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EDITORIAL

Open Access Journal

Introduction: AI for and in Urban Planning

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Abstract

As a tool serving other disciplines of enquiry, artificial intelligence (AI) offers the potential of a potent discovery, a design and analysis paradigm to address (new) questions in urban planning. This thematic issue raises a forum for cross-disciplinary dialogues at the intersection of urban planning and AI. Nine articles discuss both emerging use cases in urban planning practice and the relevant AI techniques being used and developed, as well as articulate the challenges associated. Future development of AI in urban planning shall address the ethical, inclusive, and just implications of AI applications for urban planning while navigating human and AI agents' interactions and intra-actions to facilitate a better understanding of the intentions of AI development and use, and the impacts on the behaviour of designers and users in complex urban planning practices.

Keywords

artificial intelligence; development and evaluation needs; social-technical evaluations; urban planning practices

1. Introduction

Artificial intelligence (AI) offers the potential of a potent discovery, a design and analysis paradigm to address (new) questions in urban planning. This thematic issue raises a forum for cross-disciplinary discourse at the intersection of urban planning and AI. Specifically, this thematic issue looks at two aspects of this intersection: (a) AI *for* urban planning, where existing AI techniques are applied to questions of interest for urban planning scholars, and (b) AI *in* urban planning, where (urban planning and other) scholars raise new challenges for AI or develop new methods in AI. Contributions to the thematic issue by researchers and practitioners alike who identify with communities such as urban planning, built environment, environmental geography, AI communities, or situate themselves within a multi-disciplinary lens, were welcomed.

2. AI *for* Urban Planning

AI methods are increasingly being applied to understand evolving urban processes, simulate complex urban behaviour, and predict potential scenarios or events. This section delves into specific examples of how AI has been applied to urban planning, from improving social inclusivity in public spaces by predicting suitability of public events, simulating urban behaviours, predicting outcomes for various purposes, to enabling more sustainable practices in natural-based solutions and heritage planning practices.

Research by Hamdani et al. (2025) demonstrates how machine learning models can predict the suitability of public events by analysing urban features such as comfort and crowd density. This approach could enhance the design and activation of public spaces by designing more vibrant, adaptive public spaces that can change over time in response to user needs.

The use of agent-based models (ABMs) for simulating surveillance technologies and violent urban behaviours in urban digital twins (UDTs) settings is explored by Shtaierman et al.(2025). The study shows that ABMs could be applied in such settings for crowd management and civil violence suppression. This approach demonstrates the potential in using AI-driven simulations to inform crowd management and policy-making.

Solomou and Sengupta (2025) explore the use of a cognitive agent architecture to endow agents with memory representation and experiential learning to enhance their "intelligence" for dwelling location choices. The findings showcase the improved ability of cognitive-based intelligent agents to display dynamic market behaviours.

For nature-based solutions (NBS) in urban planning practice, Forster et al. (2025) employ machine learning models to create predictive models for assessing the suitability of areas for NBS, using different land use categories, zoning plans, and environmental features as inputs. Similarly, Delavar et al. (2025) explore the applications of AI in walkability assessment and highlight the evolution of methods used.

In the context of heritage planning, natural language processing is applied for a case study on wind-catchers by Foroughi et al. (2025). The study analyses unstructured textual data from multiple stakeholders. This research illustrates the possibility of incorporating AI into heritage planning to support the inclusion of diverse perspectives, helping to identify conflicts and alignments. This inclusive approach fosters understanding to balance development and preservation.

3. AI *in* Urban Planning: Development and Evaluation Needs

While AI has shown significant promise in urban planning, current applications often struggle with the complexity and unpredictability of urban environments, along with data inaccuracy and incompleteness. Several development and evaluation needs must be addressed to reach the meaningful potential of AI in urban planning. Urban systems are characterized by multiple interconnected sub-systems that respond to social, economic, and environmental influences. Successfully leveraging AI for urban planning requires developing technologies that are not only capable of handling data but also understanding the contextual nuances that impact human behaviour, urban interactions, and the social-technical implications associated.

From the data and user perspective, the diverse behaviours and preferences of citizens need to be represented and reflected by AI models, as mentioned by Delavar et al. (2025) and Foroughi et al. (2025) to enable meaningful discussions. Furthermore, Forster et al. (2025) emphasize the need for data that can represent the diverse ecological aspects of urban systems as well.

Within AI systems themselves, different components such as learning algorithms, data processing modules, and decision models can continuously interact, adapting to one another and evolving based on new data and changes in urban environments. This adaptability is crucial for understanding and predicting the complex, nonlinear behaviours present in urban systems. AI models must evolve to use real-time or simulated data to adapt to the real-world complexities of urban environments, ultimately leading to more effective and equitable planning outcomes, as discussed by Solomou and Sengupta (2025) and Shtaierman et al. (2025).

In urban planning practice, human agents themselves also influence each other's decisions, behaviours, and perceptions. For example, city planners, community members, and developers often interact through public consultations or collaborative decision-making processes. These interactions shape urban outcomes by fostering shared understanding, aligning goals, or even creating conflicts. When AI is integrated into these processes, it adds another layer of complexity, influencing collective behaviours. Designing AI tools that respect and enhance these human relationships, rather than undermining them, is essential, as explained by Foroughi et al. (2025) and Bingöl et al. (2025).

AI system design must also consider the interactions between human agents and technological-driven agents in urban settings. The dynamic interplay between human actions and machine responses can significantly shape the intention and behaviour of urban residents. For instance, ABMs used in UDTs by Shtaierman et al. (2025) illustrate how CCTV (both visible and invisible) could impact violent behaviour in public spaces with nudging behaviour in mind. These nudges can promote desired behaviours like safer crowd dispersal, while AI systems learn from these interactions to improve future recommendations.

Looking at all these interactions/intra-actions above, the evaluation of AI models in urban planning therefore involves assessing their effectiveness, inclusivity, and the broader impacts they have on urban environments. For example, Hamdani et al. (2025) evaluated the effectiveness of machine learning models in predicting public events, demonstrating how these models can improve public space utilization and social inclusiveness. However, the risk of relying solely on AI predictions is that they may overlook the unique cultural and social contexts of different communities, leading to unintended consequences. It is of great importance that the users are included in the design, implementation, and evaluation of the AI models in urban planning.

Similarly, Bingöl et al. (2025) highlight the potential positive impact of AI on energy-efficient renovations, but also the limitations regarding the lack of proper human-computer interaction designs that enable the evaluation of AI's impacts from users, examining whether the AI contributes to meeting sustainability goals without excluding marginalized groups. Delavar et al. (2025) also emphasized that there exists a notable gap in representing the experiences of diverse demographics and geographic contexts in walkability assessments using AI, such as the needs of disabled people.

Even though AI models together with UDTs have shown potential in urban safety management, the ethical implications of using such technology require careful evaluation to prevent misuse, as the power dynamics might change in the designing and implementing phase of the technology. When AI systems are not designed with inclusivity in mind, biases can manifest in AI decision-making, leading to unequal treatment of different demographic groups, as has been suggested by Baker (2025). Baker's article draws attention to the significant biases and limitations of facial recognition technology (FRT) used in Detroit, USA, by noting that FRT has a high rate of misidentification for Black residents, which exacerbates racial inequalities. The use of AI in this context is framed as perpetuating existing inequalities rather than improving urban safety for all. It is crucial to implement transparent monitoring and validation mechanisms to assess AI performance and correct any biases that may emerge. This approach not only improves the fairness of AI models but also helps build public trust and involvement in AI-driven urban planning solutions.

Before making any decisions, it is important to ensure the multi-stakeholder deliberation process in the urban planning field for ensuring fair, participatory, and ethical practices with AI. Urban planning decisions directly impact the lives of residents, and it is essential to incorporate users' voices into the planning process. Furthermore, the different types of interactions and intra-actions need to be considered (within human agents, within AI systems, and the interaction between AI systems and humans) while designing, developing, and evaluating AI in urban planning. These tools should facilitate collaboration, helping to bridge the gap between various stakeholders or agents and ensuring that the resulting urban environments are equitable and inclusive. AI models, particularly those based on big data analysis and digital twin development, must follow ethical considerations, ensuring that they respect privacy and contribute positively to the well-being of the community. This is also supported by the research from Othengrafen et al. (2025) that the development of AI needs to include the collaborative aspects of urban planning, by integrating public participation and aligning with ethical and social values, particularly given the growing concerns about AI bias and privacy issues.

4. Conclusions

This thematic issue explores various aspects of AI for and in urban planning, ranging from its practical applications to the ethical considerations required for responsible deployment. AI is revolutionizing the field of urban planning, fundamentally altering how we sense and analyse the world as AI holds immense promise for addressing the complex and dynamic nature of urban environments. However, how the world could be managed and built with AI that is lasting and resilient to fulfil multiple users' requirements need to be further studied. Important questions to ask include: What do we intend to achieve with AI in urban planning? How do the interactions between human agents and AI-driven systems, as well as the relationships among human stakeholders, shape further the intentions and the behaviours that emerge? AI's role is not only about the tools we create but also about the ways we, as human agents, influence and are influenced by these systems (Harding, 2024; Murgia, 2024). By critically examining how AI influences both planners and residents and vice versa, we can begin to understand its range of possibilities and limitations. The goal is not just to create smart cities but also to ensure that these cities are equitable, resilient, and responsive to the diverse needs of their inhabitants.

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Conflict of Interests

The authors declare no conflict of interests.

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ARTICLE

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What Is My Plaza for? Implementing a Machine Learning Strategy for Public Events Prediction in the Urban Square

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Abstract

Plazas are an essential pillar of public life in our cities. Historically, they have been seen as public fora, hosting public events that fostered trade, interaction, and debate. However, with the rise of modern urbanism, city planners considered them as part of a larger strategic development scheme overlooking their social importance. As a result, plazas have lost their function and value. In recent years, awareness has risen of the need to re-activate these public spaces to strive for social inclusion and urban resilience. Geometric and urban features of plazas and their surroundings often suggest what kinds of usage the public can make of them. In this project, we explore the application of machine learning to predict the suitability of events in public spaces, aiming to enhance urban plaza design. Learning from traditional urbanism indicators, we consider factors associated with the features of the public space, such as the number of people and the high degree of comfort, which are evolved from three subcategories: external factors, geometric shape, and design factors. We acknowledge that the predictive capability of our model is constrained by a relatively small dataset, comprising 15 real plazas in Madrid augmented digitally to 2025 fictional scenarios through self-organising maps. The article details the methods to quantify and enumerate quantitative urban features. With a categorical target variable, a classification model is trained to predict the type of event in the urban space. The model is then evaluated locally in Grasshopper by visualising a parametric verified geometry and deploying the model on other existing plazas worldwide regarding geographical proximity to Madrid, where to share or not the same cultural and environmental conditions. Despite these limitations, our findings offer valuable insights into the potential of machine learning in urban planning, suggesting pathways for future research to expand upon this foundational study.

