Cities 156 (2025) 105576

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Exploring urban segregation dynamics: A hub-based agent model integrating preferences, social interactions, and policy interventions

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ARTICLE INFO

Keywords:
Urban segregation
Agent-based modeling
Hub-based representation
Urban dynamics
Policy interventions

ABSTRACT

Urban segregation emerges from a complex interplay of individual preferences and social interactions within varied urban landscapes. This study presents an expanded Schelling's segregation model, introducing a more granular representation of urban environments through categorization of distinct hubs: Economic, Educational, Cultural, and Green Spaces, along with unspecified areas. Agents within the model are characterized by distinct preferences for these hubs, guiding their movement decisions and thereby influencing the spatial configuration of the city. The model reflects the richness of urban life by capturing the intricacies of preference-based residential choices. Through integration of a survey-based approach, the study sources simulated agents' decision behaviors from real-world data, ensuring a realistic portrayal of urban dynamics. Our findings demonstrate how individual desires, such as the desire for economic stability, educational opportunities, cultural experiences, and environmental quality, combine with social factors to promote urban segregation in complex ways. Additionally, the study examines the impact of various policy interventions on urban segregation and individual well-being. It discusses how different interventions can produce diverse outcomes, showing that each policy can uniquely influence segregation patterns and the happiness of residents.

1. Introduction

Urban segregation, a multifaceted phenomenon, is significantly shaped by the interplay of urban form and socio-economic dynamics, where public spaces often reflect deeper social divisions (Legeby, 2010). These divisions manifest through patterns dictated by the underlying urban architecture, which not only segregates by residential location but also by interaction in public zones, highlighting the significant influence of spatial configurations on daily social interactions (Dadashpoor & Keshavarzi, 2024). The persistent challenge of effectively integrating diverse communities within urban settings calls for a reevaluation of how cities are planned and inhabited. Insights from various studies suggest that while economic and cultural hubs are intended to foster interaction and growth, they often inadvertently reinforce existing segregations due to established social and economic disparities (Goetz et al., 2020; Manley, 2021). Addressing these disparities requires an understanding of the structural and spatial dimensions of segregation, with an emphasis on creating policies that promote true socio-economic integration within urban neighborhoods (Orfield & Lee, 2005; Turner & Rawlings, 2009; Van Ham et al., 2021). This context highlights the importance of designing urban spaces that not only meet the functional needs of a diverse population but also promote equitable social interactions and opportunities.

The motivation for developing this enhanced model stems from a need to understand how individual desires for economic stability, educational opportunities, cultural experiences, and environmental quality interact with social dynamics to influence urban segregation. This is particularly pertinent in light of ongoing urbanization and the increasing challenges cities face in promoting inclusivity and integration. Our model not only reflects the intricacies of preference-based residential choices but also integrates a survey-based approach to source simulated agents' decision behaviors from real-world data, ensuring a realistic portrayal of urban dynamics.

Our research utilizes an advanced iteration of Schelling's segregation model (Schelling, 1971) to explore the multifaceted dynamics of urban segregation, focusing specifically on how individual preferences for a

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https://doi.org/10.1016/j.cities.2024.105576
Received 4 June 2024; Received in revised form 30 September 2024; Accepted 27 October 2024
Available online 19 November 2024

range of urban amenities—including economic, educational, cultural, and green spaces—affect these patterns. Central to our methodological framework is the 'Urban Area Preference Survey', comprehensively outlined in the Appendix. This survey is instrumental in collecting data regarding individual preferences and their interactions with the urban landscape. It provides critical insights into how these preferences are implicated in the spatial configuration of urban areas, thereby clarifying the underlying mechanisms driving segregation trends.

The contributions of this paper are manifold. First, we incorporate several methodological improvements to address key urban planning challenges, such as the need for more effective integration strategies and the creation of inclusive urban environments. By including a wide range of urban amenities—such as economic, educational, cultural, and green spaces—within a single framework, we provide deeper insights into how individual preferences shape urban segregation patterns and the social stratification of cities. Additionally, our survey-based approach moves beyond hypothetical assumptions commonly found in existing studies, aligning agent preferences with real-world data to enhance the model's accuracy and practical relevance. By examining both agent behavior and the impacts of various policy scenarios, our model contributes to ongoing discussions in urban studies and offers valuable insights for urban planners and policymakers seeking to foster more integrated and inclusive cities.

Furthermore, our study's findings can have practical applications in various urban planning and policy-making contexts. For instance, cities like New York and London, which are experiencing rapid gentrification and shifts in socio-economic compositions, can use our model to simulate the impacts of expanding green spaces or redistributing economic and cultural hubs to promote more equitable urban environments. Similarly, in cities facing significant challenges related to housing affordability and spatial segregation, such as San Francisco or Paris, our model could help evaluate different policy scenarios, like modifying zoning laws or increasing affordable housing near educational and cultural centers. Moreover, in developing cities such as Mumbai or Lagos, where urban expansion is often unplanned and rapid, our model could be employed to predict and manage future segregation patterns by integrating new amenities that cater to diverse population needs. By applying these examples, urban planners could foresee the potential effects of various interventions and better allocate resources to ensure sustainable and inclusive growth. The model's versatility makes it applicable across different geographical regions, socio-economic contexts, and urban development stages, providing a useful approach for enhancing social integration and reducing inequality in both developed and developing cities.

The remainder of this paper is structured as follows: Section 2 presents a review of the relevant literature. Section 3 delineates the proposed model, providing a comprehensive overview of its components and mechanisms. Section 4 details the simulation experiments, presents the ensuing results, and offers an extensive discussion of their implications. Section 5 outlines a systematic methodology for applying the model to real-world scenarios through empirical survey analysis. Finally, Section 6 summarizes the study's conclusions, reflecting on the findings and their potential applications.

2. Literature review

Drawing on the foundational insights from Luisa Maffini and Maraschin (2018), who explore socio-spatial interactions, and Cornejo (2015), who examines urban imaginaries in shaping city narratives, our approach contextualizes individual preferences within broader socio-spatial dynamics. The impact of urban configurations on these preferences is further examined by Knorr (2017), who focuses on the visual culture of segregation, and by Novaes and Bernardes (2015), who analyze urban restructuring. Both highlight how urban form and socio-economic policies shape segregation.

Mossay and Picard (2019) discuss spatial segregation in relation to competitive land prices and social interactions, highlighting the formation of distinct urban districts based on group sizes and interaction dynamics. Their analysis relates to how individual preferences for different urban amenities influence the spatial organization in cities, emphasizing how economic and cultural preferences contribute to distinct neighborhood formations and potentially to the multiplicity of spatial equilibria.

Iyer et al. (2023) explore segregation beyond residential patterns, focusing on mobility and transit. This study underscores the role of transportation in providing access to urban opportunities, aligning with our survey's focus on how accessibility influences preferences for different urban areas. Incorporating this perspective enhances understanding of how mobility contributes to or mitigates segregation.

Building on these considerations of mobility and accessibility, Collins et al. (2023) shed light on the spatiotemporal gender differences in urban vibrancy. The study uses high-frequency Call Detail Record data to analyze how urban features, such as Points of Interest and transportation networks, differently affect males and females in Italy's major cities. It reveals significant gender-based disparities in urban vibrancy, highlighting the need for urban planning that addresses these differences to promote fairer cities. The findings suggest that urban vibrancy and gender dynamics are closely interlinked, with both positive and negative spatial spillovers influencing the experiences of men and women differently.

The economic and cultural dimensions are vital to understanding urban preferences. Lu et al. (2023) illustrate the relationship between homeownership, socio-economic status, and access to urban amenities, connecting to how economic conditions and urban policies influence individual choices and segregation patterns, highlighting the intersection of housing policies and urban amenity differentiation. Bharathi et al. (2022) and Guo et al. (2019) provide insights into how economic conditions and housing policies affect urban spaces, while Bezin and Moizeau (2017) and He et al. (2023) discuss the role of cultural dynamics and migration patterns. The survey's focus on cultural areas aligns with Silver et al. (2021)'s discussion on the impact of urban venues on segregation, emphasizing the importance of cultural hubs.

Incorporating an environmental perspective, the study by Neier (2023) on the 'green divide' in Vienna brings to light the spatial analysis of segregation-based environmental inequality. This work highlights how ethnic minorities are often segregated from access to urban vegetation, exacerbating the challenges posed by climate change and urban heat. This underscores the need for equitable urban planning that ensures all residents can benefit from green spaces.

Imeraj et al. (2018) utilize individualized neighborhoods and multiscalar analysis, providing methodological inspiration for examining how preferences captured in our survey might vary across different urban scales and contribute to complex segregation patterns in cities. Methodologically, our study incorporates advanced modeling techniques inspired by Perez et al. (2019) and Feitosa et al. (2011), where agent-based models are used to simulate urban dynamics. These models help interpret the diverse demographic information collected through our survey, aligning with the spatial analyses found in Xu et al. (2019), and Kusumah and Wasesa (2023).

Policy implications are derived from zoning and urban policy studies, such as those by Shertzer et al. (2022) and Mayorga Henao et al. (2021), where long-term impacts of zoning on segregation are discussed. Insights from Vermeiren et al. (2016) and Pendergrass (2022) on urban expansion and diversity further guide our urban planning recommendations, emphasizing the need for policies that consider individual preferences and promote inclusivity. Additionally, Ilisei and Salom-Carrasco (2018) provide a concrete example of how urban projects can influence residential segregation, examining long-term effects of a neoliberal urban policy in the Cabanyal neighborhood of Valencia. This study highlights the socio-demographic shifts and increasing residential segregation resulting from the halted urban renewal projects, which aimed at the partial destruction of the neighborhood but instead led to its physical and social degradation. Analyzing data from 2004 to 2016, the study documents a notable demographic transformation, characterized by the displacement of the Spanish population and the influx of EU and non-EU immigrants, further complicating the social integration and interaction within the neighborhood.

Adding to the understanding of policy-driven segregation, Castro et al. (2015) delves into the effects of urban policies in the satellite city of Alerce, Puerto Montt, where the eradication of city camps and metropolization initiatives have led to notable segregation and vulnerability. This study employs a mixed methodology that combines statistical data analysis and GIS mapping with in-depth interviews to reveal how urban policies have spatialized vulnerability, affecting access to employment, socioeconomic opportunities, and essential services. These findings underscore the direct consequences of policy measures on urban segregation, particularly in emerging urban sectors like Alerce, and highlight the critical need for inclusive and equitable urban planning.

Cao et al. (2024) discusses the impact of urban renewal on residential segregation in Shenzhen, pertinent to our survey's exploration of how urban restructuring and renewal influence segregation patterns. This links directly to the policy implications section of our study, suggesting how urban planning could consider the diverse impacts of renewal projects.

Dos Santos et al. (2021) connects income segregation with violent outcomes like homicides, providing a stark illustration of the broader social impacts of segregation. This enhances the discussion on the need for inclusive urban policies to address socio-economic disparities highlighted in our survey.

Our comprehensive analysis integrates findings from studies on urban structures and socioeconomic homogeneity, such as those by Garcia-Lopez et al. (2020), Toro and Orozco (2018), Beaubrun-Diant and Garnica and Alvanides (Beaubrun-Diant & Maury, 2024; Garnica-Monroy & Alvanides, 2019). These studies help us understand how different urban amenities, from green spaces to educational institutions, influence segregation patterns, a key focus of our survey. Zhao and Randall (2022) introduces a heterogeneous Schelling model that incorporates wealth disparity, which could inform our model's consideration of economic factors in segregation. The insights from this work into the effects of urban infrastructure incentives could be particularly useful for discussing how urban amenities influence segregation.

