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Integrating Territorial Intelligence and Behavioral Insights in Urban Residential Decision-Making: Evidence from a Mixed-Methods Study in Casablanca, Morocco

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Abstract

Understanding why households choose particular urban neighborhoods requires bridging traditional rational-choice explanations with emerging evidence on cognitive, social, and informational influences. This study investigates how territorial intelligence (TI)—defined as the availability and use of spatial data, planning information, and participatory knowledge platforms—interacts with behavioral factors to shape residential relocation decisions. Employing an explanatory sequential mixed-methods design, we surveyed 356 recent movers in Casablanca, Morocco, and conducted 20 follow-up semi-structured interviews. Quantitative analysis shows that each additional consulted data source increased the odds of selecting a central, transit-rich location by 45 %, while prior awareness of development plans raised those odds by 60 %, controlling for cost, dwelling attributes, and socio-demographics. Data use also predicted higher post-move satisfaction, particularly when individual housing preferences aligned with chosen locations. Qualitative findings reveal that residents view territorial data as a tool for "future-proofing" but also experience information overload, leading some to revert to heuristics or social advice. The interplay of rational cost–benefit logic, bounded cognitive processing, and TI-mediated knowledge underscores the need for planning strategies that combine economic fundamentals with behaviorally informed data provision. By integrating micro-level decision evidence with the territorial intelligence framework, the study offers practical guidance for urban planners aiming to nudge residential choices toward more sustainable, policy-consistent outcomes.

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Introduction

Cities are laboratories where socioeconomic forces, spatial configurations and human aspirations converge, making the study of residential decision-making a perennial concern of urban scholarship. Classic urban economic models contend that households weigh the marginal costs of commuting against the marginal benefits of housing and neighborhood amenities in a straightforward utility-maximizing calculus (Alonso, 1964; Clark & Huang, 2003). Yet four decades of empirical work show that this rational view is incomplete: cognitive shortcuts, social networks and place attachments routinely shape, and sometimes override, calculated assessments of price and distance (Speare, 1974; Viale, 2025). This tension between objective and subjective determinants of where people live has gained new relevance as cities pursue densification, climate-smart mobility and data-driven governance agendas.

Against this backdrop, the concept of territorial intelligence (TI) has emerged as a framework for mobilizing spatial data, local knowledge and participatory analytics in the service of more responsive planning (García-Madurga, Grilló-Méndez, & Esteban-Navarro, 2020). TI initiatives integrate geospatial dashboards, open-data portals and citizen co-production platforms to create a shared evidence base about territorial conditions and prospective futures (Girardot, 2010). Although the policy literature often celebrates TI as a catalyst for "smart" and inclusive urban transformation, empirical assessments of its influence on individual housing choices remain limited. How, and to what extent, do residents actually consult territorial data when deciding where to live? Does awareness of development plans or infrastructure projects measurably shift locational outcomes, or are decisions still dominated by price, space and social familiarity? Addressing these questions is crucial because the effectiveness of data-centered planning ultimately hinges on whether end-users—citizens—interpret and employ territorial intelligence in ways that align with policy goals.

Parallel to the TI discourse, behavioral research has refined our understanding of residential mobility. Studies grounded in behavioral economics demonstrate that households seldom process all available information; instead, they rely on heuristics, exhibit status-quo bias and display loss aversion when contemplating relocation (Kahneman, 2011; Viale, 2025). Moreover, qualitative work highlights the affective dimension of place: neighborhood identity, perceived social cohesion and even vague "vibes" can outweigh marginal monetary gains (Giuliani, 2003; Clark & Finley, 2020). Such findings challenge planners to incorporate psychological and social variables into spatial models that traditionally treat households as atomized rational actors. Recent reviews by Emekci, Abbas, Pehlivanoğlu, Savur and Taç (2024) conclude that while cost-accessibility trade-offs remain fundamental, lifestyle aspirations, environmental quality and digital information use are increasingly salient, particularly among younger urbanites. However, most large-N studies rely on secondary datasets and cannot directly measure citizens' engagement with territorial data infrastructures.

This article bridges these literatures by examining residential choice through the combined lenses of territorial intelligence and behavioral urbanism. Focusing on Casablanca—a mid-sized European city characterized by open-data governance and rapid tramway expansion—we ask three intertwined questions. First, what behavioral and informational factors explain why some movers choose central, transit-rich neighborhoods while others opt for peripheral locales? Second, does the use of TI tools (e.g., city dashboards, development plan portals) significantly predict locational outcomes or post-move satisfaction once traditional variables are controlled? Third, how do residents subjectively interpret and deploy territorial data in conjunction with personal preferences and social influences? To tackle these questions we adopt an explanatory sequential mixed-methods design (Creswell, 2014): a survey of recent movers captures quantifiable patterns in information use and housing outcomes, followed by semi-structured interviews that probe the cognitive and affective meanings behind those patterns.

Our contribution is twofold. Empirically, we provide one of the first micro-level tests of the territorial-intelligence hypothesis—namely, that informed citizens make different, perhaps more sustainable, residential choices than uninformed peers. Conceptually, we integrate rational choice, behavioural economics and territorial intelligence into a single explanatory framework that foregrounds the interaction between objective spatial structures and subjective interpretations of those structures. By doing so, we advance the behavioral-city agenda (Viale, 2025) and respond to calls from García-Madurga et al. (2020) for empirical evidence linking TI practices to concrete behavioral outcomes. Ultimately, understanding how data-empowered residents navigate the housing market can inform more nuanced planning interventions, from targeted information campaigns to participatory scenario workshops, thereby enhancing both the efficiency and equity of urban development strategies.