Keywords
data classification; event prediction; machine learning; Madrid; plaza; public squares; self-organising maps; urban planning

1. Introduction

The need for event prediction models in an urban environment is essential for all kinds of applications, from natural disaster preparation to urban management, planning, and development of smart cities (Mukhina et al., 2019). This rapid change in the relationship between events and public space highlights the features of the eventful city (Richards & Colombo, 2017) and how their form defines them, duration, content, and effects, determined to a certain extent by urban space and process (Richards & Palmer, 2010). The emphasis on people's behaviour in the public space and how it is affected by the built environment (Lynch, 1964) and its underlying elements that navigate the mode of human group life (Wirth, 1938) underscores the importance of designing urban spaces that foster social interaction and community engagement.

Traditional methods focus on trending major sporting and cultural events on a large scale (Smith, 2012, 2017), ignoring the continuity across scales to predict, prepare, and manage smaller-scale events and their outcomes. In addition, small-scale events remained unprecedented (Page & Connell, 2023) despite their essential effect on specific public spaces' publicness (Brighenti, 2010). In contrast to the traditional approach of other practices within the field of event prediction, our research tests the use of machine learning (ML) to overcome those limitations of scale, where those boundaries are diminished on the shared ground of the dataset.

Our main research question is: To what extent can ML models predict public events in urban plazas based on quantifiable urban features? This study aims to achieve two main objectives: (1) to explore the affordance of urban plazas and their contemporary design, use, and role; and (2) to test the application of ML for predicting public events in these spaces.

This study fills a critical gap in the literature by applying ML to predict the suitability of urban plazas for various public events, offering a novel methodological approach that integrates spatial and temporal data. Building on Donald Appleyard's theoretical framework (Appleyard, 1981) on street and public space activation, this research highlights the importance of designing public spaces that encourage various forms of social interaction and activities.

2. State of the Art

Modern studies have shifted from event detection, which focuses on identifying events after they occur, to event prediction, which aims to anticipate events before they happen. There are many existing works about event forecasting, including disease outbreaks (Achrekar et al., 2011; Zhao et al., 2015), crimes (Rumi et al., 2018; Wang et al., 2012), and other types of events (Dencik et al., 2018; Huang et al., 2017; Jin et al., 2014). For example, Smith (2012) and Wang et al. (2012) demonstrate how predictive models can forecast events such as protests, and cultural gatherings based on social media data and urban features. Existing methods for event prediction often rely on social media data like Twitter or Instagram (Kursuncu et al., 2018) but typically overlook spatial design features integral to public spaces (Ramakrishnan et al., 2014; Zhao et al., 2016).

Public spaces in historical districts, particularly in Mediterranean countries, play a vital role in urban life due to their historical and cultural significance. These spaces are often central to social interactions, cultural events, and community activities, making them ideal case studies for examining the impact of urban design on public space utilisation (Gehl, 2011; Lynch, 1964).

3. Methods

Our methodology hinges on a comprehensive approach to model development, encompassing the encoding of quantifiable plaza metrics in different cities, data augmentation, ML model training, and rigorous evaluation. The aim is to design a methodology that could be tailored to different scenarios and urban contexts. By choosing a single city to compose the dataset, we restrict the number of variables and features that appear throughout the process. Since our goal is the evaluation of urban plazas and outdoor activities, southern European cities are undoubtedly relevant. Due to its historical configuration and tourist interest, Madrid is taken as a case study, as its urban fabric comprises enough samples to establish a balanced initial dataset regarding size, shape, and urban situations (Figure 1).

Given the potential biases in our data, we limit our study to urban plazas in similar geographical and cultural contexts to Madrid. The selection of the indicators was guided by their relevance to public space utilisation. We categorised these indicators into external factors, geometric shape, and design features, and evaluated their influence on the suitability of plazas for different events. The indicators used in our classification include 1) External factors such as pedestrian traffic and proximity to amenities, 2) Geometric shape including size and layout, and 3) Design features like seating availability and shading. These indicators were chosen for their demonstrated impact on public space usage as identified in urban studies literature. The rationale for each indicator is based on its ability to influence the suitability of a plaza for various types of events.

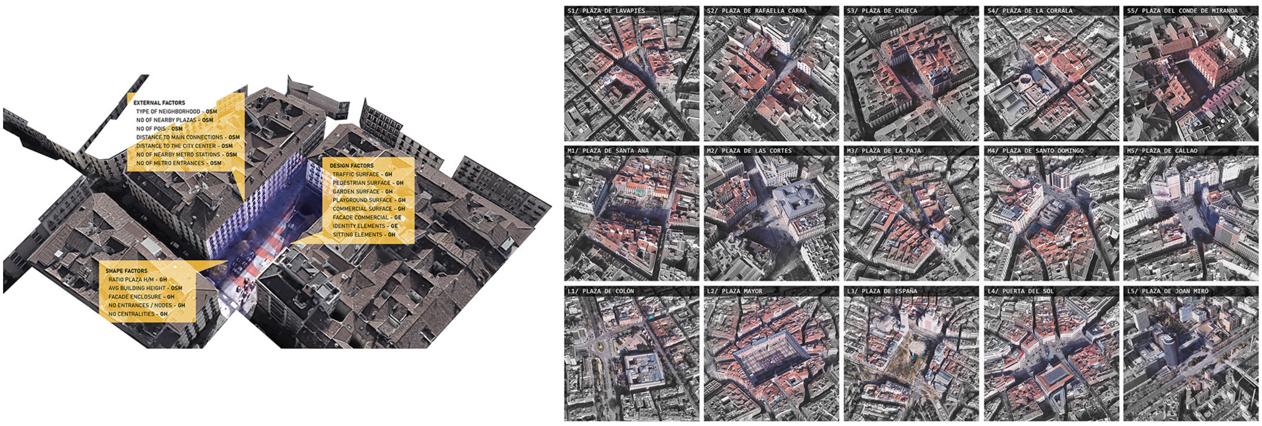

Figure 1. Initial dataset. On the left, plaza metrics are classified as External factors, Shape factors, or Design factors. Abbreviations: GH (Grasshopper plugin in Rhino software), OSM (Open Street Maps). On the right, satellite imagery of the 15 initial plazas grouped by size (first row large, second row medium, third row small). Source: Authors' creation from Google Earth.

3.1. Model Establishment and Indicators

To assess which aspects could be more relevant for the event suitability prediction we used Gehl's classification of outdoor activities (Gehl, 2011), which differentiates between necessary, optional, and social activities. Necessary activities occur in almost any condition and the physical environment only slightly influences their occurrence. Optional activities are those that people choose to do if the conditions are favourable. Finally, social activities depend on the presence of people and how they interact. With this definition in mind, optional activities are the ones greatly influenced by the physical nature of public space, so they will be the main focus of this research.

To underpin this classification, Gehl refers to a series of indicators to assess the quality and effectiveness of urban spaces:

- Degree of Comfort: Measures how comfortable people feel in a given urban space;
- Level of Activity: This indicator looks at the types of activities occurring in an urban space;
- Social Interaction: Measures frequency and quality of social interactions taking place in the space;
- Safety and Security: Evaluates how safe and secure people feel;
- Accessibility and Connectivity: Assesses how easily people can reach and move through the space.

For the specific case of Madrid, the Degree of Comfort and Level of Activity were chosen as the key indicators. Their evaluation does not include a fixed set of features; they are context-dependent and local urban knowledge is required to find the most appropriate ones. For the case of Madrid, we selected a series of features commonly used in urban studies and also specific to Madrid (Higueras García et al., 2017). They are categorised into external, geometric shape, and design factors (Figure 2).

- External factors:
  - Nearby plazas (*nearby_plazas*): Number of plazas located in the surroundings.
  - Points of interest (*poi*): Surrounding locations labelled of interest by Open Street Map.
  - Distance to the city centre (*dist_citycenter*).
  - Public transport lines (*transport_lines*): Number of transportation modes that reach the site.
  - Public transport accesses (*tr_stop/entrances*): Public transport stops in the surroundings.
  - Distance to public transport stops (*dist_connections*): Average distance to public transport stops.
- Geometric shape factors:
  - Buildings' height/plaza's width (*h_div_side*): Estimates how open the space feels in elevation.
  - Percentage of perimeter length surrounded by buildings (*per_building*): Gauges how open the space feels in the plan.
  - Number of entrances to the public space (*no_entrances*).
  - Number of centres (*centralities*): Related to the plaza's plan geometry, broken-down polycentric plan geometries are not ideal for some activities.
- Design factors:
  - Traffic surface (*traffic_srf*): Percentage of surface area dedicated to vehicular traffic.
  - Pedestrian surface (*pedestrian_srf*): Percentage of surface area dedicated to pedestrian traffic.
  - Garden surface (*garden_srf*): Percentage of surface area for green areas.
  - Playground surface (*playgr_srf*): Percentage of surface area dedicated to children-safe areas.

- Commercial surface (*commercial_srf*): Percentage of surface area dedicated to commercial activities.
- Sitting furniture (*sitting_furn*): Percentage of surface area with sitting furniture.
- Commercial facades (*fac_commercial*): Percentage of surrounding facades dedicated to retail space.
- Number of identity elements (*identity_elem*): Number of built identity elements within the plaza.

