Property Condition Index	-do-
D.10	HHI	Host Hospitality Index	-do-
E	**Renters Demographics Controls (RDC)**		
E.1	Age	Natural log of Age	Scale
E.2	GMale	Gender is Male	Dummy {1 if renter is Male, 0 if otherwise}
E.3	MSS	Marital Status is Single	Dummy {1 if renter's marital status is Single, 0 if

S/N	Abbreviation	Description	Measurement
			otherwise}
E.4	FS-FMO	Family Structure Father, Mother and One child	Dummy {1 if renter's family structure is father, mother and one child, 0 if otherwise}
E.5	FS-SPF	Family Structure Single Parent Family	Dummy {1 if renter's family structure is single parent family, 0 if otherwise}
E.6	FS-FMC	Family Structure Father, mother and children	Dummy {1 if renter's family Structure is father, mother and children, 0 if otherwise}
E.7	RO-OD	Residency Origin Outside Dar es salaam	Dummy {1 if renter's residency of origin is outside Dar es salaam, 0 if otherwise}
E.8	ES-E	Employment Status Employed	Dummy {1 if renter's employment status is employed, 0 if otherwise}
E.9	ES-SE	Employment Status Self employed	Dummy {1 if renter's employment status is self-employed, 0 if otherwise}
E.10	OS-P	Occupation Status Profession	Dummy {1 if renter's occupation status is professional, 0 if otherwise}
E.11	OS-B	Occupation Status Business	Dummy {1 if renter's occupation Status is business, 0 if otherwise}
E.12	AT	Accommodation type Private room	Dummy {1 if renter's occupation type is private room, 0 if otherwise}
E.13	LnINC	Natural log of monthly income	Scale
E.14	LnDE	Natural log of daily expenditure	Scale

Source: Author's compilation, 2024

Descriptive statistics were applied to summarize key demographic characteristics and property features of the sample population. Utilizing descriptive statistics proved instrumental in identifying preliminary behavior in Airbnb preferences, prices, types of properties favored by guests and preferred location attributes.

The Relative Importance Index (RII) technique, commonly used in ranking the potential significance of variables (Cheng, 2022), was employed in this study to assess factors that can shape guests' preferences for Airbnb in the rental market specifically those clustered as HBC in Table 3 as well as APLI, NQI, NSLI, all of them falling under LNP factors. The indices were subsequently included in the regression model. The RII was calculated according to Zervas et al. (2020), as shown in Equation 1:

$$RII = \frac{\sum_{i=1}^{N} W_i}{AN} = \frac{5n_5+4n_4+3n_3+2n_2+1n_1}{AN} \qquad [1]$$

Where:

- n is the number of property owners who rated a variable.
- N is the total number of respondents.
- A is the number of points on the Likert scale (in this case, A = 5).

Typically, the RII ranges between 0 and 1, with higher RII values indicating greater importance, meaning the variable with the highest RII is ranked as the most important. It is important to note that the RII formula does not compare variables but simply ranks them in order of importance.

Linear regression analysis based on Ordinary Least Square (OLS)was employed to investigate the relationships between the independent variables; Accommodation and Building Condition (HBC), Location and Neighbourhood Preference (LNP), and Renters Demographic Characteristics (RDC) while the dependent variables was Natural Log of Price (LNPRICE) in each submarket. The regression model was as provided in equation 2.

$$LNPRICE_i = \beta_{i0} + \beta_{i1}^{k} \sum_{k=1}^{K} LNP_{ik} + \beta_{i2}^{r} \sum_{r=1}^{R} RAB_{ir} + \beta_{i3}^{h} \sum_{h=1}^{H} HBC_{ih} + \beta_{i5}^{d} \sum_{d=1}^{D} RDC_{id} + \varepsilon_{ij}$$

Where;

$LNPRICE_i$ -is the Natural log of price in submarket i, $\{i = (LOW, MID\ or\ HIGH\}$

β_{ij} – are the coefficients of the model to be estimated

LNP_{ik} – are the K location and neighbourhood Preference indicators as summarized in Table 2

RAB_{ir} – are the R Renters Airbnb Behaviour indicators as summarized in Table 2

HBC_{ih} - are the H Accommodation and Building Condition Indicators as summarized in Table 2

RDC_{id} – are the D Renters Demographic Controls as summarized in Table 2

ε_{ij} -=are the random error term for each submarket model

4. RESULTS AND ANALYSIS

Table 1, provides the descriptive statistics for the variables of interest. In the low submarket, the daily Airbnb prices range between \$20. (LN=3) and \$79.8 (LN =4.38) with an average at \$ 37.04 (LN =3.61). A similar low and high price pattern is observable in the middle market, though the average is slightly higher at $ 41.1. In the high market, the observed daily Airbnb rent is $4.0 at the lowest and $249.6, with an average standing at $74.3. These observations suggest that the five submarkets could be re-classified as HIGH and LOW based on the observed prices.