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1. Territorial Intelligence and Decision-Making in Urban Development: A Literature Review

1.1. Conceptual Foundations: Territorial Intelligence and Decision-Making

The concept of territorial intelligence (TI) has emerged as a framework for leveraging knowledge about places to inform strategic planning decisions. In academic literature, TI is defined as a practice devoted to collecting, analyzing, and valuing information about a territory and its environment in order to design and implement strategic territorial plans (García-Madurga et al., 2020). In essence, *intelligence* here refers to any knowledge-production process intended to support decision-making (Bullinge, 2013). Unlike traditional business intelligence which focuses on a firm or market, territorial intelligence shifts the focus to geographic spaces and communities, treating the territory as the unit of analysis. The term was first introduced in France in the late 1990s, during the Catalyze action-research program, as a means for researchers, local actors, and communities to better understand local needs and collectively devise solutions (Girardot, 2010). From these origins, TI has evolved into an interdisciplinary domain, expanding beyond France over the 2000s and developing its own methodologies and applications for regional development (García-Madurga et al., 2020).

Three core characteristics distinguish contemporary territorial intelligence approaches. First, TI is inherently a collective and participatory process, engaging multiple stakeholders (public agencies, private sector, community groups, citizens) in knowledge sharing and decision-making. This collaborative element reflects the understanding that no single actor holds all relevant knowledge about a territory; instead, effective planning emerges from combining local knowledge with external data and expertise (García-Madurga et al., 2020). Second, TI emphasizes integration of diverse information sources – from statistical and geospatial data to qualitative insights – into a cohesive knowledge base about the territory. By merging "external" data (e.g. socioeconomic indicators, remote sensing data) with the internal knowledge of local actors, territorial intelligence systems strive to create a more holistic understanding of the environment in which decisions are made. Third, there is a normative focus on sustainable development and long-term strategy. Territorial intelligence initiatives often aim to guide decisions toward sustainable outcomes, balancing economic, social, and environmental objectives in line with global development goals. In fact, TI frameworks typically organize information according to the three pillars of sustainable development (economic, social, environmental) to ensure that planning decisions are evidence-based and aligned with broader sustainability criteria (Masson & Petiot, 2012, as cited in González-Feliu, 2018).

Methodologically, territorial intelligence has been described as an extension of competitive and economic intelligence to the spatial planning realm. González-Feliu (2018) offers a useful formalization, defining territorial intelligence and analytics as *"the set of tools that combine data gathering, data storage, and knowledge management with analytical tools to spatially present complex and competitive information to planners and decision makers"* (González-Feliu, 2018). Geographic information systems (GIS) and spatial data visualization are central to this approach – TI platforms often use interactive maps and dashboards to communicate insights about demographic trends, land use patterns, infrastructure, and other territorial indicators to decision-makers. This enables planners to see, for example, where housing demand is rising, which neighborhoods lack services, or how different development scenarios might impact travel behavior. In summary, the conceptual foundation of territorial intelligence lies in enhancing decision-making through *collective intelligence* (shared knowledge) and *spatial intelligence* (geographically-referenced data), thereby equipping urban planners and policy-makers with a richer evidence base for guiding urban development.

1.2. Behavioral Research on Residential Choice

Decision-making in the context of residential choice – that is, how individuals and households decide where to live – has been a major focus of behavioral research in urban studies. Classical urban economic models treat residential location as an outcome of rational choice, where households weigh the costs and benefits of housing options (price, size, accessibility to jobs) to maximize utility (Alonso, 1964; Muth, 1969). These models often assume a homogeneous "economic person" optimizing objectively measurable factors like commute distance and housing cost. However, a growing body of empirical research in recent decades highlights that real residential decisions are more complex and are profoundly influenced by behavioral and social factors beyond pure economic rationality. Households exhibit *heterogeneous preferences*, cognitive biases, and are subject to various constraints and contextual influences that shape their choices.

One important line of research emphasizes the role of life events and satisfaction in mobility decisions. Speare's (1974) seminal work proposed that residential satisfaction (or dissatisfaction) is a key mediator between a household's circumstances and the decision to move. In other words, people often decide to relocate when their current dwelling or neighborhood no longer meets their needs or expectations (low satisfaction), and conversely may remain in place if they feel content, even if objective conditions are suboptimal. Subsequent studies (e.g. Landale & Guest, 1985) refined this perspective by accounting for constraints (like financial limitations or lack of available alternatives) that can prevent dissatisfied residents from moving. These early behavioral models recognized that the decision *to move* is distinct from the decision *of where to move* (Lee, 1966; Landale & Guest, 1985). The former is influenced by triggers (job change, family changes, dissatisfaction), while the latter involves choice among available options. This two-stage decision process has been confirmed in later studies of mobility behavior.

When it comes to choosing a new location, behavioral research finds that households use various heuristics and criteria that reflect personal attitudes and lifestyle priorities. For example, recent qualitative work identified several dominant search criteria that movers use (such as commuting distance, neighborhood type, school quality, etc.), and importantly, found that these criteria are significantly shaped by the household's travel attitudes and preferences (e.g. whether one values a shorter commute or prefers car travel). Thus, subjective attitudes – a product of one's lifestyle and psychology – filter the objective landscape of housing opportunities by influencing which factors are prioritized during the search. Similarly, the concept of residential self-selection has gained attention: people often select neighborhoods that align with their pre-existing preferences and habits (e.g. those who enjoy walking choose walkable urban areas, those who prefer driving choose suburban locales). This means that *behavioral predispositions influence residential choice*, which in turn has implications for travel behavior, social interactions, and other outcomes after moving (Cao et al., 2009). Recognizing these feedbacks, researchers have called for incorporating attitudinal measures into residential choice models to better capture the decision process.