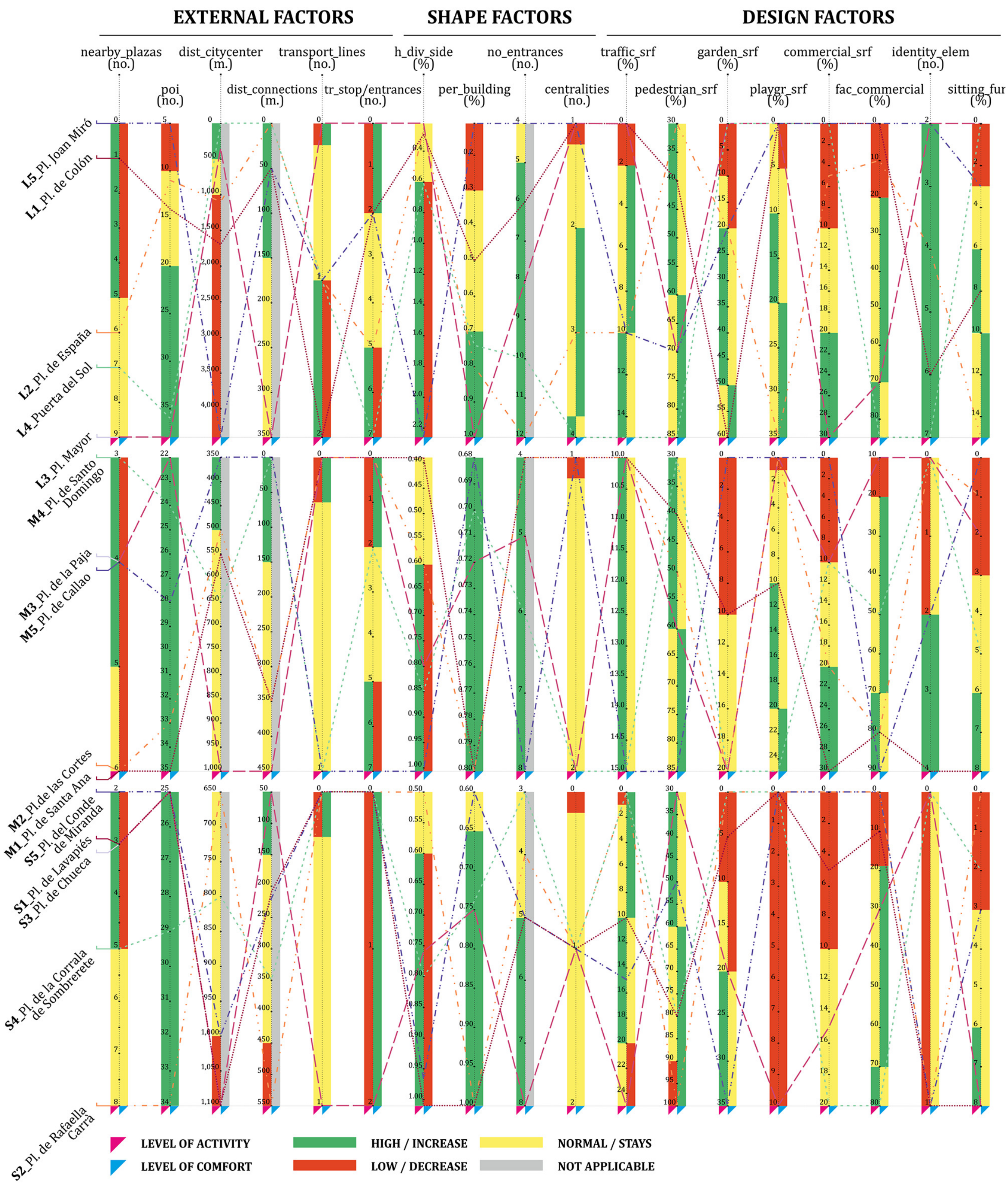

Figure 2. Multi-bar diagram showing the evaluation process (green high, yellow normal, red low, grey n/a) of each plaza (coloured lines), returning two values per input (columns); Activity Level (left bar/pink triangle) and Degree of Comfort (right bar/blue triangle). The increase/decrease of levels is driven by specific urban features such as pedestrian traffic, seating availability, and shading. The bars represent these levels concerning the type of events likely to occur.

The variables configuring our External factors were extracted from open data (OpenStreetMap) using Python's APIs. Nevertheless, due to the lack of urban data, most of the features encoded as Shape and Design factors have been geometrically rebuilt and subsequently compiled using Rhino/Grasshopper software (Version 7; Robert McNeel & Associates, 2022).

3.2. Model Fitting and Evaluation

The model was trained using a classification approach, where the selected target classes represent five different suitable events classified as optional activities following Gehl's classification. The proposed event types were chosen to reflect the programmatic diversity plazas can accommodate, focusing on those that require minimal fixed infrastructure and can attract varied demographic groups. The selected classes were: 1_Concert, 2_Market, 3_Urban performance, 4_Protest, and 5_Nothing.These categories were chosen based on common types of events identified in previous studies on public space utilisation (Smith, 2017; Wang et al., 2012). This selection allows us to examine the adaptability of public spaces to different events while excluding others like sporting activities, which typically require specialised facilities. These scenarios reflect a diverse range of events that plazas can accommodate, focusing on those that require minimal fixed infrastructure and can attract varied demographic groups.

Performance was assessed via accuracy, precision, and recall metrics, critical for evaluating the model's effectiveness in predicting event types based on plaza characteristics. Variability in event type predictions was analysed against key metrics of plaza design—Level of Activity and Degree of Comfort—to understand how different factors influence event suitability, as detailed in Figure 3.

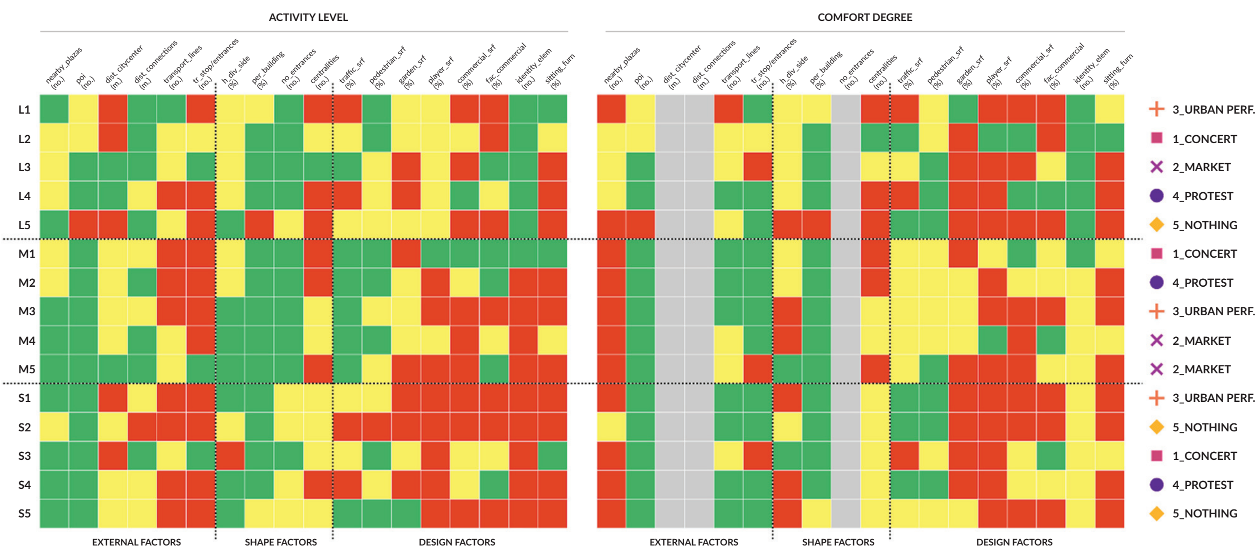

Figure 3. The figure shows the most likely event per plaza based on our model's predictions, though multiple events can occur in reality. It shows the result (green high, yellow normal, red low, grey n/a) of the evaluation process (Figure 2) of each plaza (row) per input (columns) according to its Activity Level (left matrix) and Degree of Comfort (right matrix), from which the output is assigned (right column).

3.3. Data Augmentation and Synthesis

To add variability to the initial sample in terms of shape and urban situations, the selection of the initial dataset includes 15 plazas differentiated by size: small (< 2000 m^2), medium (2000–7000 m^2), and large (> 7000 m^2). Each of them was analysed and evaluated according to the parameters established in the previous sections. Finally, the most suitable output out of the five proposed classes is assigned according to the result obtained regarding its two main indicators, Level of Activity and Degree of Comfort, which were identified based on their empirical relevance in urban studies.

There are two major drawbacks to curating a valid dataset for a single city. Firstly, encoding existing plazas, collecting, and formatting relevant metadata into a dataset is tedious. Secondly, the actual number of squares present in a single city is too few to become a valid dataset on its own. To address the challenge of a small initial dataset, we employed a self-organising map (SOM) for data augmentation, expanding our dataset from 15 initial plazas (seeds) to 2025. This approach allowed us to synthetically generate a diverse array of plaza scenarios, enhancing the model's learning potential. Of the numerous virtual sample generation methods that have proven effective for model training (DeVries & Taylor, 2017), the SOMs (Kohonen, 1995) relative mapping algorithm was used as the augmentation model in this research thanks to its Grasshopper implementation (Food4Rhino, 2021). After testing different combinations to determine which map size best allows the seeds to occupy the map boundaries, we established a square ratio of 45x45 as it produces the most distributed results.

The categorical data had to be coded as discrete quantitative variables so as not to introduce errors into the initial dataset. In addition, interpolating the discrete variables from the initial plazas yielded continuous variables in the data augmentation process, which had to be refined *a posteriori* to adopt the discrete value of their closest neighbour as a 2-dimensional interpolation method.

SOMs are a relative dimensionality reduction technique where initialisation plays a defining role in the final convergence of the map. To ensure that none of the initial seeds are underrepresented in the new synthetic dataset, there needs to be an iterative refining process where parameters could be tweaked and seeds removed until the SOM algorithm converges in a dataset that properly represents the problem.

3.4. Dataset Analysis

The produced synthetic dataset is subjected to statistical and graphical analysis to ensure it is coherent. This stage was essential for uncovering useful information and coming up with our conclusions at the end. Through this process, features were organised, transformed, cleaned up, added, or subtracted to understand the model predictability behaviour.

We analysed the correlation between our dataset's response and input variables using pair plots and correlation heatmaps. The goal was to detect features that might be redundant and therefore be able to reduce the dimensionality of our dataset through feature engineering. We also graphically analysed the distribution of the different categories' data points to understand possible challenges that could hinder model training.

3.5. ML Models

We trained different ML models on our synthetic dataset to test its quality, both shallow and deep. The three shallow learning models tested were Scikit-learn's Logistic Regression, Random Forest Classifier (Scikit-learn, 2022), and XGBoost Classifier. In addition, we chose a simple Artificial Neural Network (ANN; Tensorflow, 2022) as a deep learning model with cross entropy as a loss function. Finally, we tested two versions of our dataset with a train/test split of 80/20% (1620 train/405 test):

Raw dataset: Original dataset with all the selected 20 features.

Reduced dataset: Following the latest principal component analysis (PCA), the features were reduced to the 14 most relevant ones.

4. Results and Discussion

Following the previously presented method, we tested the approach with the 15 initial plazas.

4.1. Results From the Data Augmentation (SOM)

As mentioned, before reaching the final synthetic dataset we used for model training, we refined the initial parameters fed to the SOM algorithm multiple times. In our first attempts to produce our dataset, most seeds clustered and merged in the same synthetic data point while only two of the large ones (Plaza de Colón and Plaza de España) were distributed around the map. These two seeds and their associated programs were overrepresented compared to the rest that clustered. Despite fine-tuning the initial features, these two outlying plazas conditioned and unbalanced the dataset (Figure 4). To prevent this, they were excluded from the dataset.

When repeating the analysis with the same parameter distribution, we observed how the seeds mixed and occupied more significant portions of the board. However, they did not span toward two of the board edges, resulting in most events being underrepresented in the initial dataset and having a significant part of the synthetic data points distant from any labelled seed, meaning that most of the data generated was not within the parameter bounds of the 13 plazas used (15 initial ones minus the 2 outliers) and did not configure a valid dataset (Figure 4).

In the third attempt, we tried to find ways to occupy the board edges. We introduced two plazas from the large category, the same as the ones we removed in the previous stage. These additions added more variability to the initial plaza seeds and located themselves in the board edges without compromising the entire dataset. Finally, some of the metrics initially considered were modified or refined to avoid highly correlated values in the dataset (Figure 4).