Regarding location and neighbourhood preferences, around 32% of respondents preferred Mikocheni followed by 23% at Kinondoni. The lowest responses were observed at Masaki where around 11% of respondents preferred that location. These observations points to a mix of potential price effect as both high and low submarket exhibits substantial number of responses in terms of most preferred location. The intensity of these most preferred location ranges between 0.3 at the lowest to 1 with an average at 0.63 based on the RII scale. The observed submarket prices in terms of low and high indicate that they are well balance between 49% and 51% for the low and high price quartiles responses respectively. The Neighbourhood Quality Index (NQI) and Neighbourhood Service Location Index (NSLI) scores are at 80% and 83% respectively suggesting that renter's view on neighbourhood quality and service availability are relatively high.

Renter's Airbnb spending behaviour strongly clusters on the high side with almost 74% of respondents coming from that category (i.e. 26% for high and 48% for very high spenders) while the remaining 26% are from the low spending side. The surveyed respondents exhibits strong preferences for Airbnb as the average visit they have made stand at 5 with 1 being the lowest and 17 visits being the highest within the past 2 years.

Age-wise, the youngest renter was aged 22 years, while the oldest one was aged 62 years, with an average of 34 years. The incomes of these renters range between TZS 498,820 and TZS 16,030,440, with an average of 2,191,288 which is a relatively high income based on Tanzanian standards, where the majority are around a dollar a day. This is also reflected in their daily expenditure, starting at TZS 50,011 to around TZS 2,495,501 with an average of TZS 169,397. These observations suggest that the Airbnb accommodation submarket under study could be dominated by non-Tanzanians or some High-class Tanzanians. This is also supported by the results in Table 5 where the majority (54%) are not from within Dar es salaam. Looking at other demographics in Table 5, it is notable that Airbnb customers are primarily single with Single parent family taking around 67% of all respondents. They are also mainly employed and tend to rent mainly single rooms as also reflected by their business and professional background.

Following the descriptive statistics provided above several tests were carried out to test for normality, based on the skewness tests, multicollinearity and heteroskedasticity. Based on common practices, heteroskedasticity was addressed via transformation of the dependent variables i.e., prices for the three submarkets into natural log to stabilize the variables. To ease interpretation also several other variables like age, income and expenditure were also transformed into natural logarithm. Based on the descriptive statistics in Table 4 and 5, the variables were relatively normal based on the skewness test presented with a value closer to two. The Dublin Watson statistics provided in Table 6 further suggested that autocorrelation was minimum as the value was around 2. With these tests, the linear regression model in equation 2 was implemented for three models for the LOW, MIDDLE and the HIGH submarket.

Table 4: Descriptive Statistics of Airbnb Property Attributes in Low, Mid, and High Submarkets

S/N	Variable Name	N	Min	Max	Mean	Std. Dev.	Skewness	
							Statistic	Std. Error
A	**Dependent Variables**							
A.1	LNPRICEL	41	3.00	4.38	3.61	0.29	0.46	0.35
A.2	LNPRICEM	29	3.00	4.38	3.72	0.34	0.07	0.31
A.3	LNPRICEH	71	1.39	5.52	4.31	0.42	(0.63)	0.30
B	**Location and neighbourhood preferences**							
B.1	KIN	141	0	1	0.23	0.42	1.32	0.20
B.2	MIK	141	0	1	0.32	0.47	0.78	0.20
B.3	MWE	141	0	1	0.18	0.39	1.65	0.20
B.4	MAS	141	0	1	0.11	0.31	2.58	0.20
B.5	SIN	141	0	1	0.16	0.37	1.84	0.20
B.6	APLI	141	0.33	1.00	0.63	0.20	0.78	0.20
B.7	PRE_LOW	141	0	1	0.13	0.34	2.26	0.20
B.8	PRE_MID	141	0	1	0.36	0.48	0.58	0.20
B.9	PRE_HIGH	141	0	1	0.30	0.46	0.89	0.20
B.10	PRE_VHIGH	141	0	1	0.21	0.41	1.42	0.20
B.11	NQI	141	0.37	1.00	0.80	0.12	-1.24	0.20
B.12	NSLI	141	0.51	1.23	0.83	0.10	-0.12	0.20
C	**Renters AirBnB Behaviour**							
C.1	Low_spender	141	0	1	0.13	0.34	2.26	0.20
C.2	Middle_spender	141	0	1	0.13	0.34	2.16	0.20
C.3	High_spender	141	0	1	0.26	0.44	1.13	0.20
C.4	Vhigh_spender	141	0	1	0.48	0.50	0.07	0.20

S/N	Variable Name	N	Min	Max	Mean	Std. Dev.	Skewness	
							Statistic	Std. Error
C.5	Total Airbnb visits in 2 years	141	1	17	5	3.01	1.58	0.20

Table 5: Relative Importance Index (RII) for Accommodation and Building Condition Indicators (HBC)