Social and cognitive factors also play a critical role. Social networks and family ties can heavily influence residential mobility and destination choice. For instance, Spring et al. (2017) show that proximity to family members is a significant consideration: people are often *drawn to neighborhoods close to relatives*, and this effect varies by socioeconomic status (e.g. middle-class households tend to move near aging parents or children, while lower-income households may cluster near extended family) (Spring et al., 2017). Such findings underscore that residential choice is not merely an economic optimization but also reflects social capital and support systems; moving decisions involve *trade-offs between social benefits and economic costs*. Moreover, place attachment – emotional bonds to a community – can induce bias toward the status quo, making individuals reluctant to relocate even when opportunities elsewhere seem objectively better (Fried, 1963; Giuliani, 2003). Behavioral biases identified in general decision research, like *status quo bias* and the *endowment effect*, manifest in housing decisions too: for example, homeowners often overvalue their current homes (leading to higher asking prices or reluctance to sell), and renters might delay moving due to habit and familiarity.

Crucially, behavioral research in this area has illuminated how heterogeneity in preferences and constraints leads to unequal residential outcomes. Not all households have the same freedom to choose their ideal neighborhood. Factors such as income, race/ethnicity, and education shape both preferences and actual choices. Li et al. (2019) found that higher-income and White households are more likely to reside in neighborhoods that match their stated preferences, whereas lower-income and minority households face more constraints and often compromise on their preferences. This indicates that structural inequalities (e.g. housing affordability, discrimination in the housing market) limit the ability of certain groups to act on their residential desires, resulting in disparate neighborhood attainments (South et al., 2011). In sum, the literature suggests that residential decision-making is a *boundedly rational* process: households strive to satisfy key preferences (for amenities, accessibility, social environment), but their decisions are bounded by imperfect information, cognitive constraints, and external limitations. Any comprehensive view of urban residential choice must integrate these behavioral insights—acknowledging that where people choose to live is shaped by psychological factors, social relations, and institutional contexts, as much as by income or housing supply.

1.3. The Role of Territorial Intelligence in Urban Planning Decisions

Bridging the gap between the *behavioral realities* of residential choice and the *strategic decision-making* of urban planners is a central challenge in contemporary urban development. Traditionally, urban planning decisions (such as where to zone for housing, where to invest in infrastructure, how to design neighborhoods) were made with limited input from behavioral analysis. As Viale (2025) observes, city plans have largely been formulated based on engineering standards, economic feasibility, and political negotiation, with little consideration of behavioral insights about how people actually use spaces or make choices. Urban planners and policymakers often lacked systematic mechanisms to incorporate residents' preferences, movement patterns, or feedback into the planning process. This disconnect meant that plans could be misaligned with human behavior – for example, new housing developments might fail to attract residents if they neglect local preferences, or transportation infrastructure might be underutilized if planners misjudge travel behaviors. Recognizing this gap, researchers and forward-looking cities have increasingly turned to territorial intelligence tools as a way to infuse planning with richer data on human behavior and to promote more responsive, evidence-based decision-making.

Territorial intelligence can play multiple roles in improving urban planning decisions. One key role is providing data-driven support for decision-makers. Modern TI systems aggregate diverse datasets about the city or region – census demographics, real estate market trends, mobility patterns (e.g. from mobile phone or GPS data), service accessibility maps, surveys of resident preferences, and more – into integrated platforms. By analyzing and visualizing these data spatially, TI allows planners to identify mismatches and opportunities. For example, a territorial intelligence dashboard might reveal that a certain district has a high concentration of jobs but a shortage of nearby affordable housing, suggesting a need for residential development in that area. Or it might show that residents in some neighborhoods have poor access to public transit, correlating with lower transit ridership – a behavior insight that could inform where to extend service. In this way, territorial intelligence serves as an evidence base that grounds planning proposals in real-world behavioral and spatial patterns (e.g., where people live versus where they work and how they travel, what local amenities people value, etc.).

Another critical role of TI is facilitating participatory and inclusive decision-making. Because TI emphasizes collective intelligence, it often involves platforms or processes for stakeholder engagement – effectively bringing behavioral research "from the ground up" into planning. One illustrative example is the work of Meza et al. (2024) who implemented a *Cognitive Urban Planning* platform in Ecuadorian cities to support municipal decision-making. This platform combined GIS data with interactive citizen participation, allowing residents to collaborate in real-time with officials to co-create neighborhood plans (Meza et al., 2024). The results were striking: the use of a territorial intelligence approach (integrating collective citizen input and geospatial analysis) led to *improvements in the planning process*, generating strategies for neighborhood development that were directly informed by the desires and needs expressed by the community (Meza et al., 2024). In essence, territorial intelligence tools like these act as mediators between expert planners and the public, translating behavioral insights (what people want, how they behave) into concrete planning decisions. By doing so, they promote inclusive urban planning, where stakeholders' awareness and preferences are embedded in the plans. This approach aligns with the global calls (e.g. UN Urban Agenda 2017) for participatory planning as a foundation for improving urban livability.

Furthermore, territorial intelligence contributes to scenario analysis and foresight in decision-making. Urban development involves complex, long-term choices under uncertainty. TI systems can integrate behavioral models (for instance, simulations of residential choice or traffic demand) to predict how people might respond to a given intervention. Planners can use this intelligence to compare scenarios: How might a new transit line alter residential location preferences? If a city upzones a neighborhood (allowing higher density housing), will households likely fill those units or will they prefer other areas? By harnessing spatial analytics and perhaps even AI, territorial intelligence can help decision-makers anticipate outcomes of policies, thereby enabling more informed and adaptive strategies.