Serrati (2024) explore the relationship between residential and school segregation, which could be integrated into our survey's emphasis on educational amenities. This connection underscores the importance of considering multiple domains of segregation in urban planning. Zhou et al. (2021) examine workplace segregation among rural migrants using big data, offering a methodological approach that could be applied to analyze our survey data, particularly in understanding how workplace locations influence urban area preferences. Owens (2019) discusses how housing opportunities and their segregation impact income segregation. This analysis can be used to further substantiate the discussions in our study on how housing policies and economic conditions influence urban segregation patterns.

Finally, empirical insights from Billingham (2019), Serrati (2024), Bernelius and Vilkama (2019), and Bailey et al. (2017) on residential mobility, educational segregation, and neighborhood change provide practical applications for our findings. The survey's emphasis on factors influencing living preferences, such as proximity to work or educational institutions, directly relates to these studies, enhancing our understanding of urban segregation.

Tables 1, 2, and 3 summarize various studies that focus on urban segregation, highlighting their key aspects, the types of urban hubs they cover, and their relevance to our research. Most of the existing studies concentrate on specific aspects of urban segregation, such as economic, cultural, educational, or green spaces, often focusing on a single type of urban hub or factor influencing segregation patterns. While these studies offer valuable insights into the dynamics of segregation within specific contexts, there is a lack of comprehensive models that simultaneously consider multiple urban amenities and their combined effects on segregation dynamics. Moreover, the majority of studies rely on hypothetical or theoretical assumptions regarding agent behavior, which limits their applicability to real-world urban scenarios.

Table 1
Studies on urban segregation by urban hub preferences - part 1.

Study	Focus	Relevance to our study	Urban hub type
(Luisa Maffini & Maraschin, 2018)	Configurational approach to segregation in Brazil	Examines socio-spatial interactions, providing insights into the spatial aspects of segregation.	Economic, cultural, green
(Bharathi et al., 2022)	Impact of residential segregation on public services	Highlights the interplay between residential segregation and access to services.	Economic, cultural, educational
(Mossay & Picard, 2019)	Segregation and competitive land prices	Explores how land prices and social interactions shape segregation.	Economic
(Iyer et al., 2023)	Segregation based on mobility and transit patterns	Focuses on how mobility and transit affect segregation.	Economic, cultural
(Garcia-Lopez et al., 2020)	Spatial segregation and gentrification	Analyzes spatial segregation patterns and their link to gentrification.	Economic, cultural
(Shertzer et al., 2022)	Long-term impact of zoning on segregation	Examines how zoning influences segregation.	Economic, cultural
(Guo et al., 2019)	Relationship between urban sprawl and income segregation	Investigates how urban sprawl and income segregation are related.	Economic
(Lu et al., 2023)	Relationship between homeownership and urban amenities	Studies the link between homeownership, socio-economic status, and urban amenities.	Economic, cultural, green
(Knorr, 2017)	Visual culture's impact on segregation	Discusses how visual elements reinforce segregation.	Cultural
(Imeraj et al., 2018)	Ethnic segregation patterns using individualized neighborhoods	Utilizes a comparative approach to study ethnic segregation.	Economic, cultural
(Novaes & Bernardes, 2015)	Impact of urban projects on segregation	Analyzes how urban projects influence socio-spatial segregation.	Economic, cultural

Our study addresses this gap by integrating a broader range of urban amenities—including green, economic, cultural, and educational spaces—into a single modeling framework. By employing a survey-based approach to collect data on individual preferences, we offer a more detailed and empirically grounded understanding of how these preferences shape urban segregation. This methodology not only provides a more holistic view of urban dynamics but also offers practical insights for policymakers and urban planners, contributing to the development of inclusive and equitable urban environments.

3. Our proposed model for urban segregation

The model that we propose aims to explore how individual preferences and social interactions can lead to segregation in a heterogeneous urban environment. In our model, we introduce several key extensions to the classic Schelling model, incorporating more complex and realistic dynamics that reflect the multifaceted nature of modern urban settings. We describe the model using the ODD (Overview, Design concepts, and Details) protocol, which is widely recognized for its structured and comprehensive approach to documenting agent-based models (Grimm et al., 2010). The ODD protocol allows for a clear presentation of the model's purpose, the entities involved, and the processes driving their

Table 2
Studies on urban segregation by urban hub preferences - part 2.

Study	Focus	Relevance to our study	Urban hub type
(Billingham, 2019)	Racial segregation within urban districts	Examines racial segregation within school districts.	Educational
(Beaubrun-Diant & Maury, 2024)	Geographic decomposition of income segregation	Focuses on income segregation in different urban areas.	Economic
(Bezin & Moizeau, 2017)	Relationship between culture, mobility, and segregation	Explores how cultural dynamics affect urban segregation.	Cultural
(Serrati, 2024)	Relationship between residential and school segregation	Investigates how residential and school segregation are connected.	Educational
(Xu et al., 2019)	Spatial and social-network segregation	Examines both spatial and social-network segregation.	Economic, cultural, green
(Cornejo, 2015)	Urban imaginaries and sociospatial segregation	Analyzes how urban imaginaries reflect sociospatial segregation.	Cultural
(Mayorga Henao et al., 2021)	Patterns of multidimensional poverty and segregation	Studies the distribution of multidimensional poverty and segregation.	Economic
(He et al., 2023)	Residential segregation between migrants and locals	Focuses on residential segregation in suburban and urban centers.	Economic, cultural
(Vermeiren et al., 2016)	Simulation of urban growth and segregation	Presents a model for simulating urban growth and intra-urban segregation.	Economic
(Toro & Orozco, 2018)	Representation of urban segregation	Examines homogeneity and polarization associated with urban segregation.	Economic, cultural
(Cao et al., 2024)	Impact of urban renewal on segregation	Investigates how urban renewal affects residential segregation.	Economic, cultural

behavior, making it easier for others to replicate and extend the study. By adopting the ODD protocol, we ensure that the model's assumptions, rules, and parameters are transparently communicated, facilitating a deeper understanding of how individual preferences and social interactions contribute to segregation patterns within diverse urban environments. This choice also enables a standardized comparison with existing models in the literature, enhancing the model's credibility and relevance in the field.

3.1. Overview

3.1.1. Purpose

The purpose of this model is to explore how individual preferences and social interactions contribute to segregation in a heterogeneous urban environment. It extends the classic Schelling model by incorporating multiple types of urban hubs and a more complex decision-making process for agents based on their preferences, recent mobility history, and dynamic demographic characteristics.

3.1.2. Entities, state variables, and scales

3.1.2.1. Agents. The model consists of individual agents representing urban residents. Each agent a has the following state variables:

- Demographic attributes and movement-related factors:
  - Age(a): Age of the agent.
  - Gender(a): Gender of the agent.
  - EducationLevel(a): Education level of the agent.
  - ReasonForMoving(a): Primary reason for moving.
  - ResidentialHistory(a): Indicator if the agent has moved in the past 5 years.
  - Occupation(a): Occupation of the agent.
- Preferences for urban hubs and factors influencing preferences:
  - $\widehat{p}_h(a)$: Dynamic preference weight for hub h, calculated based on demographic attributes and movement-related factors using a regression model.
  - $\widehat{w}_f(a)$: Dynamic importance weight for factor f, calculated based on demographic attributes and movement-related factors using a regression model.
- Satisfaction threshold ($ST(a)$): The satisfaction threshold represents the minimum level of satisfaction an agent must achieve to remain in its current location. If this threshold is not met, the agent will relocate to another area in pursuit of meeting or exceeding the required satisfaction level.
- Social influence weights: These weights capture the impact of social interactions on agent behavior. Specifically, they quantify how much

Table 3
Studies on urban segregation by urban hub preferences - part 3.

(Dos Santos et al., 2021)	Relationship between income segregation and homicides	Analyzes how income segregation relates to homicide rates.	Economic
(Bernelius & Vilkama, 2019)	School catchment area segregation and residential mobility	Studies how school catchment areas affect residential mobility.	Educational
(Garnica-Monroy & Alvanides, 2019)	Spatial accessibility and urban inequalities	Examines spatial accessibility as a means to understand urban inequalities.	Economic, educational
(Perez et al., 2019)	Agent-based model of immigrant spatial dynamics	Develops an agent-based model to study immigrant population dynamics.	Economic, cultural, educational
(Zhao & Randall, 2022)	Wealth disparity and its effect on segregation	Introduces a heterogeneous Schelling model to study wealth disparity and segregation.	Economic, cultural
(Feitosa et al., 2011)	Multi-agent simulation for urban segregation	Proposes a simulator to explore urban segregation.	Economic, cultural
(Bailey et al., 2017)	Income sorting and neighborhood change	Analyzes how income sorting affects neighborhood change.	Economic
(Serrati, 2024)	Socio-economic residential and school segregation	Focuses on socio-economic segregation in schools and residences.	Economic, educational
(Kusumah & Wasesa, 2023)	Influential determinants of residential segregation	Uses agent-based modeling to analyze residential segregation patterns.	Economic, cultural
(Silver et al., 2021)	Venues as an influencing factor in segregation	Explores how urban venues impact segregation using a revised Schelling model.	Economic, cultural
(Zhou et al., 2021)	Workplace segregation of rural migrants	Studies workplace segregation using big data, focusing on rural migrants.	Economic
(Pendergrass, 2022)	Relationship between racial diversity and segregation	Investigates how racial diversity relates to segregation.	Economic, cultural
(Owens, 2019)	Relationship between housing and income segregation	Examines how housing segregation contributes to income segregation.	Economic

agents are influenced by the preferences of their neighbors, determining whether agents are drawn to or repelled by others based on shared or differing characteristics.
- The attraction weight w_{attr} reflects the degree to which agents are attracted to neighbors with similar preferences.
- The repulsion weight w_{rep} reflects the degree to which agents are repelled by neighbors with dissimilar preferences.

3.1.2.2. Environment. The urban environment is composed of discrete locations (cells), each representing a distinct area with specific attributes:

- Urban Hubs: These include Economic Areas, Educational Areas, Cultural Areas, and Green Spaces, each representing a distinct type of hub within the urban environment.
- $H_h(l)$: Presence or proximity of hub h at location l.
- Location Factors: These include key factors such as proximity to work, access to educational institutions, availability of cultural activities, presence of green spaces, cost of living, safety and security, and public transportation.
- $F_f(l)$: Level of factor f at location l.

3.1.2.3. Spatial and temporal scale. The urban environment is divided into a grid, where each cell represents a distinct urban location or a nonspecific area. The time step represents a month, and the simulation runs over multiple time steps to observe long-term dynamics.

3.1.3. Process overview and scheduling

At each time step, the following processes occur for each agent a:

1. Update agent attributes:

- Agents age over time.
- Residential history will be updated to reflect whether the agent has moved within the last 5 years.
- Agents' initial occupations and education levels are assigned based on the demographic information gathered from the survey (such as age, gender, and employment status). Additionally, agents' aspirations for future urban areas (e.g., selecting Economic or Educational areas in the survey) have an impact on their education and occupation transitions. For example, agents who aspire to move to an Educational area may have a higher probability of pursuing further education, while those who favor Economic areas might shift towards occupations in business or technical fields. During the simulation, agents' occupation and education levels evolve based on the patterns observed in the collected data. The probability of an agent transitioning between different education levels or occupations is computed from the survey data. These probabilities are used to model realistic changes over time, such as job promotions, career changes, or further education.