S/N	Variable Name	Min	Max	Mean	Std. Dev.	Skewness
						Statistic
D	**Accommodation & Building Condition**					
D.1	AAI	0.51	2.09	0.85	0.15	3.32
D.2	API	0.49	0.97	0.83	0.11	-1.04
D.3	ASAI	0.34	1.00	0.78	0.15	-0.80
D.4	IAI	0.35	1.00	0.75	0.17	-0.84
D.5	ASSI	0.40	0.97	0.77	0.15	-0.88
D.6	ASAI	0.40	0.93	0.71	0.12	-0.54
D.7	BDUI	0.33	0.98	0.75	0.15	-0.81
D.8	BQI	0.34	1.00	0.78	0.15	-0.94
D.9	PCI	0.41	0.93	0.75	0.12	-0.87
D.10	HHI	0.51	1.00	0.88	0.09	-1.58
E	**Renters' Demographics Controls**					
E.1	Age	3.09	5.54	3.52	0.30	2.40
E.2	GMale	0	1	0.53	0.50	-0.13
E.3	MSS	0	1	0.55	0.50	-0.22
E.4	FS-FMO	0	1	0.21	0.41	1.42
E.5	FS-SPF	0	1	0.67	0.47	-0.75

S/N	Variable Name	Min	Max	Mean	Std. Dev.	Skewness
						Statistic
E.6	FS-FMC	0	1	0.21	0.41	1.42
E.7	RO-OD	0	1	0.54	0.50	-0.16
E.8	ES-E	0	1	0.55	0.50	-0.22
E.9	ES-SE	0	1	0.41	0.49	0.36
E.10	OS-P	0	1	0.28	0.45	1.01
E.11	OS-B	0	1	0.18	0.39	1.65
E.12	AT	0	1	0.59	0.49	-0.36
E.13	LnINC	13.12	16.59	14.60	0.79	0.41
E.14	LnDE	10.82	14.73	12.04	0.76	0.74

Table 1: Regression Results for Determinants of Airbnb Pricing in Low, Mid, and High Submarkets

Model	Dependent Variable:	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	Natural log of LOW Airbnb price	0.95	0.90	0.78	0.13	2.23
2	Natural log of MIDDLE Airbnb price	0.93	0.86	0.78	0.16	2.31

3	Natural log of HIGH Airbnb price	0.82	0.70	0.62	0.24	2.17

Source: Compilation from SPSS analysis output,2024

Table 6 provide model fit information where the adjusted R^2 is above 70% or above for all models which is a good indicator of a “good model fit” while the standard error of estimate is relatively low for all the models. According to Smith (Smith, 2018) and Johnson (Johnson, 2020), an R-squared value above 0.50 is generally considered strong in social sciences, demonstrating a solid relationship between the variables in this model.

Table 7 provide the regression results for the three models. Regarding preference interaction effects, the LOW Airbnb submarkets (basically Sinza and Mwenge) are well supported in all Subwards where prices in the LOW submarkets falls by 72% in response to higher preferences in Kinondoni, by 34% in response to similar effect in Mikocheni, by 30% in Mwenge and by 1.5 times in Masaki. As such significant price reduction in LOW submarkets is expected from enhanced preferences in, first Masaki (a high subward) and Kinondoni (a middle subward). A similar effect is observable in Mikocheni (a high subward) and Mwenge, (a low subward). The findings confirms that increases in Airbnb preferences in the high and middle subwards has a negative price effect in the LOW submarkets suggesting for direct substitution effect. These findings are also evident in Figure 3 where, regardless of the submarket, Airbnb prices decline in response to preferences.

Table 7: Summary of Key Findings: Influential Factors in Airbnb Pricing by Submar

Code	**Variables**	**Model 1: LOW Submarket**		**Model 2: MID Submarket**		**Model 3: HIGH Submarket**	
		Coefficients	**Sig.**	**Coefficients**	**Sig.**	**Coefficients**	**Sig.**
A	(Constant)	-2.74	***	1.31		1.83	
		(0.79)		(0.81)		(0.96)	
B	**Airbnb most preferred location Location and Neighbourhood preferences**						
B.1	Kinondoni	-0.72	***			-0.45	***

	preference	(0.15)				(0.10)	
B.2	Mikocheni preference	-0.34	***			-1.10	***
		(0.07)				(0.16)	
B.3	Mwenge preference	-0.30	***				
		(0.14)					
B.4	Masaki preference	-1.47	***			-1.88	***
		(0.24)				(0.29)	
B.5	Sinza preference	0.04	**			-3.23	***
		(0.13)				(0.61)	
B.6	Airbnb most preferred location intensity	-0.92	***			-2.52	
		(0.19)				(0.41)	
B.7	Low submarket price	-0.42	***	-0.12		0.53	***
		(0.16)		(0.11)		(0.12)	
B.8	Middle submarket price	0.47	***				
		(0.06)					
B.9	High submarket price	0.16	*	-0.32	***	1.03	***
		(0.09)		(0.08)		(0.10)	
B.10	Very high submarket price	-0.76	***	-0.14	**	0.27	**
		(0.19)		(0.07)		(0.12)	
B.11	Neighbourhood Quality Index	0.71	***	-3.79		-2.76	***
		(0.25)		(2.60)		(0.73)	
B.12	Neighbourhood Service Location Index	1.26	***	10.75		0.87	*
		(0.25)		(7.79)		(0.44)	
C	**Renters' AirBnB behaviour**						
C.1	Low spender	0.25	**				
		(0.10)					