Throughout the dataset curation process, shallow learning models were trained in an iterative process. We used a logistic regression (Scikit-learn, 2022) and an XGBoost Classifier (Chen & Guestrin, 2016), with different data representations to understand how relevant the selected features were and which ones were more meaningful for the classification.

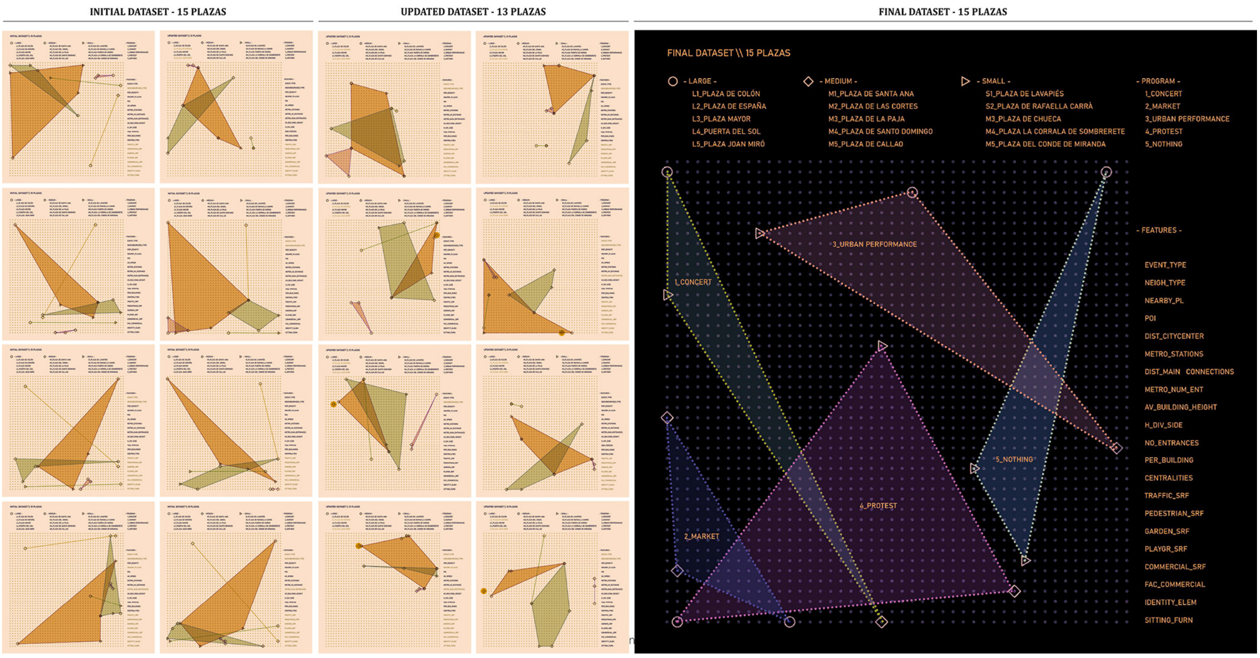

Figure 4. Results of the tests performed using the Kohonen Maps plugin. This figure shows the positions of the initial seeds relative to each program. On the left are different feature configurations with 15 and 13 plazas. On the right, the SOM displays the final dataset that was used after the data augmentation process. The x-axis represents the various features of the plazas, while the y-axis indicates the different event types predicted by the model. From the results, we observe that there is no significant correlation between the size of the plaza and the suitability of an event happening. Instead, the suitability for events appears to be influenced more by the combination of external factors, geometric shapes, and design features. This analysis highlights the complexity of predicting event suitability, suggesting that a multifaceted approach considering various urban features is necessary for accurate predictions. Source: Authors' creation from Grasshopper.

4.2. Results From the Dataset Analysis

The Correlation Matrix Heatmap showed the covariance between the different metrics and, in the case of observing a high proportionality (direct or indirect), we analysed whether this covariance implied causality or was due to the effect of a third variable, such as the type of event. For instance, we observed a high proportionality between the number of nearby plazas and the number of POIs (*nearby_pl* & *poi*). An exclusive heatmap for each type of event revealed that both variables present covariance for each output case, so we simplified our model by reducing one of these parameters. In the individual analysis by event type, some relationship was observed between other pairs of features. Still, its relevance for the model was discarded since this covariance did not appear in the overall matrix.

In our initial PCA of the input variables (Jolliffe, 2004), we observed that while most indicators contribute similarly to the overall prediction of event suitability when considering all event types collectively, there are distinct patterns when examining each event type individually. In particular, certain events are more strongly associated with specific parameters. For example, concerts are often related to larger plaza sizes and proximity to transportation hubs, while markets are more influenced by pedestrian traffic and the availability of amenities such as shops and cafes. Figure 5 illustrates these relationships by showing the loadings of each indicator on the principal components, highlighting which parameters are most influential for different event types.

In the relationship matrix between the features and the PCA analysis we observed that, for the first three iterations, none of our parameters stood out as highly determinant for the prediction of our target, which reveals that the definition of our initial metrics included enough variability to the model (Figure 5).

When graphically analysing the distribution of different features in our dataset, the output (Figure 6) reveals two challenges for the model training that the SOM induced in the dataset:

- Firstly, most classes overlap significantly throughout the different features. There is no unique feature that helps the classification.
- This is aggravated by the fact that within the same category there are gaps between the data points.

One of the main conclusions we drew from the synthetic data augmentation process, beyond the importance of defining the initial features and how to measure them, was the crucial role of urban data analysts in interpreting whether the dataset is valid and adequately represents the problem to be addressed. The researchers in charge of this process must be knowledgeable about the research topic and understand what they can do to curate a satisfactory dataset. This suggests that for most urban studies that could be investigated using this methodology, the best way to proceed is to create a specific dataset for each. Attempting to create a generalised one may not be satisfactory for all cases.

During the data augmentation process, the SOM algorithm could spawn unrealistic values that hinder learning. These data points tend to be located in the perimeters of the SOM far away from the initial seeds. In these areas, the vector interpolation of the algorithm could generate values outside of the boundaries set by the initial seeds. After achieving a satisfactory SOM result, the dataset needs to be carefully reviewed and the unrealistic data points excluded.

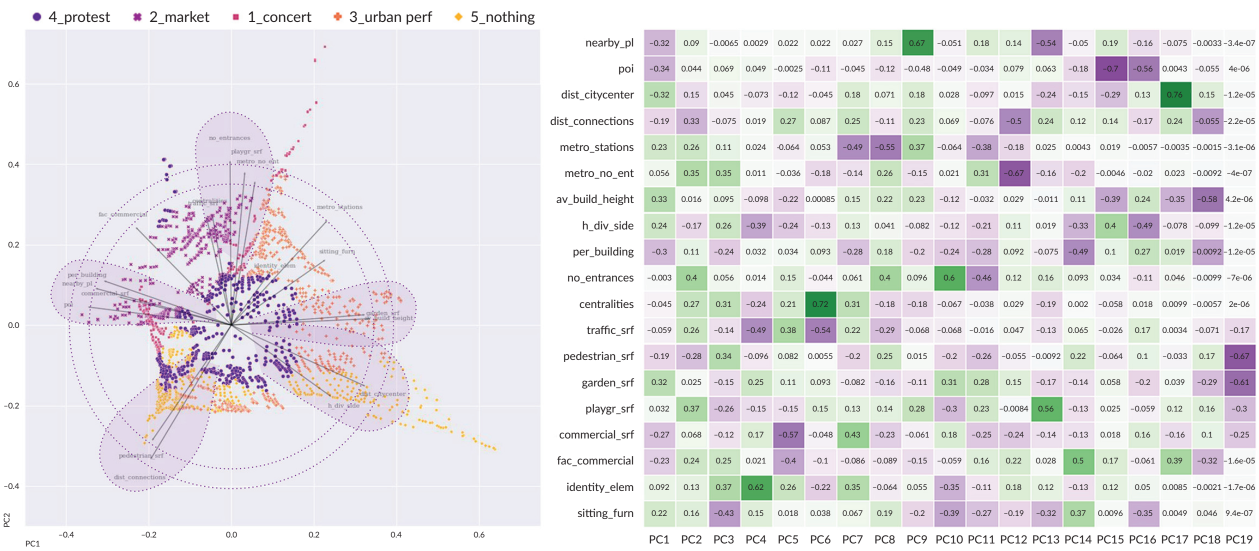

Figure 5. Results of the statistical analysis. On the left is the two-dimensional graph of the first two principal components, mapping the relationship between the output (coloured symbols) and the inputs (text). On the right, the relationship matrix illustrates the proportionality among each input (row) and each PCA analysis (columns) on a scale from 1.00 (green) to –1.00 (purple). The visuals indicate that there is no significant correlation between the size of a plaza and the suitability of an event occurring. Source: Authors' creation from Matplotlib and Seaborn Library.