2. Update preferences and importance weights:

- Recalculate $\widehat{p}_h(a)$ and $\widehat{w}_f(a)$ dynamically based on updated agent attributes.
- These updated weights are calculated using the regression model for hub preferences and location factors, as described in the Utility Function section.

3. Evaluate utility of current and potential locations:

- Calculate the utility $U(a,l)$ for the current location and a set of potential new locations using the updated $\widehat{p}_h(a)$ and $\widehat{w}_f(a)$.

4. Decision to move:

- Decide whether to move based on utility comparisons and the satisfaction threshold $ST(a)$.
- If moving, select the location l^* that maximizes utility. The decision to move is based on the comparison between the current utility and the maximum utility from other available locations.

5. Update environment and social composition:

- Update the agent's location after the move.
- Update the social composition of affected locations, including the new neighborhood and the one left behind.
- Recalculate social influence $S(a,l)$ and dissimilarity $D(a,l)$ values in both locations.

6. Life-cycle events:

- Agents may leave the simulation due to aging out (e.g., death), or prolonged dissatisfaction if they are unable to find a satisfactory location over multiple iterations. In our model, we utilized the age-specific mortality rates based on data from the 'Our World in Data' 2022 dataset (https://ourworldindata.org/grapher/probability-of-dying-by-age). This data reflects varying mortality probabilities across different age groups, with significantly higher probabilities for older individuals. For example, those aged 80–84 years have a mortality rate of 0.33, while younger individuals below 50 years exhibit much lower rates, typically below 0.01. Agents who fail to find a satisfactory location start with a 1 % probability of leaving the simulation, which increases by 0.5 % with each unsuccessful attempt. These assumptions reflect our model's approach to simulating both aging and prolonged dissatisfaction.
- New agents may enter the simulation to maintain population levels, representing immigration into the urban environment. In our model, we assumed that new agents equal to 1 % of the current population enter the simulation each month to maintain population levels, representing immigration into the urban environment.

3.2. Design concepts

3.2.1. Basic principles

The model is based on an extension of the Schelling segregation model, integrating more realistic dynamics of urban environments by introducing distinct types of hubs (Economic, Educational, Cultural, and Green Spaces) (Jamali et al., 2024; Liu et al., 2019; Turgut & Lazarova-Molnar, 2023). Agents make movement decisions based on a utility function that considers both their dynamically adjusted personal preferences and the attributes of different locations, as well as the social composition of their neighborhood.

3.2.2. Emergence

Segregation patterns emerge from the movement decisions of agents, driven by their dynamically changing preferences, attributes, and interactions with other agents. The model captures how individual decision-making, based on both personal utility and social influence, leads to the formation of homogeneous clusters in a heterogeneous environment.

3.2.3. Adaptation

Agents adapt to their environment by moving to locations that maximize their utility. If an agent is dissatisfied with their current location and finds a better option that exceeds their utility threshold $ST(a)$, they will move. If an agent remains dissatisfied after multiple attempts, they may leave the simulation entirely, representing emigration from the city.

3.2.4. Objectives

The primary objective of each agent is to maximize their utility function $U(a, l)$, which is influenced by dynamically calculated preferences for different hub types, their attributes, and social influences. The utility function is provided in detail under the Decision-making process within the Submodels section.

3.2.5. *Sensing*

Agents can sense the attributes of nearby locations (e.g., proximity to economic, educational, cultural, and green spaces) and the social composition (number of similar and different agents in the vicinity).

3.2.6. *Interaction*

Agents interact indirectly through their movement decisions and the social influence of neighboring agents. The social influence score $SI(a, l)$ is calculated as:

$$SI(a,l) = w_{\text{attr}} \cdot \text{Sim}(a, \text{neighbors}(l)) - w_{\text{rep}} \cdot \text{Diff}(a, \text{neighbors}(l))$$

where:

- $\text{Sim}(a, \text{neighbors}(l))$: A measure of preference similarity between agent a and its neighbors at location l, based on the agents' preferences for urban hubs and factors.
- $\text{Diff}(a, \text{neighbors}(l))$: A measure of preference dissimilarity between agent a and its neighbors at location l.

This formulation reflects that agents prefer to live near others who share similar preferences and are somewhat repelled by neighbors with dissimilar preferences.

3.2.7. *Stochasticity*

Stochastic elements are introduced in agents' demographic changes (e.g., aging, death), while their demographic attributes also influence both their preference weights and the factor weights of locations.

3.2.8. *Collectives*

Agents form collectives implicitly based on their preferences for certain hubs and the social composition of neighborhoods. The density of similar agents influences their movement decisions.

3.2.9. *Observation*

The model tracks segregation patterns, the distribution of agents across different hub types, the evolution of social compositions over time, and the average satisfaction level of agents.

3.3. *Details*

3.3.1. *Initialization*

3.3.1.1. *Agents.*

- Agent Attributes:

- Agents' ages are initialized based on an age distribution derived from the survey data, ensuring that the simulated population reflects realistic demographic diversity.

- Agents' genders are assigned in alignment with the gender distribution observed in the survey data to accurately represent the real-world gender balance.

- Agents' education levels, occupations, and reasons for moving are assigned in a manner consistent with the correlations observed in the survey data. For instance, agents' education levels are determined not only by their age but also by the distributions present in the survey, ensuring coherence between age, education, and occupation.

- Agents' residential histories (*moved in past 5 years*) are probabilistically assigned, following the patterns observed in the survey data, to represent different levels of mobility and migration behavior in the population.

- Preferences and importance weights for urban hubs and location factors:

- Agents' preferences for different types of urban hubs (Economic, Educational, Cultural, Green Spaces) and their importance weights for location factors (e.g., proximity to work, safety, public transportation) are derived from regression models based on survey data.

- These regression models capture the relationship between agents' attributes (e.g., age, education level, occupation, residential history) and their preferences and factor weights.

- During the simulation, these preferences and importance weights are dynamically recalculated for each agent as their attributes change over time.

- The updated preferences and factor weights are used in the agent's utility function to determine their satisfaction with their current location and potential new locations.

- Social influence weights: To balance the influence of attraction and repulsion, we set $w_{\text{attr}} + w_{\text{rep}} = 1$. In this model, we assign $w_{\text{attr}} = 0.7$ and $w_{\text{rep}} = 0.3$. These values reflect the assumption that agents are generally more influenced by similarities than dissimilarities, but still experience some degree of repulsion from dissimilar neighbors.

3.3.1.2. *Environment.*

- Each location l is assigned attributes $H_h(l)$ and $F_f(l)$ based on urban data (e.g., proximity to economic hubs, educational institutions, parks, etc.).

3.3.2. *Input data*

- Survey data: The survey used for this study utilized 500 survey responses, obtained using a stratified random sampling technique to capture a representative cross-section of urban residents. This approach ensures that the sample reflects the diversity in demographics and preferences necessary for accurate estimation of model parameters. This sample size was chosen based on a balance between model complexity, which includes multiple factors such as age, education level, and occupation, and practical data collection limitations. According to standard practices, a minimum of 10–20 responses per factor ensures sufficient representation of each demographic group. With 500 respondents, we can confidently model agent preferences and behaviors with high reliability.
- The survey data is used to learn the relationships between agents' attributes and preferences for different types of urban hubs and location factors.
- These relationships are captured through regression models that allow for the dynamic calculation of preference weights $\widehat{p}_h(a)$ and importance weights $\widehat{w}_f(a)$ for each agent based on their changing attributes during the simulation.
- While the survey data provides the foundational relationships, the agents' demographic attributes are stochastically generated during initialization to introduce variability and realism into the model.
- Urban data:

- Contains attributes of locations, including proximity to urban hubs (Economic, Educational, Cultural, and Green Spaces), levels of location factors (e.g., safety, cost of living, access to transportation), and the general social composition of each neighborhood.
- These attributes remain static during the simulation, while agents' preferences and decisions evolve based on their personal circumstances and the attributes of the locations.

3.3.3. Submodels

This section examines the submodels integrated into our agent-based framework to simulate how agents decide to relocate within urban environments. Agents assess potential locations using a utility function that captures their personal preferences, demographic attributes, the features of the locations, and social influence from neighboring agents. The utility function combines preference weights for urban hubs and location factors, which are calculated using regression models based on agents' attributes. Additionally, the social influence score is determined through measures of similarity and dissimilarity between agents and their neighbors. The following submodels detail the mechanisms underlying the utility function, explain how the regression models calculate preferences and factor weights, and describe how social influence is computed.

- Utility function: The utility function $U(a,l)$ determines the desirability of each location for an agent based on their calculated preferences, their attributes, and the characteristics of the location. The utility function is defined as follows:

$$U\left(a,l\right) = \sum_h \widehat{p}_h\left(a\right)\cdot H_h\left(l\right) + \sum_f \widehat{w}_f\left(a\right)\cdot F_f\left(l\right) + SI\left(a,l\right)$$

where:

- $\widehat{p}_h(a)$: Calculated preference weight for hub h based on agent a's attributes.
- $\widehat{w}_f(a)$: Calculated factor weight for location factor f, based on agent a's attributes.
- $H_h(l)$: Presence or proximity of hub h at location l.
- $F_f(l)$: Level of factor f at location l.
- $SI(a,l)$: social influence score of agent a at location l.

Agents evaluate potential locations and decide whether to move based on the utility function. If $U(a,l_{\text{current}}) < max_{l\in L}\, U(a,l)$ and the new utility exceeds the threshold $ST(a)$, the agent moves to the location l^* that maximizes their utility:

$$l^* = \underset{l\in L}{argmax}\{U(a,l) : U(a,l) > ST(a)\}$$

- Regression models for preferences and factors: The agent's preferences $\widehat{p}_h(a)$ and factor weights $\widehat{w}_f(a)$ are calculated using regression models. For the hub preferences, where agents rate hubs on a scale of 1 to 5, we use a ordinal logistic regression model. For the binary factors (0 or 1), logistic regression is used. To ensure that the utility function $U(a,l)$ remains within the range $[0,1]$, we normalize it by scaling the combined sum of its components accordingly. This normalization ensures that each part of the utility function—the hub preferences, location factors, and social influence—contributes proportionally to the overall utility without any single component dominating due to differences in scale. By keeping $U(a,l)$ between 0 and 1, we maintain consistency and comparability across different agents and locations. The use of regression models to calculate preference and factor weights is motivated by several key reasons:

  - Survey responses might be simplified or incomplete: Survey data reflects stated preferences, but real-world decisions are influenced by factors that may not be fully captured in these responses. For example, a respondent might express a preference for cultural hubs, but demographic factors like education, gender, or income can subtly influence their choices. Regression models help account for these “hidden” factors by adjusting preferences based on demographic attributes.
  - Demographic attributes can modify preferences: Preferences vary significantly across demographic groups. Younger individuals may prioritize nightlife or social hubs, while older individuals might favor green spaces. Similarly, occupation or residential history can influence the importance placed on factors such as proximity to work or housing affordability. Regression models allow these demographic differences to be reflected in the calculated weights.
  - Personalization and accuracy in decision modeling: By adjusting preferences dynamically, we can model real-world variations in decision-making more accurately. For instance, two individuals might express similar preferences in a survey, but someone with a stable residential history might be more resistant to moving than someone who relocates frequently. This personalized modeling helps capture these nuanced differences.
  - Capturing long-term behavior and trends: Preferences evolve over time as individuals' circumstances change. For example, an agent might prioritize proximity to work early in life but later prefer family-friendly neighborhoods. Dynamic adjustments to preferences based on agents' changing demographics allow the model to capture these long-term behavioral trends.