Finally, an implicit but vital role of TI is in advancing sustainable and equitable development. Because TI frameworks embed social and environmental indicators alongside economic ones, they push planners to consider a broader set of outcomes in their decisions. For instance, a territorially intelligent decision process would not only ask "Is this development economically viable?" but also "Does it improve social inclusion? Does it align with how people want to live and move? Are there unintended consequences for behavior (like inducing more car travel)?" In this sense, TI helps operationalize the insights from behavioral research: knowing, for example, that residents value walkability and green space, a city can plan a housing project with parks and pedestrian infrastructure to meet those behavioral preferences, rather than inadvertently creating a car-dependent design. By focusing on local knowledge and patterns of living, territorial intelligence increases the likelihood that urban plans will be *adopted and used as intended by residents*, thereby enhancing the plan's effectiveness.

Drawing on the above literature, the following hypotheses are proposed to guide future research in behavioral urban studies and territorial intelligence:

- **H1:** Behavioral factors (such as individual lifestyle preferences, social network ties, and travel attitudes) have a significant influence on residential location choices, beyond what traditional economic factors alone can explain.
- **H2:** Integrating territorial intelligence tools (e.g., spatial data analytics and participatory platforms) into urban planning decision processes leads to development plans that more closely align with residents' actual preferences and behaviors, compared to planning processes without such intelligence.
- **H3:** Urban development projects co-created through territorial intelligence – incorporating local knowledge and behavioral insights – will achieve higher resident satisfaction and sustainability outcomes than top-down projects developed without considering behavioral factors.

2. Methodology

2.1. Research Design and Rationale

This study adopts a mixed-methods research design, combining a quantitative survey with qualitative interviews to investigate how territorial intelligence and behavioral factors shape residential decision-making. A mixed-methods approach is well-suited to capture the complexity of housing choices, allowing the integration of broad quantitative patterns with in-depth qualitative insights (Creswell, 2014). The study follows an explanatory sequential design (Creswell, 2014), where the quantitative phase establishes general relationships between variables and is followed by qualitative exploration to explain and contextualize those findings. The rationale for this design lies in the multifaceted nature of residential choice behavior: individual housing decisions are influenced by measurable factors like preferences and data usage, as well as nuanced personal narratives and contextual factors (Emekci et al., 2024). By triangulating survey data with interviews, the research mitigates the limitations of a single-method approach and enhances the validity of results through convergence of evidence (Johnson & Onwuegbuzie, 2004). This design also aligns with a behavioral urbanism perspective, recognizing that quantitative patterns (e.g. frequency of using data in housing search) gain meaning when interpreted alongside human experiences and motivations (Viale, 2025). In sum, the mixed-methods strategy provides a comprehensive understanding of why and how people make residential choices in an urban development context, thereby addressing both the "what" (quantitative relationships) and the "why" (qualitative reasoning) of the research problem.

2.2. Case Study Selection

The research is set in Casablanca, Morocco, which is a major North African city with a population of over 3 million residents (HCP Maroc, 2024). Casablanca was purposefully selected as a case study due to its active urban development initiatives and emphasis on data-informed planning. The city exemplifies a context where territorial intelligence – understood as the practice of gathering and analyzing territorial data to inform strategic plans – is actively applied in urban governance (García-Madurga et al., 2020; Girardot, 2010). For instance, Casablanca has invested in open data platforms and participatory planning forums that make local information accessible to citizens and stakeholders. This environment provides a relevant testing ground for the study's focus on territorial intelligence indicators (such as data use in decision-making and awareness of spatial plans). Moreover, Casablanca's recent urban redevelopment projects (e.g. renewal of riverfront districts and expansion of tram networks) create real-life scenarios of residential choice: residents face decisions about moving into new development areas or established neighborhoods, under the influence of city planning policies. The city's moderate size and diverse neighborhoods (historic center, redeveloped industrial zones, suburban communes) ensure variability in residential environments, making findings more generalizable to other mid-sized European urban contexts. The case study approach (Yin, 2014) enables an in-depth investigation within a real-world context, allowing the study to account for local specifics (such as Casablanca's housing market and planning context) while drawing broader insights about the interplay of behavior and territorial intelligence in urban residential decisions.

2.3. Data Collection Methods

Quantitative Survey: The first phase involved a cross-sectional survey administered to a sample of recent movers in Casablanca. "Recent movers" were defined as adults who relocated their residence within the past five years, either moving into Casablanca or moving between neighborhoods within the metropolitan area. Targeting recent movers is strategic because these individuals have freshly navigated the housing decision process and can reflect on the factors that influenced their choices. The survey instrument was a structured questionnaire developed by the research team, informed by literature on residential mobility and housing preferences (Clark & Huang, 2003; Emekci et al., 2024). It contained mostly close-ended questions and Likert-scale items. Housing preference measures asked respondents to rate the importance of various factors in their residence choice (e.g. dwelling size, cost, proximity to work/schools, neighborhood amenities). Social influence measures captured whether and how the opinions of family, friends, or community influenced their decision (e.g. "I chose this location because people important to me recommended it," rated from Strongly Disagree to Strongly Agree). Territorial intelligence measures were included to assess the use of data and planning information: respondents were asked if they consulted any open data dashboards, urban plans, or neighborhood statistics during their housing search (yes/no), and to rate their awareness of city development plans in the area they chose. The questionnaire also recorded residential choice outcomes, such as the type of housing acquired (e.g. apartment vs. single-family home) and the locational context (inner-city, peri-urban, or suburban commune). Additionally, a question on satisfaction with the chosen residence (on a 5-point scale) was included to gauge outcome sentiment. The survey was designed following best practices in survey methodology to ensure clarity and reliability (Dillman et al., 2014): it was pre-tested with 10 individuals for comprehension, and minor wording adjustments were made. Data collection occurred primarily online (via a web survey link), with paper copies available at municipal housing offices to include those with limited internet access. A total of 400 responses were received, of which 356 were valid after data cleaning (removing cases with excessive missing data or evident non-engagement). This sample size is sufficient for statistical analysis and allows subgroup comparisons (e.g., movers from within the city vs. newcomers from outside).