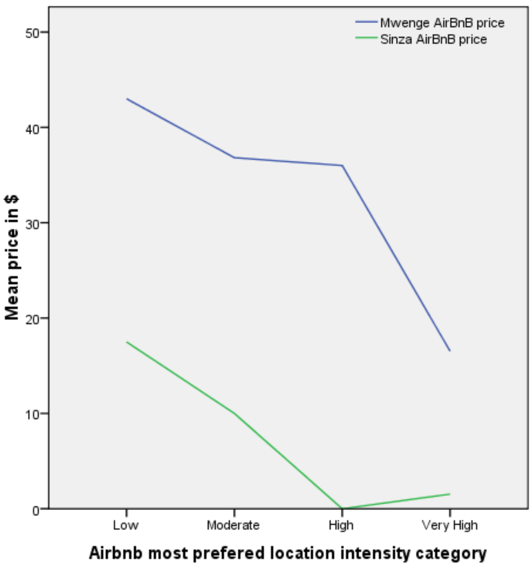
C.2	Middle spender	0.22	***	-0.11			
		(0.06)		(0.07)			
C.3	High spender			-0.17	***		
				(0.06)			
C.4	Very high spender	1.03	***			1.07	***
		(0.18)				(0.16)	
C.5	Total Airbnb visits	0.07	***	0.02	**	-0.03	**
		(0.02)		(0.01)		(0.01)	
D	**Accommodation & Building Condition**						
D.1	Accommodation Accessibility Index	-0.48	***	-3.31			
		(0.40)		(2.60)			
D.2	Accommodation Proximity Index			-3.68		-1.72	***
				(2.67)		(0.46)	
D.3	Accommodation Service Availability Index	6.30					
		(4.65)					
D.4	Internal Amenities Index	3.65	***				
		(0.21)					
D.5	Accommodation Services Space Availability Index	-11.58				2.28	***
		(9.39)				(0.46)	
D.6	Accommodation Space Adequacy Index	-3.85		-7.28	**	1.03	
		(2.66)		(2.84)		(0.63)	
D.7	Building Design Uniqueness Index	-2.85	***	-7.88	***	1.00	
		(0.27)		(2.79)		(0.67)	
D.8	Building Quality Index	-2.28		-8.17	***		
		(0.24)		(2.76)			
D.9	Property	11.91		24.30	***	0.88	***

	Condition Index	(7.95)		(8.40)		(1.19)	
D.10	Host Hospitality Index	-0.76	**				
		(0.26)					
E	**Renters Demographics Controls**						
E.1	Natural log of Age	0.48	***			-1.55	***
		(0.13)				(0.23)	
E.2	Male	0.45	***			-0.17	***
		(0.08)				(0.07)	
E.3	Single	-0.13	**	0.11		-0.39	***
		(0.06)		(0.08)		(0.09)	
E.4	Father, mother and one child	-0.61	***				
		(0.11)					
E.5	Single parent family			-0.21	**		
				(0.08)			
E.6	Father, mother and children	-1.68	***			-0.02	***
		(0.16)				(0.11)	
E.7	Outside Dar es salaam	-0.13	**			-1.00	***
		(0.07)				(0.23)	
E.8	Employed	-0.07	**				
		(0.14)					
E.9	Self employed	0.06	***	-0.07		-0.16	*
		(0.14)		(0.06)		(0.08)	
E.10	Profession	0.29	***	0.20	***		
		(0.08)		(0.06)			
E.11	Business	-0.17					
		(0.15)					

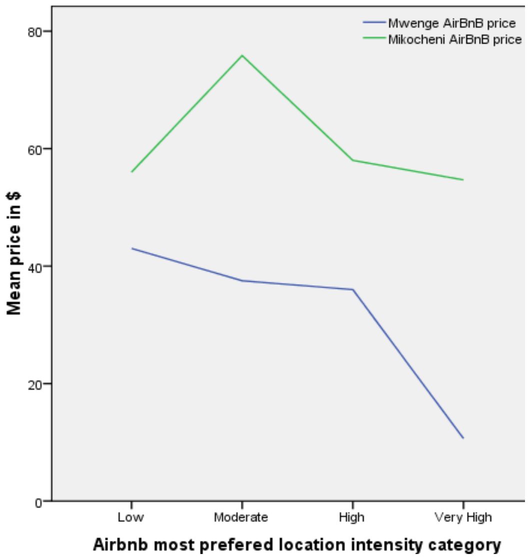
E.12	Private room	-0.35		-0.11		-0.30	***
		(0.11)		(0.08)		(0.11)	
E.13	Natural log of monthly income	0.54	***	0.13	**	0.79	***
		(0.07)		(0.05)		(0.09)	
E.14	Natural log of daily expenditure	-0.43				-0.24	***
		(0.17)				(0.06)	