1. Ordinal logistic regression model for hub preferences: For hub preferences, which are rated on a scale from 1 to 5, we use an ordinal logistic regression model to predict the preference rating $p_h(a)$ based on agents' attributes. By using ordinal logistic regression, we appropriately account for the ordinal nature of the preference ratings, ensuring that the statistical assumptions of the model align with the characteristics of the data. The model is specified as follows:

$$\begin{aligned} &log\left(\frac{P(p_h(a)\le k)}{P(p_h(a)>k)}\right) = \\ &\theta_k - \beta_1\cdot\text{Age}(a) - \beta_2\cdot\text{Gender}(a) \\ &-\beta_3\cdot\text{EducationLevel}(a) - \beta_4\cdot\text{ReasonForMoving}(a) \\ &-\beta_5\cdot\text{ResidentialHistory}(a) - \beta_6\cdot\text{Occupation}(a) \\ &\text{for } k = 1,2,3,4. \end{aligned} \tag{1}$$

where:

- $p_h(a)$: The observed preference rating for hub h by agent a, on a scale from 1 to 5.
- $P(p_h(a)\le k)$: The cumulative probability that agent a rates hub h at level k or below.
- θ_k: Threshold (cutpoint) parameters that separate the cumulative logits at each rating level k.
- $\beta_1,\beta_2,\ldots,\beta_6$: Coefficients that quantify the impact of each attribute on hub preferences.
- $\text{Age}(a), \text{Gender}(a), \ldots, \text{Occupation}(a)$: Predictor variables representing the attributes of agent a.

2. Logistic regression model for factor weights: For the location factors, which are binary (0 or 1), we use a logistic regression model to calculate the factor weight $\widehat{w}_f(a)$ based on agents' attributes. The model is as follows:

$$\begin{aligned}&\mathrm{logit}\big(P\big(F_f(a)=1\big)\big)=\\&\beta_0+\beta_1\cdot\mathrm{Age}(a)+\beta_2\cdot\mathrm{Gender}(a)+\beta_3\cdot\mathrm{EducationLevel}(a)\\&+\beta_4\cdot\mathrm{ReasonForMoving}(a)+\beta_5\cdot\mathrm{ResidentialHistory}(a)\\&+\beta_6\cdot\mathrm{Occupation}(a)\end{aligned}\tag{2}$$

where:

- $P\big(F_f(a)=1\big)$: Probability that agent a selects factor f as important.
- $\beta_0,\beta_1,\ldots,\beta_6$: Regression coefficients that quantify the impact of each attribute on the selection of the factor.

Once the regression models are estimated, the weights $\widehat{p}_h(a)$ for hub preferences and $\widehat{w}_f(a)$ for factor weights are incorporated into the utility function $U(a,l)$ to model the agent's decision-making process.

- Calculation of similarity and dissimilarity: The social influence score $SI(a,l)$ depends on the similarity $\mathrm{Sim}(a,\mathrm{neighbors}(l))$ and dissimilarity $\mathrm{Diff}(a,\mathrm{neighbors}(l))$ between agent a and the agents in its neighboring locations. These measures are defined as follows:

1. Similarity score $\mathrm{Sim}(a,\mathrm{neighbors}(l))$: The similarity score between an agent a and its neighboring agents is calculated based on the overlap in their preferences for urban hubs and important location factors. Let $\widehat{p}_h(a)$ and $\widehat{w}_f(a)$ represent the preferences for hubs and weights for factors of agent a, respectively. The similarity between agent a and an average of its neighbors at location l is defined as:

$$\begin{aligned}&\mathrm{Sim}(a,\mathrm{neighbors}(l))=\\&\frac{1}{N_{\mathrm{neighbors}(l)}}\sum_{b\in\mathrm{neighbors}(l)}\left(\sum_h|\widehat{p}_h\left(a\right)-\widehat{p}_h\left(b\right)|\right.\\&\left.+\sum_f|\widehat{w}_f\left(a\right)-\widehat{w}_f\left(b\right)|\right)\end{aligned}\tag{3}$$

where:

- $\widehat{p}_h(a)$ and $\widehat{p}_h(b)$ are the preferences for hub h of agents a and b, respectively.
- $\widehat{w}_f(a)$ and $\widehat{w}_f(b)$ are the importance weights for factor f of agents a and b, respectively.
- $N_{\mathrm{neighbors}(l)}$ is the number of neighboring agents at location l.

The smaller the absolute differences between the preferences and factor weights of agents a and its neighbors, the higher the similarity score.

2. Dissimilarity score $\mathrm{Diff}(a,\ \mathrm{neighbors}(l))$: The dissimilarity score measures the extent of difference between agent a's preferences and those of its neighbors at location l. This is calculated in a similar fashion but emphasizes the presence of larger differences:

$$\begin{aligned}&\mathrm{Diff}(a,\mathrm{neighbors}(l))=\\&\frac{1}{N_{\mathrm{neighbors}(l)}}\sum_{b\in\mathrm{neighbors}(l)}\left(\sum_h\big(1-|\widehat{p}_h(a)-\widehat{p}_h(b)|\big)\right.\\&\left.+\sum_f\big(1-|\widehat{w}_f(a)-\widehat{w}_f(b)|\big)\right)\end{aligned}$$

where the terms capture how dissimilar the preferences and factor weights are between agent a and its neighbors.

3.4. Measuring segregation

In this section, we detail the method we used to quantify segregation levels within the model, providing a clear measure of the impact of individual preferences and social interactions on urban segregation:

1. Hub proportions: For each hub type, calculate the proportion of agents currently residing in that hub type. This is performed by counting the number of agents in each hub type and dividing by the total number of agents. We denote p_i to be the proportion of agents in hub type i.
2. Mean proportion: Calculate the mean proportion of agents across all hub types. This is the average value of p_i for all hub types. We denote $\overline{p}$ to be the mean proportion.
3. Dissimilarity index: The dissimilarity index is calculated as half the sum of the absolute differences between the proportion of agents in each hub type and the mean proportion. Mathematically, it is given by:

$$\text{Dissimilarity Index}=\frac{1}{2}\sum_i|p_i-\overline{p}|$$

The derivation of the dissimilarity index employed in our analysis adheres to established methodologies in quantitative sociology and urban studies (Bandauko et al., 2022; Cole et al., 2021; Owens, 2020), which utilize this metric to assess spatial and social segregation. By calculating the absolute differences between the proportion of agents in each hub and the overall mean proportion, we capture the variance in agent distribution, reflecting underlying segregation dynamics. The inclusion of a normalization factor of $\frac{1}{2}$ ensures that the index scales appropriately from 0, indicating no segregation, to 1, denoting complete segregation. This normalization is critical for maintaining consistency with conventional uses of the index, allowing our results to be comparable across studies and applicable in diverse urban planning scenarios.

If the dissimilarity index is high, it means that there is a high level of segregation within the grid. Specifically, it indicates that agents are unevenly distributed among the different types of hubs. In other words, certain hub types are predominantly occupied by agents, while others have fewer agents. This can be a sign of clustering or grouping of agents based on their preferences or social influence, leading to a more segregated environment.

A high dissimilarity index suggests that the urban environment represented by the grid is characterized by distinct neighborhoods or areas with different compositions of agents, rather than a more integrated and diverse community where agents are evenly distributed across all hub types.

4. Simulation experiments

The primary goal of our simulation experiments is to explore the dynamics of urban segregation in response to varying parameters within an agent-based model. By manipulating elements such as the size and distribution of different types of urban hubs and the thresholds for agent movement, we aim to understand how these factors influence patterns of segregation and individual agent satisfaction within simulated urban environments. These experiments are also designed to test hypotheses about the impact of urban layout and policy interventions on the spatial distribution of agents, providing insights that could inform real-world urban planning and policy-making.

We performed the following steps for conducting the simulation experiments:

1. Parameter setting: In our agent-based simulation model, we defined the following key parameters to explore the dynamics of urban segregation.

- Number of agents (N): This parameter determines the total number of agents in our simulation. We experiment with different population sizes, ranging from 100 to 300 agents, to observe how varying densities impact segregation patterns.
- Hub sizes (H): Each hub in our grid represents a specific area type, such as an economic or educational zone. We explore different hub sizes to simulate various urban layouts and study their effects on agent behavior.
- Number of hubs per type (HPT): This parameter specifies the number of hubs for each area type in our simulation. We investigate how the density of different hubs influences the segregation patterns and agent satisfaction.
- Score threshold (ST):This parameter establishes a threshold for an agent's satisfaction score, prompting them to assess potential relocation alternatives only if their utility scores exceed this value. We will explore different threshold values to understand how they impact the overall dynamics of segregation and agent satisfaction.

By systematically varying these parameters, we aim to gain insights in the factors that influence urban segregation and the emergent patterns of agent distribution in simulated environments.

2. Initialization: We set up the initial conditions of the grid, specifying the locations of the hubs and the starting positions of the agents. To enhance the robustness of our experiment, we create different initial conditions for each trial.
3. Simulation Execution: We run predetermined number of simulation iterations, selected based on initial testing, ensuring that the agents have sufficient time to exhibit their movement behaviors. In each iteration, agents may move up to 5 cells towards their preferred hubs, facilitating a more realistic approach to reaching desired locations on the grid. This adjustment ensures that agents can adequately respond to changes in the environment and move efficiently towards areas that best match their preferences. The agents move according to the defined model that considers their preferences and the current state of the grid. The model evaluates potential moves by calculating the utility of each location for every agent, taking into account their preferences along with the proximity and attractiveness of different hubs. After the agents move, the model calculates the segregation pattern, dissimilarity index, and average happiness score for each iteration. This methodological approach enables a dynamic and responsive simulation that closely mimics real-world urban mobility and choice.
4. Data analysis: After completing the simulations, we analyze the results. We visualize the segregation patterns and plot the changes in the dissimilarity index and average happiness score over time. Comparing the outcomes of different trials helps us understand the consistency and variability of our model.
5. Confidence interval calculation: To improve the accuracy of our results and reduce the size of confidence intervals, we conduct multiple runs of the simulation with varying numbers of iterations (e.g., 10, 50, 100, 200). We calculate the mean and standard deviation of the dissimilarity index and average happiness score for these runs. Using this data, we compute the 95 % confidence intervals and display them on the graphs.
6. Interpretation of results: Finally, we interpret the results, attempting to identify emergent patterns and the effects of different parameters and initial conditions on the segregation patterns, dissimilarity index, and average happiness score. This analysis provides insights into the dynamics of the model and the factors influencing agent satisfaction and segregation.

4.1. Iteration number in simulation experiments

In our study, we originally utilized a time step of one year for simulating the urban segregation dynamics. However, upon further evaluation and initial simulation runs, we discovered that a time step of one month provides a more granular and realistic portrayal of urban dynamics for the following reasons:

- Responsiveness to rapid urban changes: Urban environments can undergo significant changes within a year, especially in fast-developing areas. Monthly iterations allow us to capture these rapid changes more effectively, aligning with the pace at which new amenities are introduced and economic opportunities evolve (Xiong et al., 2023; Zhang et al., 2023).
- Alignment with dynamic policy and socioeconomic cycles: While major policy changes and socioeconomic updates are often evaluated annually, their impacts can be felt on a much shorter scale. Monthly simulations allow us to more closely monitor the immediate effects of such changes and their influence on residents' decisions (Rafieian & Kianfar, 2023).
- Detailed simulation of migration decisions: A monthly time frame enables the simulation to capture the nuances of decision-making processes among urban dwellers. People often react to changes in their environment on a short-term basis, and a monthly step provides the granularity needed to simulate these reactions more accurately (Asadzadeh et al., 2022).
- Computational manageability: While increasing the frequency of iterations adds computational load, modern computational resources are typically well-equipped to handle more detailed simulations. The monthly step strikes a balance between detail and computational efficiency, ensuring that the simulation remains manageable yet detailed enough to be meaningful (Vilanova et al., 2024).
- Consistency with empirical data availability: Data on urban changes, such as housing prices, rental rates, and demographic shifts, is often available on a monthly basis. Simulating on a monthly basis allows us to use this data more effectively, enhancing the empirical grounding of our model (Otto et al., 2024; Zhang et al., 2020).