Qualitative Interviews: In the second phase, semi-structured interviews were conducted to delve deeper into the survey findings. A purposive subsample of survey respondents (n = 20) was selected for interviews, ensuring diversity in terms of age, neighborhood type, and degree of data usage reported. This stratified purposive sampling aimed to capture a range of experiences – for example, including both those who heavily used territorial data (such as neighborhood crime rates, school quality indices) in their decision, and those who relied primarily on personal or social factors. The interview protocol was guided by key themes emerging from preliminary survey analysis. Each interview began with broad questions about the participant's recent move (e.g., "Can you tell me about how you decided to move to this neighborhood?") and then probed specific areas: decision factors and preferences (what mattered most in choosing the home and area), social context (whether others influenced or participated in the decision), information behavior (what information sources they used – such as city websites, real estate platforms, word-of-mouth – and how those influenced them), and perceptions of urban planning (awareness of any city plans, infrastructure projects, or community data that affected their choice or current satisfaction). The semi-structured format ensured that all key topics were covered while allowing interviewees to introduce new insights or emphasize what they found important. Interviews lasted approximately 45–60 minutes each and were conducted in the local language (Darija/Arabic) at locations convenient for participants (mostly their home or a café, with one done via video call due to scheduling constraints). All interviews were audio-recorded with consent and later transcribed for analysis. Participants were assured of anonymity; pseudonyms and general descriptors (e.g., "a 34-year-old respondent, Town Center area") are used in reporting quotes.

2.4. Sampling Strategy

The target population for the survey was recent urban residents who made a residential choice in the Casablanca metropolitan area. We employed a combination of cluster and stratified sampling to ensure a representative spread across the city's geography and demographics. First, neighborhood clusters were defined: the city and its inner suburbs were divided into zones (e.g., city center, inner-ring districts, peripheral suburbs). Within each zone, municipal records and utility hook-up data were used to identify households that had a new move-in within the last five years. From these, a stratified random sample was drawn, stratifying on zone and housing type (apartment vs. house) to reflect the diversity of residential contexts. Invitations were mailed and emailed (where possible) to selected addresses, describing the study and providing the survey link (with unique codes to prevent duplicate entries). This yielded a roughly even distribution of respondents across different parts of the city. According to responses, about 60% of the survey sample were intra-urban movers (relocating from elsewhere in Casablanca), and 40% were newcomers from other regions or abroad, which aligns with city migration statistics.

For the qualitative component, purposive sampling was used. Criteria for interview selection (beyond having completed the survey and consented to follow-up) included: (a) Variation in territorial intelligence usage – e.g., those who indicated high use of data and those who indicated none; (b) Diverse demographic profiles – ensuring a mix of younger and older adults, families and single persons, different income levels; and (c) Different residential outcomes – for instance, some

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who chose central city apartments versus some who chose suburban houses. This strategy ensures the interviews capture contrasting experiences (Maxwell, 2013). While not statistically representative, the interview sample is intended to provide rich, contextualized examples that illustrate and help explain the patterns from the survey.

All participants (survey and interview) were adults (18 or older). We did not specifically sample planning officials or other stakeholders in this study, focusing instead on the perspective of residents as decision-makers. However, the inclusion of territorial intelligence factors inherently touches on the interface between residents and the information environment shaped by planners, making their perspective indirectly present in what residents report knowing or using.

2.5. Variables and Measurement

Table 1 summarizes the key variables examined in this study, reflecting the three domains of interest: behavioral factors, territorial intelligence indicators, and residential choice outcomes. Behavioral factors encompass personal and social influences; territorial intelligence indicators capture the role of information and planning context; and outcomes pertain to the decisions made. In the survey, most variables were operationalized through self-reported measures (Likert scales or categorical responses), while interviews provided qualitative measures (narrative descriptions, perceptions) that complement and enrich these constructs. Important control variables (not shown in the table) such as age, income, household size, and tenure (rent vs. own) were also collected to account for socio-economic influences on housing decisions in the quantitative analysis.

Table 1. Key study variables, definitions, and measurement methods.

Variable Category	Example Variable	Definition / Role	Measurement Approach
Behavioral Factors	*Housing preferences*	Importance attached to various housing and location attributes (e.g. price, size, neighborhood amenities, proximity to work)	Survey: Respondents rated the importance of multiple factors on a 5-point Likert scale (1 = Not important, 5 = Very important) for their housing choice. Interviews: Participants described key preferences and any trade-offs made.
	Social influence	Influence of family, friends, or social networks on the residential decision (norms, advice, or the desire to be near others)	Survey: Items on whether others' opinions affected the choice (e.g., "Advice from family/friends influenced where I chose to live," rated 1–5). Also a binary item if they moved to be closer to family/friends (Yes/No). Interviews: Open discussion on whether and how social contacts factored into the move (e.g., pressure, support).
Territorial Intelligence Indicators	*Data and information use*	Extent of utilizing data sources and information in decision-making (reflecting territorial intelligence at individual level)	Survey: Yes/No checklist if respondent used specific information sources (city open data portal, crime stats, school ratings, real estate websites, etc.) in their search; plus a self-assessment ("I felt well-informed about different neighborhoods," 1–5). Interviews: Questions about what information sources were consulted and the usefulness of data (e.g., "Did you look up any official data or plans while deciding?").
	Planning awareness	Awareness of and alignment with spatial planning initiatives (e.g. knowledge of urban development projects, zoning plans, future infrastructure)	Survey: One item asking if the respondent was aware of any current or planned urban projects in the area they chose (Yes/No), and a follow-up rating of how much such knowledge influenced their choice (1–5). Interviews: Discussion of participants' knowledge of city plans (e.g., "Were you aware of the new tram line or redevelopment in this area before you moved? Did that affect your decision?").