Figure 3: Comparing the Submarket effect on prices

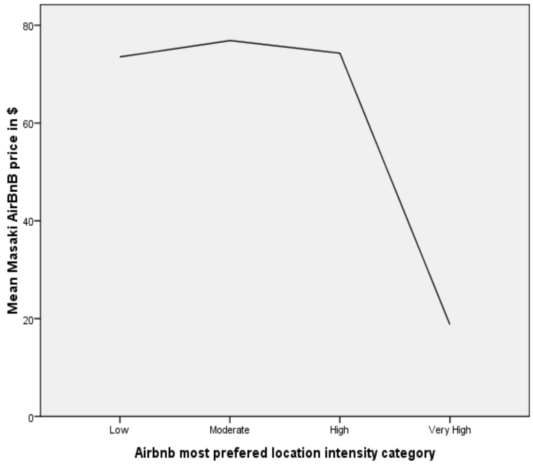
a. Airbnb preferences in relation to price in the LOW submarket



b. Airbnb preferences about price in the MID submarket

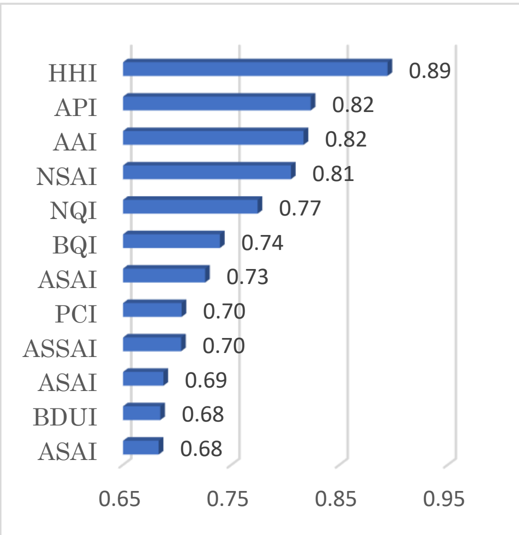


c.Airbnb preferences in relation to price in the HIGH submarket

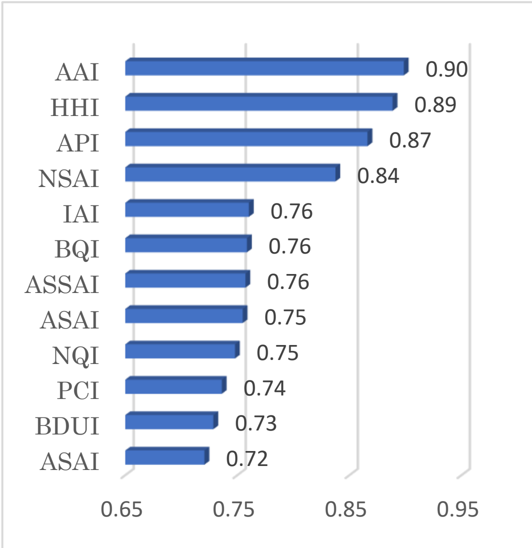


Source (Field data compilation, 2024)

Figure 4: Relative Importance Index (RII) Rankings for Accommodation and Neighborhood Factors: The overall RII rankings show that hospitality of the host matter most in low and high submarkets while neighbourhood quality highest ranking is No. 3 in High submarket.



A: Ranking of Neighbourhood and Property Attributes in the LOW Submarket



A: Ranking of Neighbourhood and Property Attributes in the MID Submarket

A: Ranking of Neighbourhood and Property Attributes in the HIGH Submarket

Increases in Airbnb prices in the LOW submarket are potentially linked to higher preferences in Sinza (low subward) though the effect is small in magnitude. A higher

Airbnb preference in low quality subwards like Sinza increase Airbnb demand locally thus exerting a general upward pressure only in LOW Airbnb submarket leading to higher price hence a complementary effect. If Mwenge and Kinondoni subwards are regarded as transition Airbnb accommodation submarkets, thus imitating the characteristics of both LOW and HIGH submarkets, it is possible to conclude that Airbnb preferences in HIGH and Transition submarkets indirectly substitute Airbnb accommodation demand in LOW submarkets while such preferences complement demand within LOW submarket. The overall price effect of preferences is however negative, stronger preferences are associated with lower price while weak preferences are associated with higher prices.

Regarding price interaction effects, Table 7 provide mixed results. The increase in low subward prices yields a negative price effect in LOW submarkets with an upward general trend. Generally, Airbnb prices increases with an increase in LOW subward prices especially (Kinondoni and Mwenge). When such prices are high enough, the effect tends to reverse especially in Masaki subward, a HIGH Submarket. Looking at these finding, it is evident that LOW submarket prices respond positively to upward changes in prices of transition subwards only, in stabilized LOW subwards and stabilized HIGH subwards, the effect is negative.