These reasons collectively justify our choice of a time step of one month, ensuring that our simulation not only aligns with the rapid pace of urban changes but also remains computationally viable and empirically robust, providing insightful and actionable results.

4.2. Experiment results

Before examining the outcomes of our simulations, it is essential to outline the methodological framework and initial conditions that governed our experimental setup.

Firstly, we defined the simulation parameters that govern the environment and agent dynamics, as shown in Table 4. This table provides an overview of the key parameters and their corresponding values, which define the structure and scope of the simulation, ensuring consistency and replicability across runs.

Secondly, we established the initial conditions for our simulations through the generation of heterogeneous data. This data, representing agents' preferences and attributes, was randomly generated to reflect the diversity typical of urban populations. Such an approach ensures that our model accurately captures the complex interplay of individual

Table 4
Simulation parameters.

Parameter	Value
Grid size	50 × 50
Number of agents	100
Sizes of hubs	[8, 8, 8, 8]
Number of hubs per type	[2, 2, 2, 2]
Score threshold for agent movement	0.5
Number of iterations per simulation	20 years
Number of runs	50

preferences impacting urban segregation dynamics.

Furthermore, the simulation is entirely implemented in Python without relying on any specific simulation library. The model uses custom-written code for defining agent behaviors, interactions, and movement algorithms. Python's built-in functions and NumPy are utilized for efficient numerical operations, such as calculating distances, preferences, and utility scores. Scikit-learn is employed for implementing logistic regression models, providing robust methods for binary classification tasks. For ordinal logistic regression analyses, we use the statsmodels library, which offers comprehensive statistical modeling capabilities. For data management and visualization, we use Pandas to handle and manipulate datasets, and Matplotlib and Seaborn to generate clear visual representations of segregation patterns, changes in dissimilarity index, and average happiness scores. SciPy is employed for statistical analysis, including the calculation of confidence intervals to assess the robustness of our findings. Fig. 3 illustrates the flow diagram of the simulation process for our urban segregation model.

Fig. 1 offers a visual narrative of agent dynamics within a simulated environment, reflecting movement preferences influenced by certain demographic attributes.

In Fig. 1a, we observe the initial stage of the simulation, where agents are scattered throughout the grid. This initial distribution serves as a baseline for the simulation, capturing agents' starting points prior to the execution of the model's steps. The hubs, represented by colored squares, are not yet densely populated, suggesting a random placement of agents irrespective of their preferences.

Fig. 1b depicts the culmination of the simulation at the 20th year, or after 20 iterations. It is evident that a significant shift has occurred, with agents now more concentrated within specific hubs. This aggregation reflects the underlying preference mechanisms dictating agent movement, leading to a pronounced segregation within the grid. Each color corresponds to a hub type, and the clustering of agents within these hubs illustrates their tendency to move towards preferred areas over time.

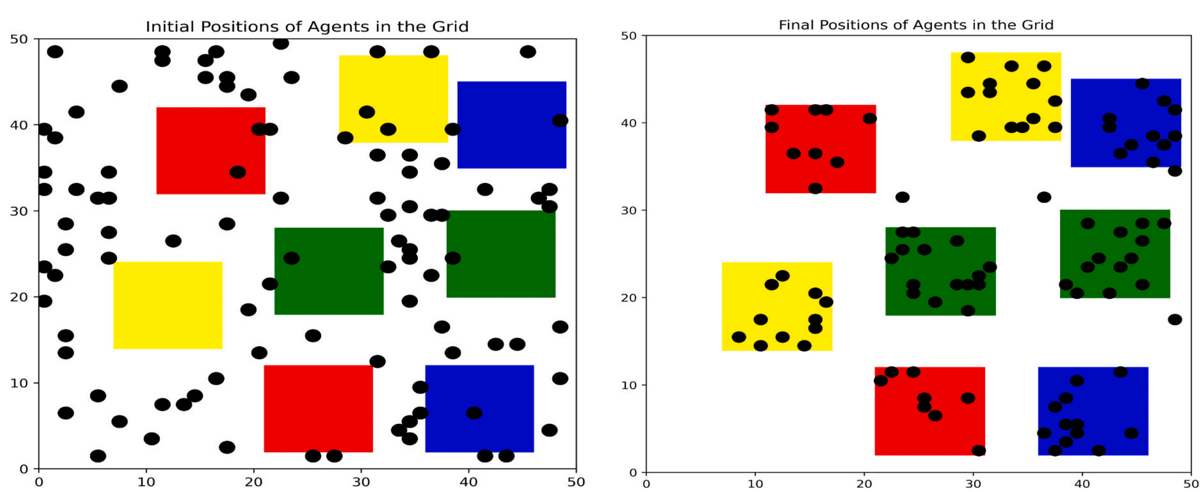
Fig. 2 quantitatively reinforces the observations from Fig. 1. It provides a temporal account of the number of agents in each hub over the 20 years of simulation. The traces show fluctuating trends but generally indicate a decrease in the 'Non-Specific' category, paralleled by an increase or stabilization within the designated hubs. The transitions within these lines encapsulate the migratory patterns of the agents, underscoring the pull of the hubs' attributes on the agents' locational choices.

Collectively, Figs. 1 and 2 underscore the dynamic nature of agent distribution and the impact of preference-driven movement within a controlled environment. They provide a visual and quantitative testament to the process of segregation and aggregation that is emblematic of such simulations.

Fig. 4 illustrates the trajectory of the average normalized score across iterative time points, denoted as years. We observe an initial value of approximately 0.4, indicative of a lower degree of satisfaction or fitment to preferred conditions among agents. The graph exhibits a steady increase in the normalized score, reaching a value closer to 0.85 as iterations advance towards the 20-year mark. This progressive increase can be interpreted as an enhancement in the overall satisfaction of agents within the simulated environment. The agents are likely finding or transitioning to hubs that align more closely with their preferences, whether these are dictated by socio-economic factors, environmental desires, or other modeled criteria within the simulation. The shaded region represents the 95 % confidence interval around the mean score, providing a statistical buffer that suggests variability and uncertainty inherent in the simulation's dynamics. The width of this confidence interval denotes the expected fluctuation in the mean score and implies a convergence of agent preferences over time as the breadth narrows in later years, which could indicate a stabilizing of agents' satisfaction levels within the urban model.

Fig. 5 presents the dissimilarity index, a quantitative measure of segregation within the grid. A cursory analysis reveals a precipitous decline in the index from its initial value, hovering around 0.5, to plateau near a value of 0.1. This suggests a rapid de-segregation in the initial years, followed by a slower rate of integration as the simulation progresses. The high initial value points towards a significant level of segregation, where agents are possibly clumped by hub types, reinforcing homogeneity within certain areas while others remain less inhabited. Over time, as the dissimilarity index decreases, it signals a transition towards a more integrated urban landscape where agents are more evenly distributed among the various hub types. The notable drop in the dissimilarity index can be attributed to the agents' mobility within the grid, pursuing their preferences, or perhaps as a result of evolving socio-dynamic factors that incentivize a dispersion that counters initial clustering tendencies. The gradual nature of this decline also underscores the interplay between agents' individual decisions and the broader systemic pressures that guide urban evolution in the model.

The confidence interval around the mean dissimilarity index mirrors this trend and tightens over time, indicating an increasing predictability and uniformity in the agents' distribution across the grid. This might suggest that the variability of segregation levels is reducing, potentially due to the diminishing impact of initial conditions or the efficacy of implemented policies within the simulation that promote diversity and integration.



(a) Initial grid. (b) Final grid.

Fig. 1. Distribution of agents in the grid through years.

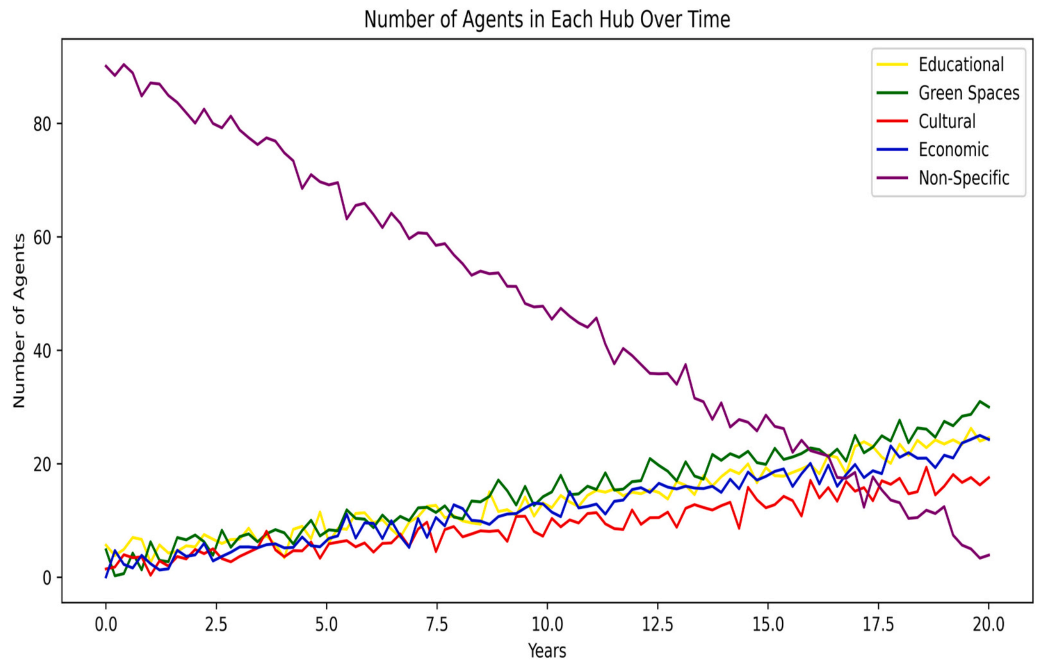


Fig. 2. The Change of the number of agents in each hub through iterations.

In conclusion, Figs. 4 and 5 provide insights into the temporal dynamics of agent satisfaction and urban segregation. It allows for the characterization of the simulated environment in terms of agents' preferences satisfaction and segregation levels, showcasing the complex interdependencies and adaptive nature of the agents' interactions with their urban settings.

4.3. Heterogenity effect on model outputs

This subsection focuses on a key experiment designed to examine the dynamics of urban segregation with a specific emphasis on agent heterogeneity. Drawing inspiration from Schelling's segregation model, we extend its application by incorporating a diverse array of fixed-location urban hubs. The motivation behind this experiment is to assess how varying levels of heterogeneity among agents influence the emergence and evolution of segregation patterns over time. The goal is to understand whether a richer mix of individual preferences for urban amenities—such as economic centers, educational institutions, cultural hotspots, and green spaces—leads to more integrated urban areas or if it exacerbates segregation. By analyzing the interplay of these factors, the experiment aims to shed light on the potential for urban planning interventions to foster more cohesive urban landscapes.