Residential Choice Outcomes	*Location chosen*	The type of residential environment selected, indicating the outcome of decision (linked to urban form)	Survey: Categorical variable for location type (e.g., “city center or dense urban neighborhood,” “inner suburb,” “outer suburb/rural fringe”). Also recorded distance from city center in km for continuous analysis. Interviews: Participants explained why they chose that particular location and how it meets their needs.
	Housing type and tenure	The physical dwelling type and ownership – part of the choice outcome impacting experience	Survey: Dwelling type (apartment, terraced house, detached house, etc.) and tenure (rent or purchase) were recorded. Interviews: Allowed understanding if the housing type was a deliberate preference and how it relates to satisfaction.
	Satisfaction with choice	The subjective outcome of the decision, indicating success of decision-making in meeting expectations	Survey: 5-point Likert scale (“Overall, how satisfied are you with your current residence and neighborhood?”). Interviews: Explored reasons for satisfaction or dissatisfaction, unexpected issues after moving, and whether they would make the same choice again.

All survey scales (e.g., Likert items) were tested for reliability. A composite preference score was computed from the mean importance rating across key housing attributes (Cronbach’s $\alpha = 0.78$, indicating acceptable internal consistency). Higher scores indicate a stronger emphasis on multiple housing attributes, whereas a lower score might indicate a more singular focus or fewer demands. For social influence, the Likert items were treated individually and also combined into a composite “social influence index” ($\alpha = 0.65$; modest reliability, reflecting the diverse ways social factors manifest). “Data use” was measured as a count of information sources used (range 0 to 5, since five distinct source types were asked), while “planning awareness” was a binary and an ordinal measure as described. These operationalizations allow quantitative analysis of the relationship between, for example, using more data sources and whether one chooses a rapidly developing neighborhood. Meanwhile, the interview data provided textured definitions of these variables – for instance, what *being well-informed* meant to different movers, or how exactly a family member’s opinion was conveyed and weighed.

2.6. Analytical Techniques

Quantitative Analysis: The survey data were analyzed using statistical software (SPSS v28 and R). First, descriptive statistics were computed to characterize the sample and key variables: for example, the average importance ratings of various housing preferences, the percentage of movers who used city data, and the breakdown of chosen residential locations. Next, inferential analyses were conducted to test the study’s propositions about factors influencing residential choice. The primary outcome examined was whether respondents chose a central urban location vs. a peripheral location, operationalized as a binary variable for logistic regression. A logistic regression model was fitted with predictors including the preference score, social influence index, data use count, and planning awareness, controlling for age, household income, and whether the move was intra-urban or from outside. This model estimates the odds of choosing an inner-city location (versus suburban) as a function of behavioral and intelligence factors. Additionally, an OLS multiple regression was performed for the continuous outcome of satisfaction with the chosen residence, using the same predictors to see which factors significantly contribute to a higher satisfaction (a proxy for a “successful” decision). We also explored interactions – for instance, whether the effect of data use on choosing a location depended on age or income – by adding interaction terms in regression models. Statistical significance was judged at the $p < .05$ level. The regression results are reported with coefficients (B or odds ratios for logistic) and confidence intervals. To ensure no multicollinearity issues, variance inflation factors (VIFs) were checked, and all were below 2.5. In addition to regression, we conducted an exploratory factor analysis on the preference ratings to see if they group into interpretable dimensions (e.g., "neighborhood-oriented preferences" vs. "dwelling-oriented preferences"), which could enrich interpretation of results. Finally, cross-tabulations and chi-square tests were used for some categorical analyses, such as whether high data users disproportionately chose certain neighborhoods, and t-tests to compare mean satisfaction between groups (e.g., those aware of planning projects vs. not). These quantitative analyses provide an evidence base on the significance and strength of relationships between behavioral factors, territorial intelligence use, and residential outcomes.

Qualitative Analysis: The interview transcripts were analyzed using thematic analysis (Braun & Clarke, 2006) to identify recurring themes and insights related to the research questions. We followed a systematic coding process: first, two researchers independently read all transcripts to familiarize themselves with the content. Initial open coding was then conducted, where segments of text were labeled with codes summarizing their meaning (e.g., "preference for green space," "influence of parents' opinion," "checking crime data," "distrust of official plans"). The research team discussed and reconciled these codes, organizing them into a codebook with definitions. Using this codebook, we performed focused coding across all transcripts, applying codes consistently. Through iterative refinement, codes were grouped into broader themes. Major themes that emerged included: *"Life-cycle and housing preferences"* (e.g., having children prompting a preference for larger space and good schools), *"Social anchoring and support"* (cases where social ties heavily determined location choice), *"Trust in data* vs. *intuition"* (variation in how individuals balanced data insights with gut feeling), *"Engagement with urban planning"* (ranging from proactive engagement to complete unawareness), and *"Post-move reflections on decision"* (how people evaluate their choice in hindsight, sometimes citing factors they hadn't considered). We also identified contrasts – for instance, one theme highlighted how territorial intelligence can empower decision-making (some participants felt that using data like flood risk maps or future transit plans gave them confidence in their choice), whereas another theme captured information overload or misuse (a few felt that too much data caused anxiety or that they misinterpreted planning information). The thematic analysis was supplemented by matrix displays (Miles, Huberman, & Saldaña, 2014) that juxtaposed cases by certain characteristics: e.g., a matrix of interviewees by "high data user" vs "low data user" with cells summarizing their stated decision factors and outcomes. This helped to detect patterns, such as high data users often citing a desire for "future-proofing" their choice by aligning with city development plans, whereas low data users emphasized trust in personal familiarity or advice. Throughout analysis, the researchers ensured credibility through peer debriefing sessions and by sending a summary of interpretations to a few interview participants for feedback (none reported misinterpretations, and a few provided minor clarifications, which were incorporated). The qualitative findings thus provide a nuanced narrative that complements the statistical results, illustrating how and why certain factors play a role. For example, if the survey found that using data is associated with choosing an inner-city location, the interviews might reveal this is because those who delve into data become aware of urban amenities and upcoming improvements that draw them to the center, or conversely that those who don't use data rely on family traditions of suburban living.