As such significant price falls in LOW submarkets can be expected from enhanced price in, first Masaki (a high subward) and Sinza (a low subward). These are considered to have stabilized at their respective status as LOW or HIGH leading to two notable observations; The first observation confirms that increases in Airbnb prices in the high subwards (Masaki) has a negative price effect in the LOW submarket suggesting for complementarities. The second observation relate to LOW submarket (Sinza) where, a well-established low subward Airbnb price increase will only be detrimental within the LOW submarket potentially linked to lower prices in Sinza (low subward) due to limited alternatives.

Observations regarding NQI and NSLI suggest a positive price effect in the LOW submarket for both variables. In the MID and HIGH submarkets NQI yields an unexpected negative and statistically significant effect on Airbnb prices. As expected, low spenders positively fuel higher prices in the LOW submarkets while Moderate spender do have a positive effect in LOW submarkets and a negative effect in the MID submarket. High spender negatively affects MID submarkets while "very high spender" is positively associated with both LOW and HIGH submarket prices. The results also suggest that Airbnb renters' visits increases with prices in the LOW and MID submarket but declines with prices in the HIGH submarket. This visitation effect is relatively straightforward, Airbnb "visit" declines (inelastic) as a function of the HIGH submarket prices while it is positive (elastic) in the LOW submarket. Overall, the findings suggest for an inverted "U" shape for renter's behaviour in relation to Airbnb prices. Airbnb spending will generally decline as the renters move from LOW towards MID and then rise over the HIGH end of the market.

The results in Table 7 further suggest that AIA and API have a negative effect on Airbnb prices. The former (accessibility) reduce prices in LOW submarkets by almost 48% while the later (proximity) reduces Airbnb prices in MID submarket by more than three times and in the HIGH submarket by around 1.7 times. The other indices that have a negative effect in the LOW submarket include; ASSA Index, ASA Index, BDU Index, BQI, PCI and HHI. In LOW submarkets, the link between Airbnb price and preferences is strongly downward regardless of quantity and quality of accommodation. The only possibility to obtain price premium in LOW submarket is via internal Accommodation amenities (IAI) and services. In the MID submarket the negative price effect is observed for ASA Index, BDU Index, and BQI while a positive price effect is observed for PCI. The MID submarket suggests for a significant decline in price in response to increase in Space adequacy. As noted above the API is the only factor that was observed to be associated with lower prices in the HIGH submarket whereas HSSA Index, ASA Index, BDU Index and PCI were associated with high Airbnb prices in HIGH submarket. The expected positive price effect of P2P accommodation quality and quantity, seem to be relevant only in the HIGH submarkets.

For the demographic controls that were included in the models, the higher price in the LOW submarket is positively associated with relatively older renters (Airbnb price increases with age), male headed households and those who are self-employed. These observations suggest that although price and preferences could be generally negatively correlated in the LOW submarkets, the relatively older, self-employed and male headed household pay a premium over and above their counterparts. However, this is not in the case for HIGH submarket where even if the income effect is still positive on Airbnb price, all the three demographic characteristics have a negative and statistically significant effect on Airbnb prices (Airbnb price decline with age, self-employed status and Male headed household). Airbnb rented by the relatively older, self-employed and Male headed households have lower prices in the HIGH submarket thus reinforcing the overall preference effects where renters prefer relatively cheaper Airbnb. This is also supported by the Single-family parent status in the MID submarket.

Regardless of whether the Submarket is classified LOW of HIGH, there is a unanimous negative effect on Airbnb accommodation price from full family renters (large family), renters from outside Dar es Salaam, renters of private rooms and daily expenditure. In terms of Marital status, Singles behave similarly in LOW and HIGH submarkets but in transitioning, they would pay higher thus being responsible for the inverted “U” Airbnb preferences across submarket. The downward preferences in relation to prices is further reinforced by employment status being “employed”, small family size and occupation being “business”. While occupation in business has a negative effect on Airbnb prices in LOW submarket, professional occupation has a positive effect in both LOW and transition markets.

5. DISCUSION AND CONCLUSION

The findings of this study align with broader global trends in the Airbnb market, particularly regarding the emphasis on property quality, location, and hospitality as key factors shaping rental prices. The inverse relationship between rental price and Airbnb preference, as indicated in Table 7, highlights the importance of affordability in all subwards except Sinza (LOW submarket) where an increase in price is associated with higher preferences. Regardless of the submarket under consideration, Airbnb accommodation is price inelastic if we assume preferences are a good measure of demand alongside Gunter & Önder, (2018). However, when one uses the number of visitations as an indicator of Airbnb demand, these accommodations demand tend to be relatively inelastic in the HIGH submarkets an indicator that hosts in LOW submarkets can significantly increase their revenues/visitors by simply lowering the price slightly alongside observations of a positive price effects of visitation by Perez-Sanchez, et al., (2018). In a competitive environment this would lead to downward price spirals but this is not happening probably due to some monopoly in the industry.