In Fig. 6, the y-axis quantifies the average normalized happiness score of agents, providing an index of their contentment within the urban model over a span of 20 years. The data reveals a trend where higher levels of agent heterogeneity—represented by scores ranging from 0.8 to 1.0—correlate with increased happiness scores. These agents consistently reach and sustain elevated scores, suggesting a more stable satisfaction with their environment. In stark contrast, agents characterized by lower heterogeneity levels (0.1–0.3) experience more fluctuations and, on average, lower happiness scores. This observation suggests that a greater diversity of agent preferences may contribute to an improved overall satisfaction with the urban spaces they inhabit.

Turning to Fig. 7, ‘Dissimilarity Index by Heterogeneity Level,’ we observe an inverse correlation. A higher dissimilarity index, indicating greater segregation, is associated with lower heterogeneity among agents. As heterogeneity increases, the index decreases, signaling more integrated communities. Noteworthy within this figure are the significant declines in the dissimilarity index at certain points, suggesting that particular model changes or events may have substantially reduced segregation.

From these figures, we infer that the diversity of agents' preferences is crucial for their happiness and the integration of the community as a whole. This highlights an important consideration for urban development: promoting a variety of urban amenities that cater to diverse preferences could be essential in developing more cohesive urban areas. The experiment's findings are particularly valuable for urban planners and policymakers, as they underscore the potential of diversity to reduce urban segregation.

This experiment demonstrates the value of modeling to understand complex social phenomena. By simulating individual preferences and observing their effects on urban segregation, we gain a clearer picture of how a range of needs and desires impact the structure and happiness of urban communities. These insights are crucial for developing strategies to create inclusive and harmonious urban environments. Moreover, the dynamic visualization tools utilized in this study facilitate the communication of these complex dynamics, making them accessible to a broader audience and enriching the decision-making process. Overall, the experiment stands as an informative and educational resource in the ongoing effort to understand and address urban segregation.

4.4. Impact of policy interventions on model outputs

This section presents an analytical exploration of the effects of policy interventions on the dynamics of urban segregation. We consider an array of interventions, conceptualized as alterations to the parameters governing the heterogeneous Schelling's model—specifically, the number and size of hubs, and the score threshold dictating agent movement. The heterogeneity in hub sizes and types within the simulation provides a realistic ground for assessing the outcomes of such policies, with the aim of understanding how strategic urban planning can influence social integration and satisfaction.

The following interventions are examined:

- Modification of hub sizes (H): Policies that directly affect the physical space, such as development or downsizing of certain hub types, are simulated. We vary the dimensions of the hubs to observe how

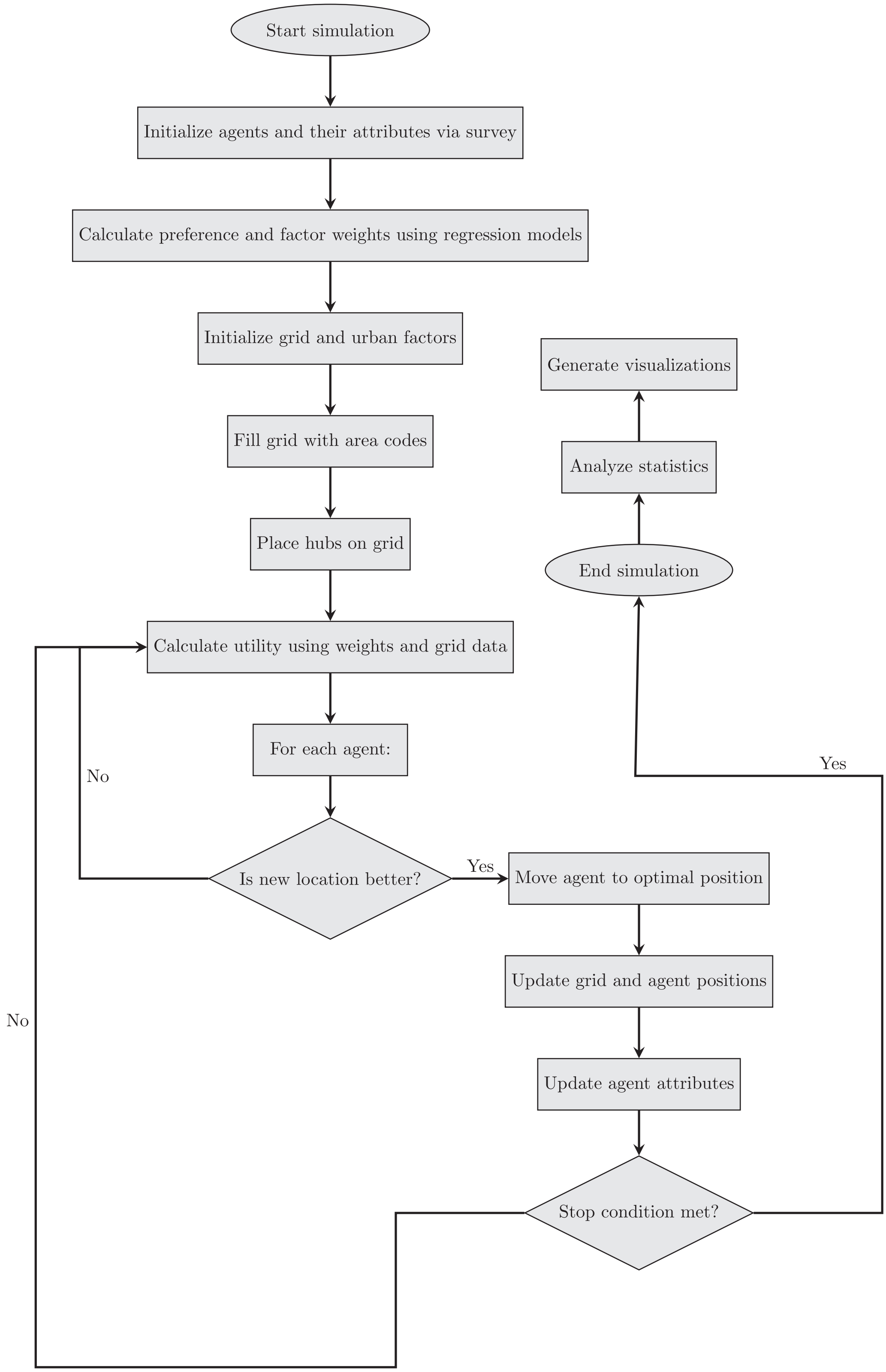


Fig. 3. Flowchart of the simulation process for urban segregation modeling.

changes in the size of economic, educational, cultural, and green spaces affect agent happiness and segregation.

- Alteration in the number of hubs per type (HPT): Interventions that result in the addition or reduction of hubs reflect changes in urban amenities and infrastructure. We analyze scenarios where the number of each type of hub is systematically adjusted to reflect different urban development strategies.
- Adjustment of score threshold (ST): Policy-induced modifications in the score threshold reflect changes in the socio-economic environment that could alter agents' satisfaction levels. This could simulate

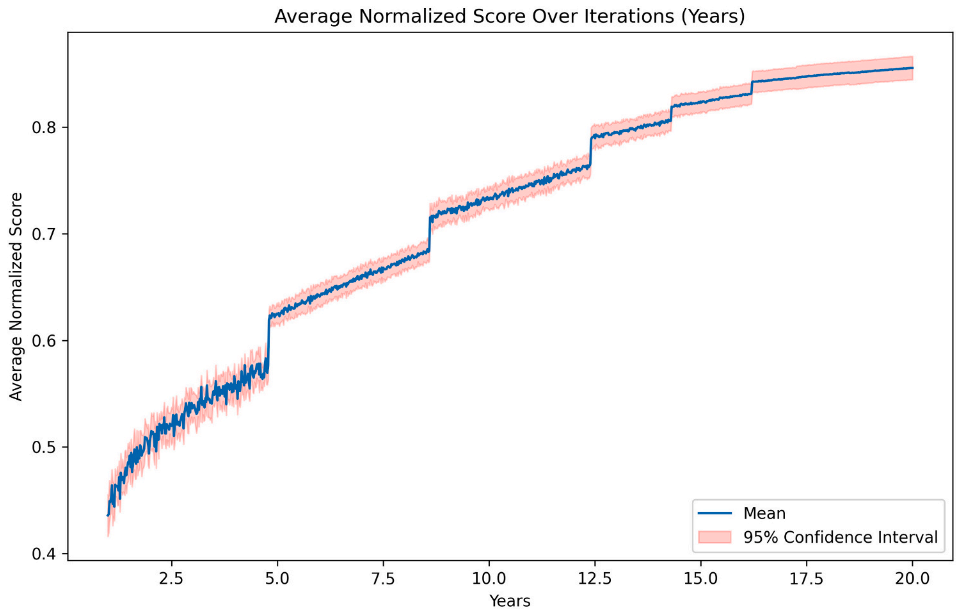


Fig. 4. Evolution of the average normalized happiness score over time.

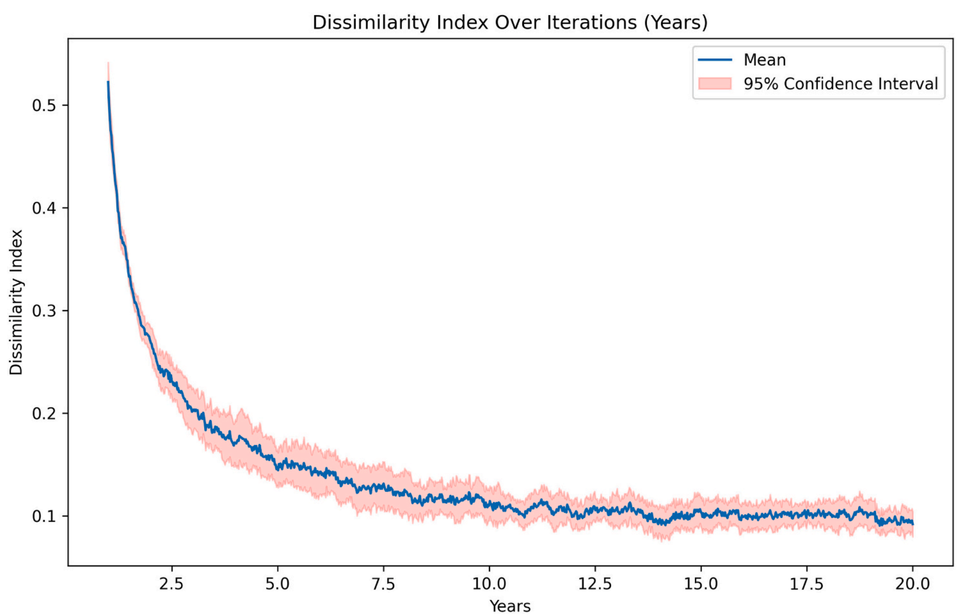


Fig. 5. Trend in the dissimilarity index across simulation years.

the effect of initiatives designed to enhance the appeal of certain hub types or improve general living conditions.