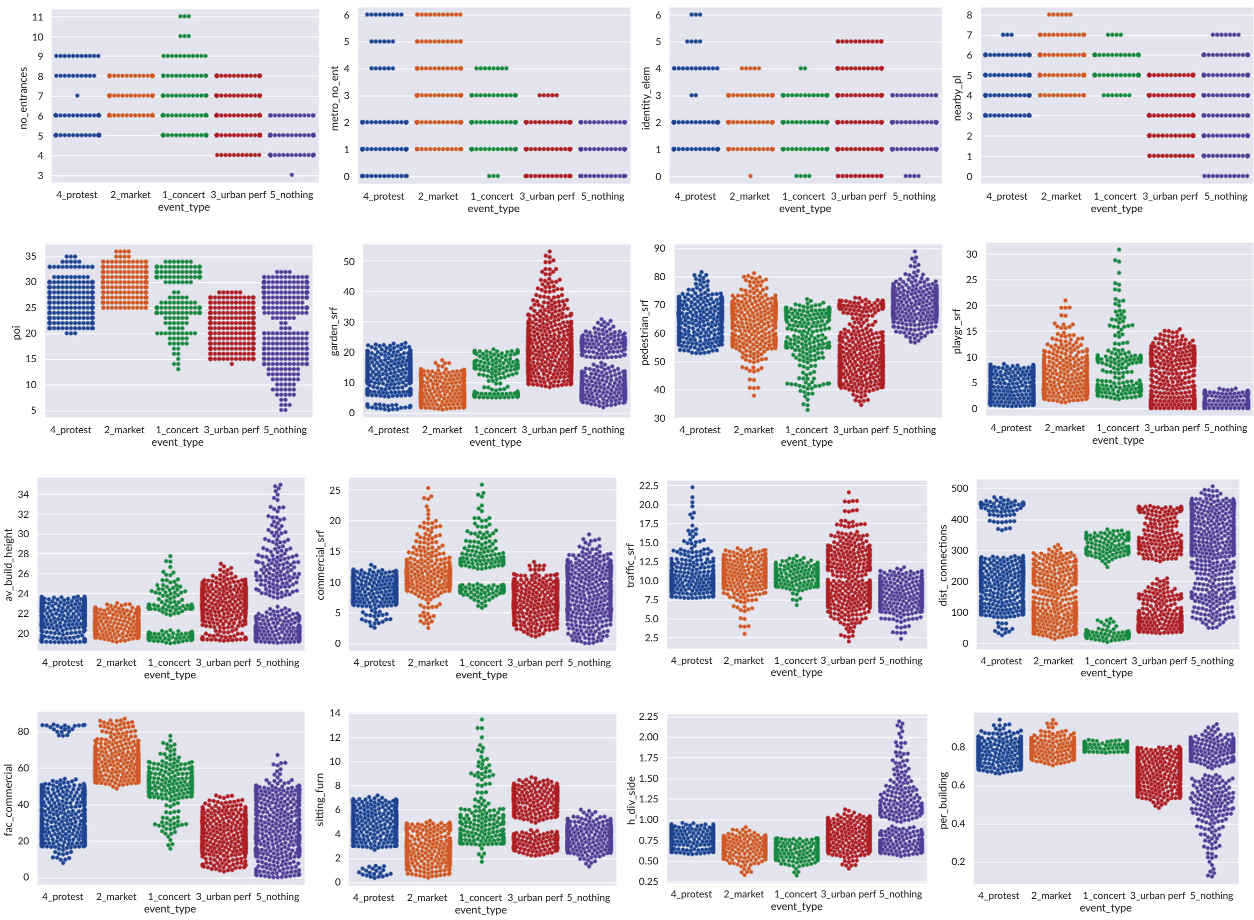

Figure 6. The exploratory data analysis of 15 out of the 20 features shows a great overlap between classes throughout features and the existing gaps between data points of the same class in different features. Source: Authors' creation from Matplotlib and Seaborn Library.

4.3. Results From the Learning Process

As mentioned in Section 3.5, during the learning process we tested multiple shallow and deep learning ML models and two versions of our dataset: a raw dataset with the initial 20 features considered and a reduced one with the 14 most relevant ones following the PCA.

With the raw dataset, the three shallow learning models had a good performance, over 0.93 (Table 1). XGBoost Classifier (score: 0.978) performed better than the linear regression (score: 0.938) and the Random Forest Classifier (score: 0.968) (Table 1). Precision and recall values are high throughout the different classes, especially with XGBoost, and, in general, the class 2_market stands out over the rest (Figure 7).

Table 1. The table compares train and test accuracies between the different models.

Model	Train accuracy	Test accuracy
Logistic regression	0.93703	0.93827
Random Forest Classifier	1.0	0.96296
XGBoost Classifier	1.0	0.97778

The ANN performed better with shallower architectures and the use of Dropout layers to try to reduce overfitting. The performances, in general, were below the three shallow learning models explored and, in any case, outperformed by the two best-performing ones (Random Forest Classifier and XG Boost). The batch size hyperparameter was changed to verify that the learning process was not stuck in local minima. Still, learning did not improve. As seen in Figure 7, all architectures tend to overfit after a few epochs, meaning that the complexity of the ANN appears excessive with the current features.

Good accuracy and low loss were considered in choosing the best-performing deep learning model. It is important not only to label the plazas adequately but also, if failing on the labelling, to not have them labelled with a program that did not suit them. The selected architecture is composed of a Dense layer of 64 neurons (activation function: relu), a Dropout layer, a Dense layer of 32 neurons (activation function: relu), and lastly, a Dense layer of five neurons (activation function: softmax), one per class.

When using the PCA Reduced dataset, the three shallow learning models and the best-performing ANN performed worse than the original dataset, meaning that the considered features were all relevant to the problem definition.

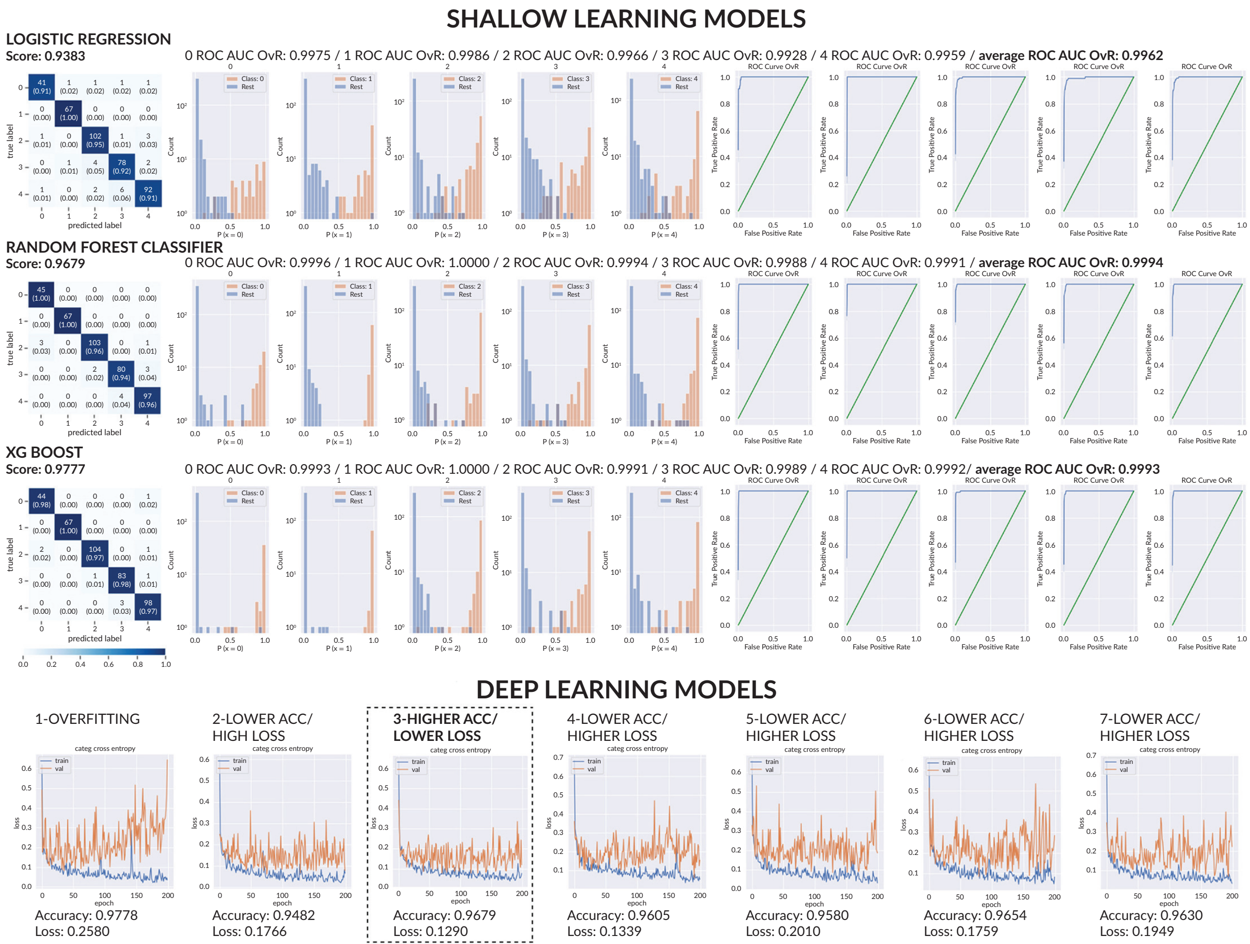

Figure 7. This figure compares both types of ML models used—shallow and deep. As mentioned, the three shallow learning models used—the upper part of the image—perform better than the different ANN architectures used. For the shallow learning models, the first two classes (1_concert and 2_market) are more clearly depicted than the rest. The deep learning models tend to overfit.

The three shallow learning models seemed to have greater potential and were further explored to understand their confidence when labelling the different data points. The Area Under the Receiver Operating Characteristics (AUC-ROC) was used following a One vs. Rest approach. As seen in Figure 7, the first two classes—1_concert and 2_market—are more appropriately depicted with the selected attributes, as there is a clear distinction between positives and negatives. In the remaining classes—3_urban performance, 4_protest, and 5_nothing—there is a greater overlapping threshold, and in the last two the model's confidence drops. It is also worth mentioning how the best-performing model, XGBoost, has a lower AUC-ROC average than the Random Forest Classifier model.

Our experiments showed that shallow learning models tend to overperform ANNs when training on our synthetic dataset. This is because they are easier to tune and can pick up the inherent patterns of our data, given our limited number of data points and features. On the other hand, deep learning models tend to overfit the sample space due to their high complexity and large number of parameters. Unlike shallow learning models, which are simpler and more constrained, deep learning models can learn intricate patterns and noise in the training data. The model that performed better was the XG Boost.

To finalise the process of data gathering, dataset curation, and ML model training, we deployed the XG Boost model in a designer-friendly interface like Rhino (Robert McNeel & Associates, 2022) via Grasshopper using the Hops component. This tool outputs the predicted class given the necessary information, plaza coordinates, and the features previously explained (Figure 8).

This presented a double use. First, the research team can easily input existing plazas to test the model's accuracy. It has the potential to allow other designers with knowledge from certain public squares to do the

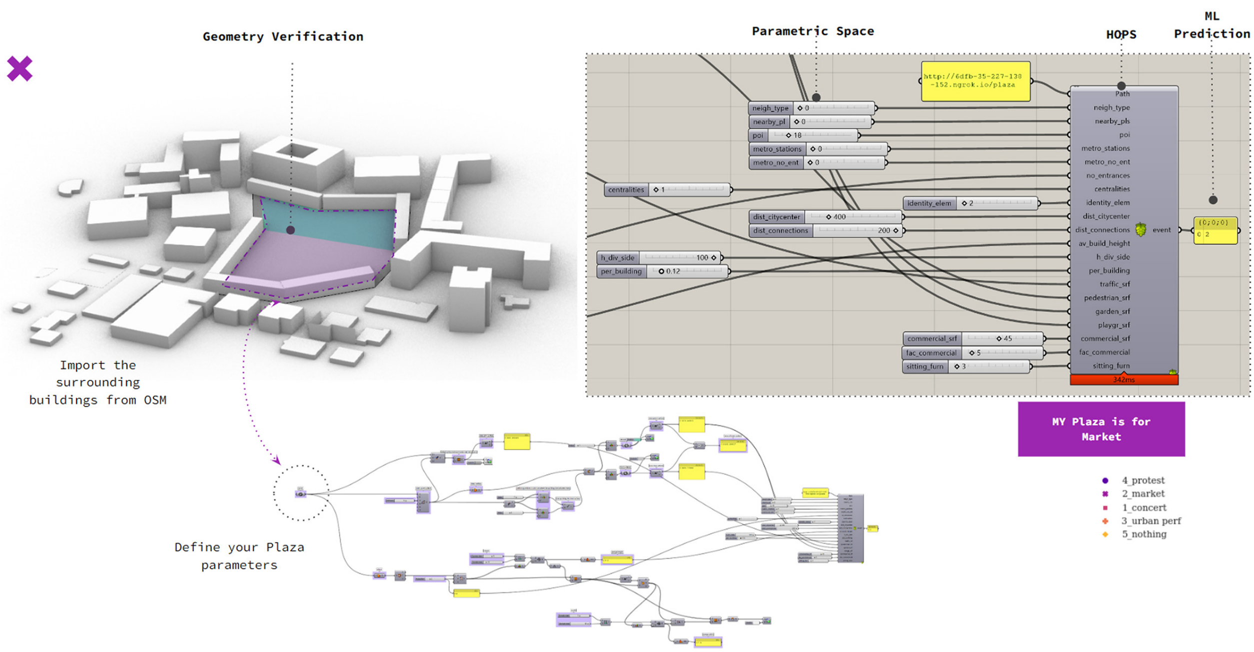

Figure 8. The Hops component from Grasshopper allows the user to predict the use of a plaza just by inputting the necessary features that can also be extracted from Rhino geometry. Source: Authors' creation from Grasshopper.

same and help improve the process. Second, it is the first step to making a tool for preliminary urban studies during the initial design stages of a project.