Hosts targeting the LOW submarkets specifically Sinza, are observed to be competitive in terms of pricing while size, quality, quantity, accessibility host hospitality and proximity consideration operate in the negative side of price contrary to expectations (Perez-Sanchez, et al., 2018). These negative consequences especially regarding hotel-like practices involving some host hospitality in Airbnb are however, compatible with Gibbs, et al., (2018) and (2017) where the effect of free breakfast was to lower prices, but contrary to Yobesia, et al. (2024), who observed a positive breakfast in Kenya. Quang, et al. (2024) findings suggest that guests achieve satisfaction from host families' attitudes and language abilities, high-quality facilities in the bedrooms and grounds, authentic cuisine, a peaceful location, the availability of complementary services, and affordable prices. This suggests for a price premium on these facilities in Ghana, contrary to quality attributes in the LOW submarkets of Tanzania. Geographically, at the subward level, the finding from this study suggests that significant price reduction in such LOW submarkets is expected from enhanced preferences in, first, Masaki (a high subward) and Kinondoni (a middle subward). Therefore, an increase in Airbnb preferences in the high and middle subwards has a negative price effect in the LOW submarkets, suggesting for direct substitution effect. This is could be because the high preferences for HIGH submarkets Airbnb accommodation increases the willingness to pay for such properties thus reducing transitions towards middle or low subwards.

The study further suggests for some flexibility in mobility among renters of MID subwards' Airbnb, where the relatively lower submarkets (transition subwards) tend to be potential destination of STRONG preference renters should there be any upwards pressure on HIGH submarkets resulting into a substitution effect. This interconnectedness between LOW and MID submarkets has been noted in the effect of accessibility on prices;as Airbnb accessibility improves in MID submarkets, the price for such accommodation falls an indicator that many of Airbnb accommodation in MID submarkets are accessible thus leading to a downward price spiral to catch the limited customers that visit such submarkets.

Subsequent analysis at factor level provided strong evidence that high preferences in the HIGH submarket Airbnb are linked to quality, quantity, as well as service availability, design, and condition of the building, thus yielding a positive price effect at the margin, although generally renters prefer cheaper alternatives. Yobesia, et al. (2024) observed that the facility's status as an ecolodge had a significant effect on room rates (B = .41) in Kenya. Therefore, in an environment where "cheaper is better" (High submarkets), enhanced quality and quantity of Airbnb properties accrue a price premium alongside the existing literature (Magno, et al., 2018; Toader, et al., 2022). Further, the observation suggests that increasing Airbnb preferences in HIGH and transition submarkets indirectly substitute Airbnb demand in nearby LOW submarkets but in an environment where such LOW neighbor is lacking increased Airbnb preferences end-up complementing demand within LOW submarket thus leading to higher prices. A similar complementary effect has been observed specifically, the increase in Airbnb prices in the high subwards (Masaki) has a negative price effect in the LOW submarket suggesting for complementarities.

The findings in this study suggest that a well-established low-quality subward Airbnb price increase will only be detrimental within the LOW submarket potentially linked to lower prices in Sinza (low subward) due to limited alternatives. As a result, a downward price spiral may ensue in response to increased prices by some other properties within the LOW submarket. These observations suggest that price adjustment in LOW submarkets is an internal process fueled by interactions of Airbnb properties (a localized effect). This observation could also be explained by the negative effect of HHI in LOW submarket which auger well with previous observation regarding Airbnb service failure given the limited experience of hosts and customer service in the hospitality industry (Chen & Tussyadiah, 2021; Wang & Nicolau, 2017). As such in LOW submarkets, the link between Airbnb price and preferences is strongly downward regardless of quantity and quality improvement. The only possibility to obtain price premium in LOW submarket is via AIA and services (Suárez-Vega & Hernández, 2020), which mean that for a person to pay higher price for Airbnb in LOW submarket, she/he must be very familiar with the property. Internal amenities including space are among the key factor in Airbnb service failure as identified by Contu, et al., (2023) and Chen & Tussyadiah, (2021) and hence could be responsible for downward price spiral in LOW submarket. However, Yobesia, et al. (2024) observed that he availability of a plunge pool and provision of a bathrobe in the room had the weakest but significant influence on room rates (B = .20) in Kenya suggesting a positive effect for internal amenities improvement.

Although the stronger preferences for Airbnb is fueled by lower prices and property condition (PCI), price premium are still observable in the HIGH submarkets for Airbnb properties with improved quality, quantity and design because high-end prime renters are primarily choosing this submarket before any other submarket. Property quality, both globally and locally, remains a significant factor influencing Airbnb prices (Wang & Nicolau, 2017; Toader, et al., 2022). Guests in Dar es Salaam, particularly in high subwards of Masaki and Mikocheni, markedly prefer high-quality, well-maintained properties equipped with modern amenities. This aligns with global consumer behavior, where travelers seek accommodations that offer both internal and external amenities for comfort, privacy, and convenience (Gibbs, et al., 2018; Suárez-Vega & Hernández, 2020). Ntongani (2024) addresses the satisfaction factors in Airbnb properties to including location, property specific and services. Based on Relative Importance Index (RII), He concluded that Airbnb are located, proximity to shops, cleanliness, presence of clean water, easy communication with hosts and privacy are likely to achieve higher RII score.