In our exploration of urban segregation dynamics through the lens of the Schelling's model, we tested several policy intervention scenarios. These scenarios were designed to alter key aspects of the urban environment to understand how changes in urban planning could influence social integration and the overall satisfaction of city residents. Below is a summary of the specific scenarios we tested, along with their intended objectives:

1. Increasing the number of educational hubs: This scenario aims to simulate the impact of a significant investment in the city's educational infrastructure. By increasing the number of educational hubs, we sought to explore how improved access to education affects the spatial distribution of agents and their overall satisfaction. This policy could reflect a strategic initiative to enhance educational opportunities, potentially leading to broader socio-economic benefits such as a more skilled workforce and a vibrant, knowledgeable community.
2. Expanding the size of green spaces: In this intervention, we expanded the size of green spaces within the simulation to examine the effects of larger parks and recreational areas on urban residents. The goal was to assess how these enhancements contribute to public health, happiness, and reduced urban segregation. Enlarging green spaces is often seen as a means to improve the quality of urban life, offering residents more room for leisure, exercise, and social interactions in natural settings.
3. Decreasing the score threshold for moving: This scenario reduced the threshold score required for agents to relocate within the city, aiming to create a more dynamic and adaptable urban environment. By facilitating easier movement, we tested whether policies aimed at

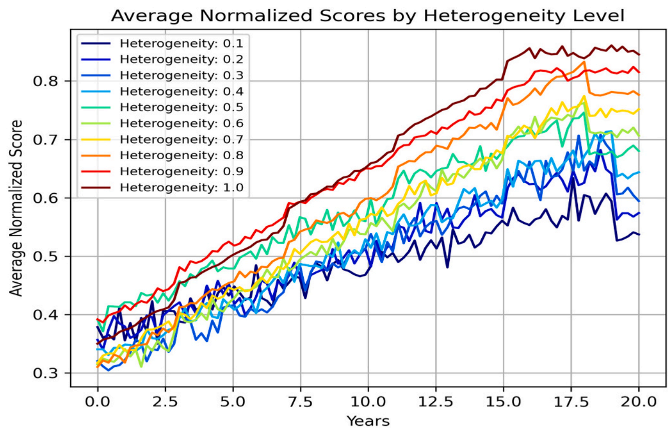


Fig. 6. Impact of heterogeneity on average normalized happiness over 20 years.

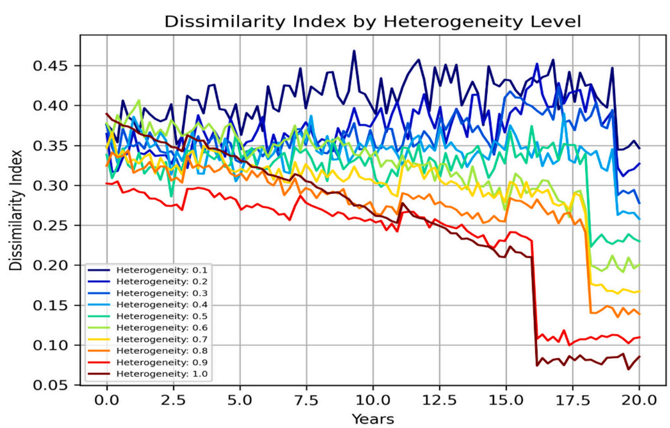


Fig. 7. Dissimilarity index trends across varying levels of heterogeneity over 20 years.

increasing housing flexibility and affordability could lead to less segregated and more integrated urban communities. Such a policy might simulate the impact of reduced barriers to moving, allowing residents to more freely choose their living arrangements based on personal and familial needs.

The simulations conducted to analyze the impact of various urban policy interventions on segregation dynamics and resident satisfaction are summarized in Table 5. This table outlines the distinct parameter values for each scenario, representing the respective policy focus areas. For instance, the 'Increased Educational Hubs' scenario reflects a policy decision to enhance the city's educational facilities, while 'Expanded Green Spaces' and 'Lowered Movement Threshold' scenarios indicate a prioritization of recreational space and mobility, respectively. Each scenario has been carefully crafted to gauge the potential effects of these policy choices on the urban environment.

Each scenario provides valuable insights into how different types of urban planning interventions might affect the living conditions and choices of urban residents. By altering the parameters that govern hub sizes, the number of hubs, and the mobility of agents, these simulations offer a data-driven glimpse into potential strategies that urban planners and policymakers might employ to foster more inclusive and harmonious urban environments.

Upon reviewing the outcomes of our urban segregation model under various policy interventions, we can infer the following implications from the figures relative to the default model settings:

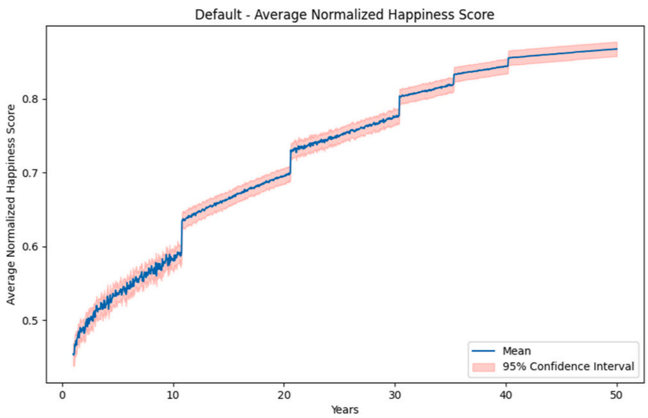
1. Default scenario: Fig. 8a shows a steady increase with a stepwise pattern, suggesting periodic adjustments by agents or policy changes. In Fig. 9a, the dissimilarity index decreases rapidly initially and then stabilizes, indicating initial integration followed by a steady state of segregation dynamics.
2. Expanded green spaces: Fig. 8b shows a higher trajectory for the average normalized happiness score compared to the default model. This indicates that policies which enlarge recreational areas could lead to increased agent satisfaction. In Fig. 9b, the dissimilarity index initially follows a similar sharp decline but remains lower than the default scenario throughout the simulation, implying more effective integration and less segregation as a result of expanded green spaces.
3. Increased educational hubs: Increasing educational hubs leads to a higher average normalized happiness score than the default scenario, suggesting that more educational facilities contribute positively to agents' contentment (see Fig. 8c). This aligns with expectations that access to education can enhance life satisfaction. The dissimilarity index declines at a similar rate to the default scenario but maintains a slightly lower profile over time, indicating a modest reduction in segregation through this policy (see Fig. 9c).
4. Lowered movement threshold: Lowering the threshold required for movement shows the most significant impact on average normalized happiness scores, climbing steadily and surpassing other scenarios (see Fig. 8d). This suggests that easier mobility across the city allows agents to find their preferred locations more readily, leading to higher overall happiness. The dissimilarity index reduces sharply, like in other scenarios, but shows a more pronounced decline over time, indicating that facilitating movement can lead to a more integrated urban environment (see Fig. 9d).

The results of these interventions suggest a clear correlation between policy initiatives and improved agent satisfaction and integration within the city. Expanding green spaces and increasing educational hubs both lead to higher happiness and slightly reduced segregation compared to the default model, with the former having a more notable impact on integration. Meanwhile, reducing barriers to movement appears to be the most effective approach to boosting satisfaction and minimizing segregation, highlighting the importance of mobility and accessibility in urban planning.

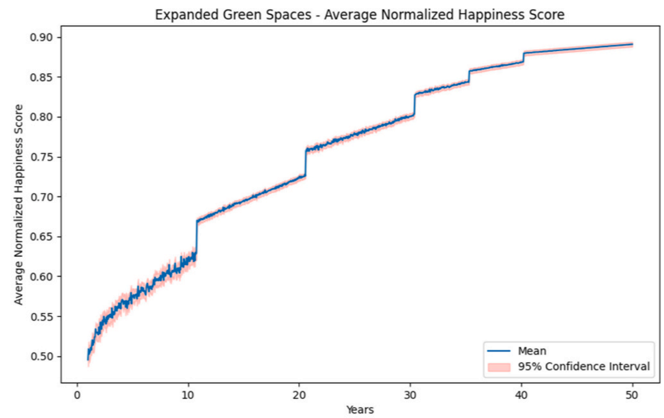
These findings advocate for policies that prioritize the expansion of communal and educational spaces and reduce restrictions on movement, indicating that such strategies could significantly enhance urban living conditions. The model results serve as a quantitative backing for urban planning initiatives aimed at fostering inclusive and desirable cities. These insights could guide future policy-making, focusing on the development of dynamic urban environments where residents have the freedom and capacity to choose where they live based on their preferences and needs, leading to more harmonious and integrated communities.

5. Exploring real-world dynamics: a survey-based approach to applying the extended Schelling's model of urban segregation

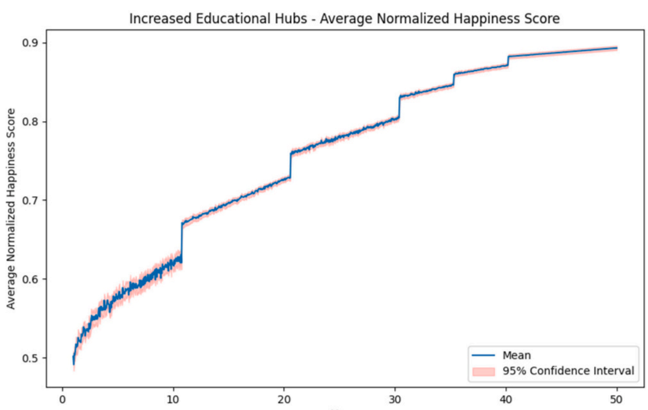
The effectiveness of any urban model hinges on its ability to accurately reflect real-world complexities. As we explore the multifaceted issue of urban segregation, grounding our theoretical models in robust empirical evidence becomes crucial. The extended Schelling's Model is particularly adept at capturing the dynamic nature of urban environments. This model serves as a practical guide for researchers and practitioners who aim to apply it to their specific contexts. To facilitate this, we provide a detailed methodology for conducting surveys and gathering data that reflects the actual preferences, behaviors, and choices of urban residents. This section outlines the steps necessary to adapt our model to different urban areas, ensuring that users can accurately simulate and analyze segregation patterns based on localized data. By aligning the model's parameters with survey-derived insights, we enable



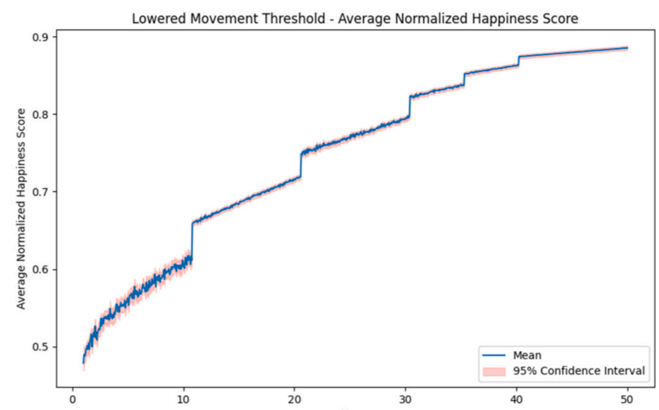
(a) Default scenario



(b) Expanded green spaces



(c) Increased educational hubs



(d) Lowered movement threshold

Fig. 8. Trends of average normalized happiness score over 50 years for different scenarios: (a) Default scenario, (b) Expanded green spaces, (c) Increased educational hubs, (d) Lowered movement threshold. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

users to not only comprehend but actively shape the evolutionary dynamics of urban spaces. The following steps should be performed for implementing the survey-based extension of the proposed model.

1. Survey design Objective Definition: Clearly define the objectives of the survey, focusing on understanding agents' preferences for different urban areas and the factors influencing these preferences.

- Questionnaire development:
  - Demographic questions: Include questions on age, gender, income level, education, and occupation. Preference assessment: Use a Likert scale (e.g., 1 to 5) to assess preferences for economic, educational, cultural, and green Spaces.
  - Factors influencing preferences: Ask open-ended questions about factors that influence their preferences (e.g., proximity to work, educational opportunities, cultural amenities, recreational spaces).
- Residential history: Include questions about past and current residential locations and reasons for choosing these areas.
- Future Aspirations: Inquire about future residential plans and how they align with current preferences.
- Pilot testing: Conduct a pilot test of the survey with a small group to identify any issues with question clarity or survey length.