The model was tested in nine real plazas which do not stem from our synthetic dataset. Having created the dataset exclusively from plazas in Madrid, a poorer performance was expected the further away we moved from that city, especially from Mediterranean European plazas, as they share cultural, social, and historical backgrounds as well as climatic and physical similarities.

We deployed the model in nine plazas worldwide grouped by their geographical proximity to Madrid. These were:

Spanish:

- Plaza de la Corredera, Córdoba, Spain—37.8836° N, 4.7746° W.
  Approximate distance to Madrid: 300 km.
- Plaça de Catalunya, Barcelona, Spain—41°23′12″ N, 2°10′12″.
  Approximate distance to Madrid: 510 km.

European Mediterranean coast:

- La Place Masséna, Nice, France—43.6977° N, 7.2703° E.
  Approximate distance to Madrid: 980 km.
- Piazza del Duomo, Milan, Italy—45.4642° N, 9.1897° E.
  Approximate distance to Madrid: 1,190 km.
- Klafthmonos square, Athens, Greece—37.9794° N, 23.7311° E.
  Approximate distance to Madrid: 2,380 km.

European:

- Platz der Republik, Berlin, Germany—52.5186° N, 13.3732° E.
  Approximate distance to Madrid: 1,870 km.
- Sergels Torg, Stockholm, Sweden—59.3324° N, 18.0645° E.
  Approximate distance to Madrid: 2,600 km.

International:

- Union Square, San Francisco, USA—37.7879° N, 122.4075° W.
  Approximate distance to Madrid: 9,340 km.
- Hachiko Square, Tokyo, Japan—35° 39’ 32.7168’ ’ N, 139° 42’ 1.6920’ ’ E.
  Approximate distance to Madrid: 10,790 km.

The main challenge during this process was finding a unique program for each square. The selected uses were chosen according to the news available for each one of them. Even though this method is not reliable for validation, the accuracy shift is observed when applying the model to plazas outside Madrid, as seen in Figure 9. This can be attributed to differences in cultural, social, and environmental factors. For example, plazas in Northern Europe may have different usage patterns and climatic conditions compared to those in Southern Europe, affecting the model’s performance. Further tests should be conducted to support these results, and more data should be collected from diverse geographical locations to improve the model’s generalisability.

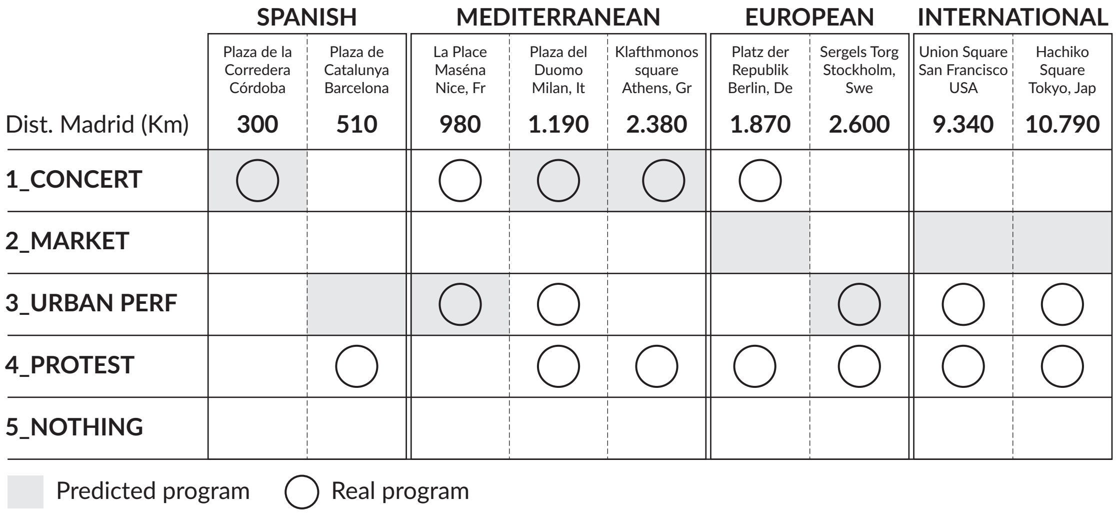

Figure 9. The figure shows the real plazas grouped by their geographical relationship to Madrid, the base of the dataset. The coloured rectangles are the predicted label by the XGBoost model. In contrast, the circles show the relevant programs on the squares.

In addition, the multitude of programs for which information was found highlights the difficulty of associating a single label with public space.

5. Conclusions

This study presents an initial exploration into the application of ML for predicting events in urban plazas, demonstrating the potential of data-driven approaches in urban planning. While our study primarily focuses on the application of ML for event prediction, it also touches upon the design and usability of urban plazas. However, due to space constraints, the latter aspect is briefly addressed and will be the focus of future research.

As an initial approach, the results have been satisfactory. However, the methods chosen for the dataset generation and the strategies for solving the issues during its curation are characterised by the team's common cultural background and similar urban experiences. This raises awareness of the possible bias that might have been induced while numerically encoding complex urban features.

The aforementioned bias could have been caused by using plazas solely from Madrid as seeds for the SOM, which already skewed the dataset and feature selection toward European Mediterranean cities. A possible solution to overcome this problem could be to use more seeds from different geographical areas for the SOM generation. However, as presented in Section 4.2, people's urban experience has a cultural component, and encoding these social nuances might overcomplicate the dataset curation and hinder the model training. In this sense, the research team believes that having local urban designer teams with multiple social backgrounds generating bespoke datasets for different geographic areas that share common cultural contexts could reduce complexity and allow the use of simpler ML models.

As mentioned in Section 3.3, after using the SOM relative mapping algorithm, there was a manual input process in which some data was refined and included *a posteriori* using the Euclidean distance from data points to seeds.

Depending on the feature selection used for creating the SOM, the resulting data distributions varied greatly, highlighting the complexity of including the right metrics to analyse public spaces without oversimplifying the parameters that define them. This questions the adequacy of this type of data augmentation algorithm for this research, and the feasibility of other methods needs to be further studied.

It was also mentioned that data augmentation processes might generate unrealistic values in the dataset that hinder learning and that need to be removed. Further studies should be carried out to look for more suitable data augmentation processes.

Concerning the ML models, two main conclusions are drawn. Firstly, from a theoretical perspective, the beauty of urban spaces is the diversity of uses that can take place on different dates or share the same time span. A multiclass classification model capable of outputting a single class per plaza is a rather simplistic way of understanding urban life, even though it sets a promising initial step. A multiclass multi-label classification model, capable of outputting various suitable scenarios for a given urban space, is a promising further step to improve the dataset curation and model selection.

Future steps include adding more features that better depict the different classes, especially the underperforming ones, 3_urban performance, 4_protest, and 5_nothing, as mentioned in Section 3.5. These features could also include more complex and intangible characteristics like sentiment analysis that could numerically encode a subjective yet shared opinion over a given space. This would mean the inclusion of analysis parameters that characterise the mental image of the public space based on an identity hierarchy established by the users.

Finally, the generation of a validation dataset made from real plazas poses two significant challenges. Firstly, assigning a unique class to an existing public square is complicated, and gathering sufficient reliable data would be extremely time-consuming and complex as the information is not readily available. Secondly, the class selection might be biased by the urban experiences of the individuals tagging the space. With these two drawbacks, the validity of the dataset could be easily compromised if not periodically verified. Therefore, we acknowledge the limitations of our work, particularly the small dataset size and the methodological challenges in data augmentation. Future research should aim to collect more comprehensive datasets, possibly through collaborative urban data initiatives, to enhance model accuracy.

To conclude, this article presents a methodology that opens up a new branch of research in the urban studies field: event suitability prediction for urban spaces. The different phases proposed, from data collection to model training and deployment, imply a series of challenges that will have to be solved for each specific application case: data scarcity, tedious dataset curation, model overfitting, etc. However, the greatest difficulty lies in encoding physical spaces that host unexpected and changing events with measurable values. In this regard, we believe this methodology requires local knowledge brought in by urban designers to reach its full potential. All stages of the process must be closely followed by designers knowledgeable about the research topic and capable of detecting possible failures or biases throughout. This combination of ML and local knowledge has the potential to strengthen the impact of urban studies.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The data in this article is available at the Institute for Advanced Architecture of Catalonia (IAAC).

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The Potentials and Limitations of Agent-Based Models for Urban Digital Twins: Insights From a Surveillance and Behavioral Nudging Simulation

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Abstract

Although urban digital twins are still at an embryonic stage of development, their use cases are multiple, ranging from big data aggregation to simulations. Additionally, predictions can be rendered and quickly implemented using actuators to transform physical environments and influence urban life. In this article, we investigate the potential of an agent-based model in a smart city setting to predict emergent behavior in relation to the suppression of civil violence by implementing crowd management practices. To this end, we designed a simulation environment that includes cameras in public spaces and wearable sensors, and considers nudging and self-nudging processes supported by a surveillance apparatus. Building on Epstein's threshold-based model of civil violence, the proposed simulation is informed by surveillance theories and contemplates methods for crowd monitoring and social control. The experiments' results provide insights into how specific measures and combined actions may influence the suppression of civil violence in public spaces and can be useful to inform crowd management activities and policymaking. Moreover, we use the simulation to reflect upon the potentials and limitations of integrating agent-based models into urban digital twins and emphasize the imminent risks for individuals and democratic societies of employing a ubiquitous surveillance apparatus endowed with the autonomy to trigger actuators.