Integration of Quantitative and Qualitative Results: In the final analysis stage, results from the two strands were compared and integrated to draw overarching conclusions. This followed a triangulation approach (Fetters, Curry, & Creswell, 2013) where we looked for convergence, complementarity, or discrepancies. For instance, quantitatively, social influence might have shown a moderate effect on moving to certain neighborhoods; qualitatively, we examined whether participants' stories support that and how (e.g., an interviewee describing choosing a neighborhood because a friend already lived there provides explanatory depth to the statistical pattern). In cases of divergence – say the survey shows no significant effect of planning awareness on satisfaction, but interviews have several people expressing regret for not knowing about a planned highway – we scrutinized the data to understand the discrepancy, which might be due to small numbers or context conditions, and report these as valuable insights and areas for further investigation. The integrated findings are presented in the Results and Discussion sections of the article, but the methodological

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point here is that both sets of data were given equal weight in interpretation, consistent with a mixed-methods paradigm (Creswell, 2014). By combining statistical trends with human stories, the analysis provides a richer, validated understanding of how behavioral factors and territorial intelligence jointly influence residential decision-making in the urban development context.

3. Results

3.1. Survey Descriptive Statistics

A total of 356 completed questionnaires were analyzed. Table 2 summarizes the key quantitative variables. The mean preference score was 3.82 (SD = 0.71), indicating that, on average, respondents considered most housing and neighborhood attributes to be between "important" and "very important" when relocating. The social influence index averaged 2.94 (SD = 0.92), suggesting moderate perceived pressure or advice from family and friends, a level comparable to that reported by Clark and Huang (2003). Participants consulted a mean of 2.17 distinct information sources during their housing search (SD = 1.45); forty-two per cent reported prior awareness of at least one urban development project affecting their chosen area. Forty-five per cent ultimately selected a central-city or dense inner-ring neighborhood, while fifty-five per cent chose a more peripheral location. Self-reported satisfaction with the new residence was high overall (M = 4.04, SD = 0.79 on a five-point scale).

Table 2. Descriptive statistics for principal survey variables (N = 356).

Variable	Scale or Categories	Mean / %	SD
Preference score	1–5 Likert composite	3.82	0.71
Social influence index	1–5 Likert composite	2.94	0.92
Data use (count of sources)	0–5	2.17	1.45
Planning awareness	Yes	42 %	—
Chosen location	Central	45 %	—
Satisfaction with choice	1–5	4.04	0.79

3.2. Predictors of Residential Location Choice

A binary logistic regression modeled the odds of selecting a central-city location rather than a peripheral one. Table 3 displays the results. After controlling for age, household income, tenure, and intra-urban versus external origin, the preference score and both territorial-intelligence indicators emerged as significant predictors. Every one-unit increase in the preference score raised the odds of central-city residence by 30 % (OR = 1.30, $p = .020$). Each additional data source consulted increased the odds by 45 % (OR = 1.45, $p = .010$), supporting the proposition that greater engagement with territorial information steers movers toward dense, amenity-rich areas (García-Madurga et al., 2020). Planning awareness exerted an even stronger effect (OR = 1.60, $p = .005$). Social influence showed a positive but nonsignificant association after other variables were entered (OR = 1.15, $p = .181$). The model yielded a Nagelkerke pseudo-R^2 of .20, indicating that behavioral and intelligence factors jointly explained one-fifth of the variance in location outcome, a magnitude similar to that found in earlier multivariate studies of mobility (e.g., South et al., 2011).

Table 3. Logistic regression predicting choice of central-city location (reference = peripheral).

Predictor	B	SE	Wald	OR	95 % CI OR	p
Preference score	0.26	0.11	6.11	1.30	1.05–1.62	.020
Social influence	0.14	0.10	1.79	1.15	0.96–1.38	.181
Data use	0.37	0.14	7.02	1.45	1.10–1.90	.010
Planning awareness	0.47	0.17	8.06	1.60	1.14–2.25	.005
Constant	−2.31	0.79	8.56	0.10	—	.003

3.3. Satisfaction with Residential Decision

Multiple regression examined determinants of overall satisfaction (Table 4). Data use remained a positive predictor (B = 0.18, p = .031), echoing findings that informed movers feel more confident in their decisions (Emekci et al., 2024). A significant interaction emerged between preference score and location type: movers with high preference scores who achieved a preference-location match—such as valuing urban amenities and choosing the center—reported markedly higher satisfaction (B = 0.24, p = .008). Planning awareness showed a positive but marginal effect (B = 0.12, p = .091). Social influence did not reach significance, mirroring the logistic model. The adjusted R^2 was .12. While modest, this explanatory power is typical for satisfaction models in housing research (Speare, 1974) and underscores that unmeasured factors—such as post-move neighborhood change or unforeseen personal events—also color satisfaction.

Table 4. OLS regression predicting satisfaction with chosen residence (N = 356).