2. Data collection

- Sampling: Determine the target population and sampling method (e.g., random sampling, stratified sampling) to ensure representativeness.
- Distribution: Choose the appropriate distribution method (e.g., online platforms, face-to-face interviews, phone surveys).
- Response Monitoring: Monitor response rates and follow up as needed to ensure sufficient data collection.

3. Data analysis

- Data cleaning: Check for incomplete responses, outliers, and inconsistencies.
- Descriptive analysis: Analyze demographic data and preferences for urban areas to identify patterns and trends.
- Factor analysis: Use factor analysis to identify underlying factors influencing preferences.
- Correlation analysis: Examine correlations between demographic variables and preferences to understand how different factors are related.

4. Model Application

- Parameter calibration: The model's parameters, such as agents' preferences and factor weights, are calibrated using survey data through regression models. These models take into account the relationships between demographic attributes (such as age, education level, and occupation) and preferences for different hubs or

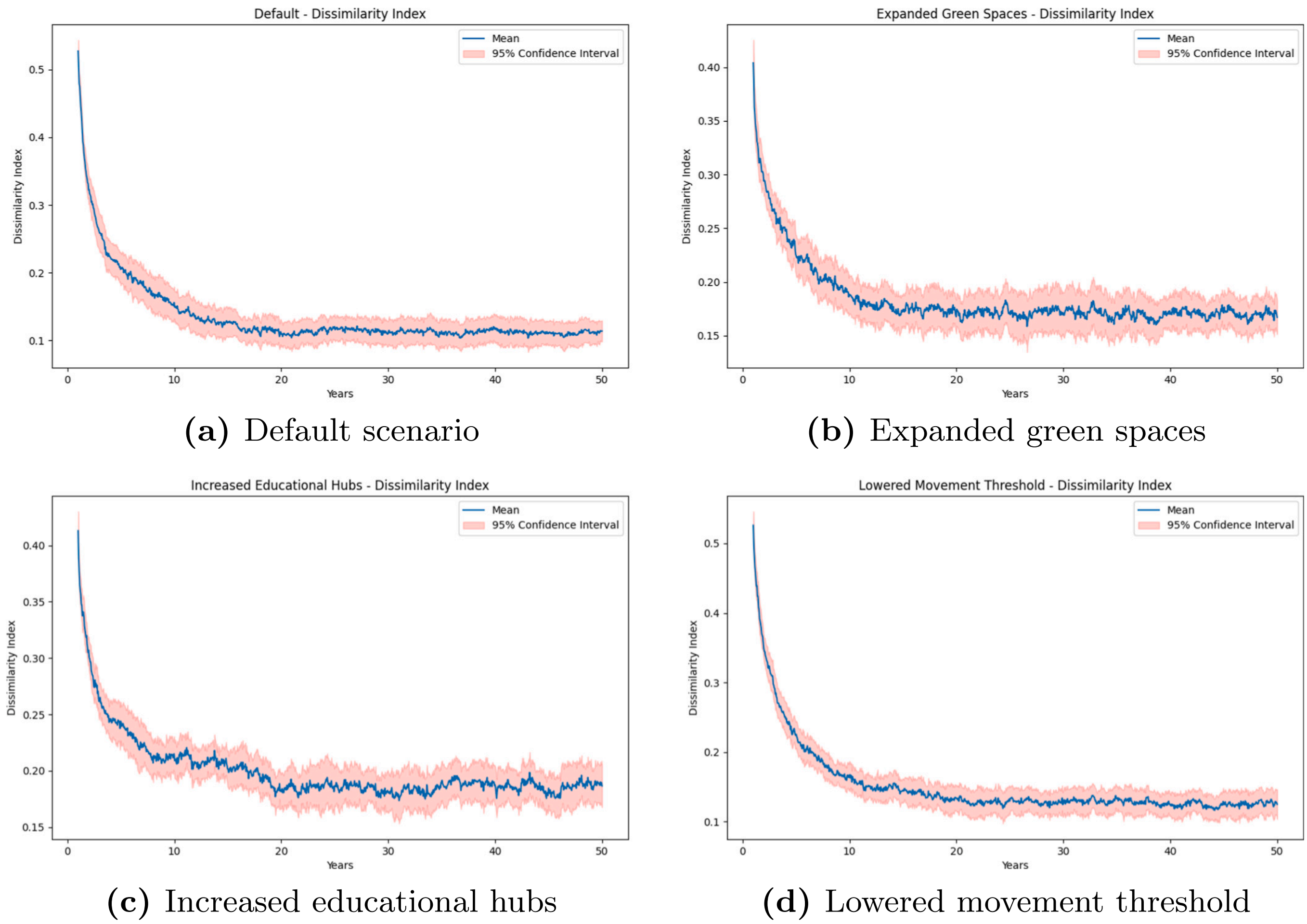


Fig. 9. Evolution of the dissimilarity index over 50 years for different scenarios: (a) Default scenario, (b) Expanded green spaces, (c) Increased educational hubs, (d) Lowered movement threshold. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Policy scenarios and their parameter values used in the simulation.

Scenario name	Hub sizes (H)	Number of hubs per type (HPT)	Score threshold (ST)
Default	[8, 8, 8, 8]	[2, 2, 2, 2]	0.5
Increased Educational Hubs	[8, 12, 8, 8]	[2, 3, 2, 2]	0.5
Expanded Green Spaces	[8, 8, 8, 12]	[2, 2, 2, 3]	0.5
Lowered Movement Threshold	[8, 8, 8, 8]	[2, 2, 2, 2]	0.3

important factors. This approach ensures that the weights for preferences and factors are not arbitrarily assigned but are derived from empirical data, capturing the real-world variation observed in the survey findings.

- Simulation runs: Run simulations with the calibrated model to observe how different preferences lead to segregation patterns.
- Scenario analysis: Test different scenarios (e.g., changes in urban policies, development of new amenities) to assess their impact on segregation dynamics.
- Validation: Compare simulation results with real-world data to validate the model's accuracy and reliability.

5. Policy implications

- Insight generation: Use the model's insights to identify key drivers of urban segregation and potential areas for intervention.
- Recommendations: Develop recommendations for urban planners, policymakers, and developers to create more inclusive and integrated urban environments.
- Stakeholder engagement: Engage with relevant stakeholders to discuss findings and explore opportunities for collaboration in addressing urban segregation. By integrating the survey data into the extended Schelling's model, researchers can enhance the model's realism and applicability, providing valuable insights into the complex dynamics of urban segregation.

6. Conclusion

In this paper, we present an extended Schelling's model, tailored to reflect the multifaceted dynamics of urban segregation, underscored by individual preferences and social interactions. Through our innovative approach that incorporates distinct hubs reflective of real-world urban amenities, we have furnished a more granular insight into the patterns of urban segregation and the ensuing social stratifications.

Key findings from our simulation study indicate that heterogeneity in agent preferences and mobility significantly influences the spatial configuration of cities, thereby affecting segregation indices and satisfaction levels. Our research has highlighted several core insights:

- The inclusion of diverse urban hubs such as Economic, Educational, Cultural, and Green Spaces adds depth to the classic Schelling model, allowing for the representation of more complex urban dynamics.
- Agents' preferences play a significant role in determining the landscape of urban segregation. A greater diversity in preferences tends to result in higher satisfaction and lower segregation indices.
- Policy interventions, such as the expansion of green spaces and educational hubs, as well as lowered thresholds for movement, can lead to improved agent happiness and a more integrated urban fabric.
- Our survey-based approach for data collection enables the alignment of the model's parameters with empirical evidence, thus enhancing its realism and applicability to real-world scenarios.

In conclusion, our proposed extended Schelling model offers a robust methodology for visualizing and analyzing urban segregation, providing valuable insights for urban planners. Our findings demonstrate that by incorporating diverse urban hubs—such as economic, educational, cultural, and green spaces—the model captures the complex dynamics of modern cities. Understanding individual preferences and applying strategic policy interventions, such as expanding green spaces or redistributing hubs, can significantly influence urban planning outcomes. This approach helps policymakers simulate the effects of various strategies, supporting balanced socio-economic development, reducing segregation, and enhancing residents' mobility. Moreover, the model enables planners to align short-term solutions with long-term goals, fostering more integrated and inclusive urban environments.

To enhance the model's reliability and applicability across diverse regions, future studies should consider validating the proposed segregation model with real-world data. Although our study used a survey-based approach to align model parameters with empirical evidence, this method represents a form of evidence-based modeling, as it directly incorporates real-world preferences and behaviors into the model. This approach has helped ensure the model's reliability by grounding its assumptions in actual data. However, further validation efforts could involve applying the model to various urban settings and comparing the outcomes with observed data, providing a more comprehensive understanding of how segregation evolves under different scenarios. Furthermore, incorporating additional layers of complexity, such as economic factors, employment dynamics, and environmental policies, could offer a more comprehensive understanding of urban segregation. The integration of longitudinal real-world data would also refine the model, allowing for a dynamic perspective on the evolution of cities over time and further strengthening the robustness of the findings.

Through our contributions, we aim to spark continued research and discussion on the topic, fostering advancements in the field of urban planning and providing meaningful insights for the development of vibrant and equitable urban communities.

CRediT authorship contribution statement

Yakup Turgut: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Sanja Lazarova-Molnar:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Survey

Urban Area Preference Survey

Introduction

Thank you for participating in our survey. Your responses will help us understand people's preferences for different urban areas, which is essential for our research on urban segregation. The survey should take about 5–10 min to complete. Your responses will be kept confidential.

Demographic information

1. Age: ____
2. Gender:

☐ Male
☐ Female
☐ Prefer not to say
☐ Other: ____

3. Education Level:
☐ High School or lower

☐ Some College
☐ Bachelor's Degree
☐ Master's Degree

☐ Doctorate or higher
4. Occupation: ____

Urban area preferences

Please rate your preference for living in or near the following types of urban areas on a scale from 1 to 5, where 1 is "Not at all preferred" and 5 is "Highly preferred."

1. Economic Areas (areas with job opportunities, businesses, and financial institutions):

☐ 1
☐ 2
☐ 3
☐ 4
☐ 5

2. Educational Areas (areas with schools, universities, and educational institutions):

☐ 1
☐ 2
☐ 3
☐ 4
☐ 5

3. Cultural Areas (areas with museums, theaters, and cultural events):

☐ 1
☐ 2
☐ 3
☐ 4
☐ 5

4. Green Spaces (parks, gardens, and natural landscapes):

☐ 1
☐ 2
☐ 3
☐ 4
☐ 5

Factors influencing preferences

1. What factors are most important to you when choosing where to live? (Select up to three)

☐ Proximity to work

☐ Access to educational institutions
☐ Availability of cultural activities
☐ Presence of green spaces
☐ Cost of living
☐ Safety and security
☐ Public transportation
☐ Other: ____

Residential history

1. Have you moved in the past 5 years?

☐ Yes
☐ No

2. If yes, what was the primary reason for your move?

☐ Job/Employment

☐ Education
☐ Family
☐ Lifestyle
☐ Cost of Living
☐ Other: ____

Future aspirations

1. If you were to move in the future, which type of urban area would you prefer to live in?

☐ Economic Area

☐ Educational Area
☐ Cultural Area
☐ Green Space
☐ Other: ____

Conclusion

Thank you for your participation! Your responses are invaluable to our research on urban segregation and preferences. If you have any additional comments or thoughts, please feel free to share them below.

Additional Comments: ____.

Data availability

No data was used for the research described in the article.

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