Keywords

agent-based model; crowd modeling; smart city; surveillance systems; urban digital twin; urban planning

1. Introduction

The rights to freedom of peaceful assembly and association are essential components of democracy, allowing citizens to hold meetings, sit-ins, strikes, rallies, events, or protests both offline and online. They guarantee freedom of expression, letting people take part in public affairs by, for instance, interacting and organizing to collectively express, promote, pursue, and defend common interests. These liberties are deemed vital enough to be enshrined in the Universal Declaration of Human Rights (UN General Assembly, 1948). Peaceful assembly and association are acquired rights and a manifestation of democratic values as they enact social change through the power of crowds. However, given that such movements mobilize crowds, they are often monitored by public authorities to prevent civil violence.

In urban planning, the idea of controlling crowds through surveillance has been addressed throughout centuries, informing many theories and the design of urban landscapes. For instance, the panopticon is proposed as a prison, in which each cell is observable by a tower placed at the center giving the impression that the cells are continuously watched and leading inmates to regulate their behavior in expectation of a potential gaze, orchestrating a ubiquitous form of surveillance that could be used to discipline them anytime (Bentham, 1791). Another example is the original plan of Brasília. Streets as a space of convergence between pedestrians and cars were to be abolished, while the low building density was intended to dissipate crowds, thus affecting immanent forms of socialization and assembly in public spaces (Holston, 1989).

As the smart city emerges, social control and the exercise of power increasingly rely on digital tools and technology. The smart city has become an umbrella concept that branches off in multiple approaches to the digitization of services, using, for instance, embedded sensors in public spaces or wearables carried by citizens. Urban-applied projects related to different spheres of planning and management are driven by technology-based solutions, often intertwined across many scales and connected through multiple networks (Batty, 2018; Batty et al., 2012). All these sensors feed a data collection apparatus that urban digital twins (UDTs) are intended to govern as a holistic digital replica, reproducing the real urban setting and activities within. UDTs are ultimately supposed to digitally represent and simulate scenarios based on a continuous feed of real-time sensor data, allowing distributed actuators within the city to automatically act on their predictions. Endeavors like the Cybersyn project (Espejo, 2014; Medina, 2011) and the City Brain (Liu et al., 2022; Zhang et al., 2019) are aligned with holistic visions for UDTs that entail leveraging ubiquitous sensing and relying on autonomous machines to infer and perpetrate urban management activities.

When proposed to capture urban complexity, crowd monitoring and social control are among the many use cases of UDTs (Caldarelli et al., 2023). Similarly, agent-based models (ABMs) are widely used in a variety of disciplines aiming to simulate complex systems and study emergent behavior, namely in relation to civil violence (Epstein, 2002; Fonoberova et al., 2012; Lemos et al., 2013). Nonetheless, the integration of ABMs into UDTs and their potential to predict and suppress civil violence leveraging surveillance systems and autonomous actuators inspired by a smart city scenario has not been fully explored. Addressing this gap in research, we propose a simulation investigating the agents' emergent behavior when encountering measures employed to suppress the escalation of civil violence based on a surveillance-driven approach, leveraging state-of-the-art technologies and nudging practices.

In the next section, we present the theoretical framework behind the design of an ABM to explore surveillance and behavioral nudging practices to suppress civil violence. In Section 3, we explain the model's design (further detailed in the Supplementary Material), the experiments' setup, and results. In Section 4, we discuss the potential of ABMs in relation to UDTs and the challenges both technologies and the underlying idea of surveillance represent to society. We finalize by highlighting how ABMs associated with UDTs can transform society and introduce a paradigm shift.

2. Urban Surveillance and Behavioral Nudging

2.1. Surveillance Theories

Surveillance in relation to urban spaces and urban life has led to several theories, some of which became particularly relevant to question the role of surveillance in social control and due to the novel frameworks introduced to address social change in relation to the ways spaces are scrutinized and designed in order to promote or dissuade specific activities. Below we present some of these theories, which inspired the conceptualization of the ABM proposed.

Foucault's (1977) theory addresses society through power structures and their relations to discipline and has its roots in the panopticon (Bentham, 1791). The panopticon is illustrated as a prison, designed to automize and deindividualize power, thereby rendering it insignificant whether someone is actually monitoring the prisoners. The same applies to the watchmen, who in turn fear being watched by their superiors at any given moment. According to Foucault, postindustrial societies have established institutions that function identically. Schools, universities, hospitals, or factories subject individuals to work in isolation and train them to internalize discipline and anticipate punishment with the goal of achieving social conformity and productivity (Foucault, 1977). Building on Foucault's theory, it has been proposed that society is trapped in a sort of prison created around a fixation on self-optimization and productivity (Han, 2015) or that synoptic surveillance allows mutual monitoring, including public and media scrutiny of politicians which may deter deviant behavior (Mathiesen, 2017).

Deleuze (2017) introduces the concept of "society of control," defined by the dissolution of spatial and temporal boundaries. In a society of control, individuals are no longer confined to a certain location where a task is performed for a certain amount of time. The theory rejects a holistic conception of individuals, which in turn are opposed to the masses, in favor of multiple, simultaneous dividuals that are transient and fluid. Fractured into multiple demographics, these abstract descriptors provide a rough facsimile of an individual when put together but fail to characterize an actual human being (Deleuze, 2017).

Whereas the subject of a disciplinary society lives in constant fear of punishment, the dividual of a society of control may even fail to realize their own subjugation, rendering organized resistance nigh impossible. Another difference is that a society of control moves away from centralized institutions visibly exerting their power on individuals to propose a dispersed and transient power structure, aligned with the ethos of smart city-enabled mass surveillance.

Haggerty and Ericson (2017) propose the surveillant assemblage, where surveillance manifests as the convergence of heterogeneous, unrelated systems that form an all-encompassing web of control. This assemblage consists of a unity of items that form a functional entity in the broadest sense and is inherently unstable and fluid, thereby impossible to institutionalize or codify. It is also rhizomatic in nature, thus it does not target or exempt certain parts of society but subjects everyone to varying kinds of comprehensive surveillance. The world and the humans populating it are described as a system of flows that must be broken up, redirected, and analyzed for the purpose of management, profit, and entertainment (Haggerty & Ericson, 2017). The reference to doubles, which roughly correspond to the concept of dividuals in the society of control, further illustrates how information and data flows are used to manage society as a system. A major purpose of the surveillant assemblage and surveillance in general is the classification and monitoring of people to manage crowd behavior through social control. The analysis, visualization, and bundling of disparate data streams is linked to urban management and governance practices, which, in turn, seeks to streamline the former. We consider that UDTs as a tool primarily devised for city management may become the culmination of surveillant assemblages.

Jacobs' conceptualization of surveillance emerges from the discussion on safety of urban spaces, underscoring the potential of crowds, i.e., continuous and large affluence of people and casual surveillance undertaken by both pedestrians and residents, to ensure urban safety (Jacobs, 1961). Casual surveillance refers to the friendly gaze of a curious onlooker, and citizens who develop a sense of belonging in relation to their neighborhood taking on an active role in monitoring their surroundings, promoting urban safety. Mutual surveillance becomes a natural activity between strangers who share the same space and the author suggests that such community-grounded mechanisms are more effective than police surveillance in fostering urban safety. The idea of citizens monitoring their surroundings transported to a smart city setting resembles activities related to crowdsourcing data and participatory practices leveraging digital platforms.

2.2. Surveillance and Automation in the Smart City

The smart city is driven by the digitalization and automation of services and infrastructures (Kitchin, 2017). Sensors and actuators are becoming dominant elements of urban landscapes and can work complementarily to enable the automation of components of the urban infrastructure. Sensors are deployed to collect data, i.e., to take measurements and convert them into an electrical current, while actuators work through electrical impulses converted into visible phenomena, thereby transforming urban environments (Arshi & Mondal, 2023). In extension, UDTs introduce a holistic vision for urban twinning processes leveraging ubiquitous computing, 3D reconstruction, big data, and artificial intelligence (AI) and promise numerous paradigm shifts by enabling the integration of multiple sources of heterogeneous data and moving away from control to prevention and emergence (Sadowski & Pasquale, 2015). UDTs are also considered to plan and manage cities as complex systems (Khajavi et al., 2019), harnessing citizens as both sensors and actuators (Wang et al., 2012). In the aftermath, citizens can be nudged towards decisions at the individual and societal level due to an apparatus of intelligent mass surveillance, managed with little to no human interference.

2.2.1. Sensors

CCTV systems including cameras, recorders, and monitors that capture, store, and view video footage were first introduced in public spaces in the 1980s and have been increasingly adopted to monitor urban spaces (Hempel & Töpfer, 2009). With AI they can be endowed with facial recognition features, enabling remote and real-time identity checks and tracking (Fontes & Perrone, 2021; Kumari et al., 2023; Norris & Armstrong, 2017).

There are multiple types of cameras that may be adapted to urban surveillance systems. Video cameras can be further categorized into fixed and pan-tilt-zoom cameras. The latter can have a flexible view range when controlled by a remote operator. Infrared and thermal cameras, particularly suited for poor lighting conditions, detect near-infrared and short-wavelength infrared radiation, while thermal cameras capture long-wave and far-infrared emissions. Radar (radio detection and ranging) and LiDAR (light detection and ranging) make use of radio waves or utilize lasers to detect their surroundings, delivering high accuracy and robustness under different lighting conditions and offering a large range of vision. Nonetheless, these promising technologies are still considered ill-suited for detecting humans or recognizing objects (Ibrahim, 2016; Kumari et al., 2023).

In public spaces, multiple cameras of the same (or different) type are strategically deployed to supplement each other's data. Auditory, ultrasonic, passive infrared, and pressure sensors, among many others, can be used complementarily (Elharrouss et al., 2021). Nonetheless, the integration of multi-sensor systems poses countless technical difficulties and challenges stemming from data fusion (Sreenu & Durai, 2019). Surveillance can also be undertaken through wearable sensors and smartphones. On-body sensing using smartphones and wearables has become a powerful source of both personal and environmental data, making use of, for instance, built-in accelerometers and humidity sensors. Smartphones are used to sense crowd densities and model their behavior through GPS, cellphone signal, and WiFi triangulation (Borean et al., 2015). In extension, the metadata produced by mobile telephony (e.g., the identification number of SIM cards, call duration, or whether a phone was switched on or off) can be utilized by government agencies to monitor suspicious behavior and track individuals under suspicion (Leistert, 2012).

A variant of on-body sensing is crowd-powered human sensing, i.e., crowdsourced data that is voluntarily provided through digital apps for diverse purposes including, for instance, noise mapping and air quality control (Rana et al., 2010; Zhuang et al., 2015). However, there are challenges in assuring data quality (Wang et al., 2012), which relate to existing infrastructure (Franke et al., 2015; Tewksbury, 2012) and lack of participants, although incentive mechanisms such as virtual credit are also used (Lee & Hoh, 2010).

2.2.2. Actuators

Actuators are instruments or processes that convert control or input signals into actual motion, force, or other desired actions (Arshi & Mondal, 2023). Under the smart city paradigm, actuators are meant to enact physical changes based on processed data collected by distributed sensors. This means, for instance, self-adapting roads in response to traffic jams or automatic water supply management (Pompigna & Mauro, 2022). Despite the existence of a variety of actuator types (for example hydraulic, pneumatic, and thermal), we focused on actuators related to crowd management, crowd control, or crowd steering. In Table 1, we summarize three main approaches to crowd management according to the literature.