However, what distinguishes the Tanzanian context is the emphasis on neighbourhood safety. In areas like Mwenge and Sinza, where safety concerns are more pronounced, Airbnb properties with enhanced security features, such as gated communities and private security services (Medina-Hernandez, et al., 2024), was expected to explain upward price pressure. Karubi (2024) suggest that Tanzania is safe to tourists because of low crime rates, political stability, effective tourist safety measures, and friendly locals. The findings are clear, NQI and NSLI have a positive price effect in the LOW submarket, indicating its strong influence on Airbnb preferences in LOW submarkets in line with Chang & Li, (2021), Chen & Xie, (2017) and Kakar, et al., (2016). This positive effect of amenities can be linked to Lancaster's characteristics theory that predicts a positive relationship between "utility yielding services" attributes and prices (Lancaster 1966) while the negative proximity effect can be attributed to the distance decay principle where facility close to attractive environmental amenities can accrue a premium in the price paid (Kim, et al. 2020).

However, there are contradictory observations regarding the effect of NQI in the MID and HIGH submarkets where it yields a negative and statistically significant effect on Airbnb prices. This unexpected behaviour can be explained through the normal demand theory since NQ is a normal good in High Submarket and there are many suppliers of high-quality Airbnb, suppliers must combine more quality with lower price to attract guests. Unlike in Low submarkets where neighbourhood quality is scarce, those who can afford to increase it slightly get a premium for it.

API is the only factor that was observed to be associated with lower prices in the HIGH submarket in sharp contrast to Toader, et al., (2022) who observed a positive effect of proximity to CBD but distantly related to Jiang, et al., (2022) who observed a negative effect of distance on Airbnb distributions. In particular, proximity to shopping centers, restaurants, and public transport hubs, is associated with high preferences mirroring global trends where convenience plays a crucial role in Airbnb price determination (Perez-Sanchez, et al., 2018). Yobesia, et al. (2024) observed that proximity to landscape aesthetics hotspots had a negative effect on hotel room (B = −.22) in Kenya. The observation in Kenya augers well with the current study findings, where STRONG preferences are not translated into higher prices in the HIGH end (aesthetics hotspots) of the market because Airbnb are strategically positioned with respect to location where relatively cheaper and easy to transact accommodation will be closer to these amenities (Medina-Hernandez, et al., 2024). The observation points also out that, as Airbnb accessibility (IAI) increases in LOW and MID submarkets' price response for such accommodation is negative an indicator that many of Airbnb accommodation in LOW and MID submarkets are accessible although are relatively small in size, intended to accommodate singles or very transient form of families thus leading to a lower price to catch the type customers that visit such submarkets.

Demographic characteristics, including employment status, income level, family size and age, also played a significant role in shaping Airbnb prices contrary to theoretical expectations (Chen & Xie, 2017; Kakar, et al., 2016). Airbnb preferences seem to be shaped positively by family characteristics where larger families dominate the Airbnb accommodation due to cost saving behavior and the home "feeling" (Medina-Hernandez, et al., 2024; Chang & Li, 2021). Employed and self-employed individuals made up a large portion of Airbnb guests, particularly in higher-end areas like Masaki and Mikocheni, indicating that professionals seeking short-term accommodations are drawn towards Airbnb's offerings of comfort and privacy. The regression results support this view only for the self-employed and professionals where prices tend to be relatively higher while it contradicts for the employed and business people. Airbnb prices are likely to respond positively when the background of the renters is self-employed professionals. The employed and business renters are more likely to reside in LOW submarkets given the nature of their residency.

In terms of policy implications, it is evident that monopolistic characteristics of the Airbnb market in Tanzania restrict downward price adjustment thus making accommodation unnecessarily expensive. Although there is apparently no clear restriction on entry, barrier to entry stem from uncertainty due to lack of clear regulation for the subsector. Having a place clear policy relating to establishment, taxation and ultimately management of Airbnb could attract entry thus enhancing competitiveness. Furthermore, the high submarket seems to be shielded away from the low and middle submarkets thus transitioning between them seem to be highly difficult. Potentially, this reflect accommodation quality differences which could be addressed by having in place guidelines on the minimum threshold for a building to be pout to Airbnb customers. Although this may increase hurdles in the market, it can be an important tool towards enhancing customer experience and thus increase demand in the future.

These demographic insights hold critical implications for targeted marketing strategies. Hosts in more affordable areas, such as Sinza and Mwenge, could attract younger, employees, business people, and lower-income guests by emphasizing affordability and proximity to urban amenities. In contrast, hosts in affluent areas could focus on offering premium services and luxurious features to cater to wealthier professionals and self-employed clientele.

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