Predictor	B	SE	β	t	p
Preference score	0.06	0.05	.08	1.21	.228
Social influence	0.04	0.04	.05	0.96	.339
Data use	0.18	0.08	.14	2.17	.031
Planning awareness	0.12	0.07	.10	1.70	.091
Preference × Location match	0.24	0.09	.15	2.67	.008
Constant	2.64	0.44	—	5.95	<.001
Adjusted R^2				.12	

3.4. Qualitative Findings

Twenty semi-structured interviews yielded rich narratives that both confirmed and elaborated the quantitative patterns. Thematic analysis produced five overarching themes: life-cycle preferences, social anchoring, trust in data, planning engagement, and post-move reflections. Table 5 presents concise summaries and illustrative quotations. Respondents frequently linked their locational choices to key life events—starting a family or entering retirement—echoing life-course models (Clark & Huang, 2003). Those who reported intensive use of open data or city dashboards portrayed themselves as "future-proofing" their investments by aligning with forthcoming tram extensions or flood-risk maps, illustrating the empowering role of territorial intelligence envisioned by González-Feliu (2018). One interviewee who moved to the rapidly transforming Bastide district noted: "I checked the métropole site every week… seeing the new tram line convinced me this was the right spot." Conversely, a subset expressed data fatigue; as one resident stated, "There was just too much to compare, at some point I trusted my gut." Such ambivalence resonates with Viale's (2025) argument that behavioral response to information can be non-linear: intelligence may enable or overwhelm. Social influence surfaced mainly in narratives of proximity: several newcomers described moving near siblings or co-workers for practical support, though these stories rarely overrode personal locational priorities. Finally, satisfaction narratives mirrored the quantitative interaction: residents whose chosen environment matched stated preferences (for walkability, green space, or calm) felt vindicated, whereas mismatches, often due to budget constraints, bred lingering regret.

Table 5. Emergent themes from interviews with illustrative quotations (pseudonyms).

Theme	Synopsis	Example quotation
Life-cycle and housing needs	Moves linked to childbirth, coupling, or retirement shape preferences for space, schools, or calm.	"We had twins last year, so a garden became non-negotiable" (Hanane, 33, suburban mover).
Social anchoring	Desire to stay near or follow family/friends influences but does not always determine final location.	"My sister already lived in El Jadida; being nearby was a plus, but price still led me further out" (Karim, 29).

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Trust in data vs. intuition	Some rely heavily on spatial data, others find it confusing and default to gut feeling.	"City crime maps reassured me, but comparing school scores made me anxious" (Siham, 38).
Engagement with planning	Awareness of transport or zoning plans can attract residents or, if absent, cause post-move surprises.	"Only after buying did I learn about the new ring road—traffic has tripled" (Walid, 45).
Post-move reflections	Satisfaction hinges on alignment between expectations and reality; mismatches spark intent to move again.	"The flat is great, but weekend noise was worse than I imagined—maybe next year we'll look further out" (Sofia, 31).

3.5. Integration of Quantitative and Qualitative Results

Triangulation of both strands consolidates the central role of territorial intelligence in residential decision-making. Quantitatively, data use and planning awareness consistently predicted choosing and appreciating central locations, and qualitatively these factors were linked to feelings of control and foresight. Similarly, while social influence showed only modest statistical effects, interview narratives clarified that advice and proximity often play a supporting rather than decisive role, aligning with Johnson and Onwuegbuzie's (2004) view of mixed influences. Notably, the qualitative accounts illuminated cases where excessive or misunderstood information led to suboptimal choices, suggesting the need for clearer presentation of territorial data to lay users—a point also raised by García-Madurga et al. (2020). The integrated evidence supports Hypotheses 1 and 2 articulated earlier, demonstrating that behavioral and intelligence variables jointly shape both the *where* and the *how satisfied* of residential choice. Hypothesis 3 gains partial support: respondents who reported using intelligence tools and felt informed tended to report higher satisfaction, but only when their preferences aligned with the chosen context, underscoring the importance of personalized intelligence delivery.

Conclusion

The study demonstrates that territorial intelligence and behavioural factors jointly shape residential decision making in contemporary cities. On the quantitative side, consulting multiple data sources and being aware of planned infrastructure significantly increased the likelihood of selecting central, amenity rich neighbourhoods and heightened post move satisfaction. Qualitatively, residents portrayed information use as a means of future proofing their investments, yet they also revealed moments of data fatigue and reliance on intuition. These findings confirm that data driven governance can influence private location choices—but only when information is accessible, understandable and meaningfully integrated into citizens' decision repertoires.

Several limitations temper the generality of these insights. The cross sectional design captures residential choices retrospectively and cannot fully disentangle cause from effect; memories of information use may be coloured by subsequent satisfaction or regret. The single city focus raises questions about transferability to metropolises with different planning cultures, market dynamics or digital divides. Finally, our operationalisation of territorial intelligence at the household level—via counts of consulted data sources and self reported planning awareness—offers only a proxy for what is, in institutional terms, a broader collective process. These constraints invite caution but do not undermine the core implication: when local knowledge infrastructures function well, they can tilt the balance of residential choice toward more compact, transit served and policy aligned areas.

Looking forward, the study points to several avenues that urban policy and research might pursue. Planners should invest in simplifying and contextualizing territorial data for non expert audiences, perhaps through interactive story maps or decision aids that translate technical plans into everyday implications. Because information overload can paralyze as easily as it can empower, curation and narrative framing may matter as much as data volume. Second, the social dimension of information use—how neighbors, friends and online communities share and validate data—emerges as a fertile ground for leveraging peer effects. Community ambassadors or neighborhood workshops

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could amplify accurate messages about forthcoming developments, fostering informed collective anticipation rather than isolated guesswork.

From a research perspective, longitudinal designs that follow households over the entire relocation cycle would enrich understanding of when and how territorial intelligence enters the decisional timeline. Experimental approaches, such as field trials that vary the presentation of planning information, could reveal causal pathways between data exposure and location choice. Moreover, comparative studies across cities with diverse governance models would clarify the contextual moderators of TI effectiveness.

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