2.3. Defining Centralized Surveillance, Coveillance, and Selfveillance

We propose a classification of surveillance types inspired by a combination of social and technology-based approaches to urban surveillance. We first divide surveillance types into centralized surveillance and decentralized surveillance. Centralized is enforced through an apparatus managed and controlled through identifiable power structures reinforcing governmental bodies, drawing on Foucault's theory. On the other hand, decentralized surveillance is inspired by Deleuze's society of control theory and Haggerty and Ericson's surveillance assemblage theory, relying on decentralized and more subtle forms of surveillance, leading to self-regulation, i.e., individuals watching their own behavior and self-nudging practices. The coveillance approach is inspired by casual surveillance drawing on Jacobs' theory and entails relying on communities to self-regulate themselves by having individuals watching others (see Section 2.1 and Table 2).

Table 1. Three approaches to crowd management.

Crowd management	Examples of actuators operating	References
Dynamic spatial changes	Manipulating entrances, exits, and barriers, the spatial configuration may either encourage or deter crowds from gathering. Manipulating train schedules or outright skipping stations to prevent people from assembling. Radio-frequency identification (RFID), GSM-based (i.e., phone-based) identification, and biometric door locks can prevent specific people from entering or leaving certain areas.	Franke et al. (2015); Sadowski and Pasquale (2015); Shetty et al. (2020)
Crowd communication	Wearable devices or smartphones to monitor locations and movements, as well as nudge their users to certain actions, i.e., expose them to conditions that subtly encourage a specific change in behavior through visual, tactile, and auditory cues. Text messages and warnings widely sent to citizens' private smartphones by the public authorities. Customized social and monetary incentives using smartphone applications. Phone jamming or tracking used to prevent communication among the crowd.	Benartzi et al. (2017); Sadowski and Pasquale (2015); Singla et al. (2015); Tewksbury (2012)
Physical dissuasion	Military technology such as drones or sublethal weapons like long-range acoustic devices (LRADs) can be used for crowd control.	Sadowski and Pasquale (2015)

Table 2. Classification of surveillance informing the design of an ABM.

Surveillance types		Examples of actuators operating	Representation in the ABM*
Centralized surveillance		Systems based on observation and data collection by, e.g., CCTV cameras deployed in public spaces.	Visible and hidden surveillance cameras. Phone tracking, phone jamming, and mass messaging.
Decentralized surveillance	Coveillance	Describes mutual surveillance between citizens, albeit nudged by technology intentionally or unintentionally promoting urban safety.	People inflow. Monetary reward to monitor peers.
	Selfveillance	Citizens monitor their own behavior despite a seeming absence of external surveillance, promoted under the guise of self-improvement and as a measure of self-protection.	Regular informational campaigns. Encouraging self-tracking apps.

Note: * See Table 1 in the Supplementary Material.

The ABM was designed to simulate how different combinations of the defined surveillance types affect the population agents, using pattern-oriented modeling (see Table 2 and Table 3). The approach is based on layering multiple observable phenomena to promote structural realism and aims to address a still unresolved question in the literature—which surveillance practices are most effective at preventing and suppressing emergent violent behavior in crowds.

In terms of how the surveillance types informed the ABM's design, the first decision was to translate the approaches into techniques supported by sensors and actuators mimicking a smart city setting. In centralized surveillance systems, visible or signaled cameras are more recognizable and therefore avoidable by who passes by, while hidden cameras represent both their namesake and miscellaneous sensors that a citizen cannot recognize, thus they cannot be avoided. In the ABM, visible cameras can be destroyed by violent agents under certain conditions whereas hidden cameras cannot be destroyed, unless located within the neighborhood of a destroyed visible camera. This models collateral damage and discoveries by violent agents sweeping the vicinity in search of other surveillance devices.

Phone tracking describes targeted phone espionage, while phone surveillance entails general mining of data generated by smartphones. Phone tracking covers the process of monitoring the location and activities of specific individuals. Additionally, phone jamming describes the interruption of phone communication between population agents, while mass messaging is a form of crowd communication by sending the citizens messages on the phone.

In decentralized surveillance systems, we consider people inflow a form of casual surveillance. In the ABM, the number of new agents entering or old agents exiting the grid can be artificially promoted and controlled through actuators. A monetary coveillance reward is introduced to simulate incentivized crowd-powered actuators, testing whether citizens receiving a reward for using apps that foster coveillance could be an effective measure. Selfveillance measures the efficacy of adopting an educational approach to foster self-nudging, which includes providing information material on public safety, encouraging self-tracking apps and promoting proximity between government and citizens.

Selfveillance was inspired by measures adopted during the Covid-19 pandemic, when contact tracing apps became widely used public surveillance systems, voluntarily accepted by citizens around the world (Fontes et al., 2022). Similarly, many other tools for crowd control and the monitoring of individuals' mandatory isolation were proposed, although ethical and legal concerns were raised (Fontes et al., 2023).

2.4. Civil Violence and Surveillance

In this article, we use the definition of civil violence as a spontaneous violent outburst against a central authority and aim to test measures employed that relate to authorities' ability to suppress it. In this sense, we underscore the strong relation between civil violence and surveillance. The latter is used by the state to ensure governability (Giddens, 1986), inextricably tied to policing activities, enforcing a social contract between citizens and authorities. Certain forms of surveillance are therefore established as an extension of the state's authority and in some cases refer to the exercise of power and a manifestation of authoritarianism. Thus, the emerging possibilities of surveillance linked to even early stages of UDTs might trigger resistance movements and community backlash, as seen in the case of face recognition technologies (Fontes & Perrone, 2021). Such resistance may involve the avoidance and destruction of surveillance devices (Ullrich & Knopp, 2018), which we explore on the proposed ABM.

3. Designing an ABM for Predicting and Preventing Civil Violence

3.1. ABMs of Civil Violence

Agent-based modeling is a way of investigating complex systems, initially proposed in the 1980s, based on individual actors (agents) that act according to pre-programmed rules within a certain environment. The goal is to observe and explore significant emergent behavior while varying environmental or starting conditions in each experiment (Railsback, 2019). Regarding ABMs of civil violence, such as protests, riots, and uprisings, there are two distinct approaches. The first is the so-called rational behavior model, which iteratively optimizes a utility function. The second option yields rule-based models, in which agents change their behavior when certain thresholds are crossed. This approach is widely used when studying collective behavior and contagion effects (Lemos et al., 2013). The most influential rule-based model of civil violence was developed by Epstein (2002), modeling a central authority attempting to resist a decentralized rebellion. The results proved to capture many real phenomena qualitatively, such as deceptive behavior of population agents and sudden outbursts of violence after crossing certain tipping points (Epstein, 2002).

We build on Epstein's model and consider relevant criticism that followed the presentation of this ABM. Indeed, significant shortcomings were identified in follow-up research, such as unrealistic agent movement, simplistic cop modeling, and the agents possessing no memory and not having the capacity to learn from past events (Lemos et al., 2013). Consequently, improvements were proposed to investigate how many policemen are required to maintain low crime rates in urban settings (Fonoberova et al., 2012) or by adding a personality vector and a third class of media agents to simulate street protests (Lemos et al., 2013). Other approaches looked at modeling more realistic social contagion processes of civil disorder during public demonstrations (Kurland & Chen, 2016) or replacing the arrest probability with an Iterated Prisoner Dilemma game and introducing more granular parameters for population agents (Goh et al., 2006). Overall, a major concern in designing an ABM refers to the selection of components and rules to capture reality, as overly complex models are hardly interpretable (Railsback, 2019).

3.2. Entities and Environment

The proposed ABM simulation takes place within a two-dimensional 40x40 patches large grid, modeling an open public space such as a town square. Each discrete time step (tick) corresponds to 10 seconds. All experiments are set to run for four hours each (i.e., 1,440 ticks). Population agents refer to citizens who move across the grid. They can be created and removed from the simulation during runtime, i.e., enter or leave the public space. Although place-making factors are not explicitly included in the design of the grid, controlling the influx of new population agents as well as the speed at which they move across the board mimics the dynamics of public spaces and their importance to a local community. Furthermore, population agents can switch between four different states (quiet, agitated, violent, and jailed) according to certain rules, further determining their role and behavior in the simulation (Table 3). For more details see the Supplementary Material provided.

The objective of the simulation is to predict and prevent civil violence. This translates into maximizing the number of quiet agents, i.e., reducing the amount of agitated and violent agents. Quiet, agitated, and violent agents may switch back and forth between these states. However, only agitated and violent agents may be

Table 3. Types of agents and their characteristics.

Type of agents	Characteristics
Quiet agent	Neither agitated nor violent, they do not interact meaningfully with their environment beyond moving across the lattice.
Agitated agent	Do not behave differently from quiet agents, but are at higher risk of turning violent.
Violent agent	Avoid visible surveillance cameras and cops. Might destroy the former and incapacitate the latter when certain conditions are met.
Jailed agent	Remains idle for a specified number of ticks before becoming active again. By adjusting the jail term we can determine whether to model full-fledged arrests or only brief encounters with cops.
Policeman	Randomly move across the grid or stay on their patch to arrest violent agents, depending on the user settings. They do not meaningfully interact with surveillance devices.

jailed. This has no immediate influence on which state an agent will adopt once active again. As we are modeling a smart city scenario, two types of static surveillance cameras (visible and not visible) are randomly placed across the grid for each simulation. Every 60 ticks the camera identifies whether violent agents are within its range of vision. If that is the case, those violent agents are permanently removed from the simulation. Additionally, all centralized and decentralized forms of surveillance were included in the simulation (see Table 2 and description of the experiments below).

3.3. Experiments and Results

3.3.1. Effect of Surveillance Cameras

We wanted to investigate the effects of both visible and hidden cameras on the sum of agitated and violent agents divided by the total number of agents, which for this research we interpret as the civil violence rate, over the course of four hours (1,440 ticks). For this purpose, we run several experiments (Figures 1 and 2), modeled according to the following rules:

- Varying the number of mixed visible and hidden cameras (both within a range of [10,40]), thereby investigating combinations of visible and hidden cameras at different ratios;
- Varying the number of visible cameras within a range of [10,50] in steps of 10, without hidden cameras;
- Varying degrees of aggressive police interference in a range of [0.2, 0.8] in steps of 0.2 for a fixed number of visible and hidden cameras (both either 20 or 40);
- Varying radii of camera vision within a range of [1,4] in steps of 1 with a threshold of –0.25, and 10 visible and hidden cameras respectively;
- In all the cases, coveillance is set to 0.51, while selfveillance is set to 1.02, i.e., a low level for both. All cameras remove violent agents by default.

The effect of hidden cameras on civil violence results in a step function that reduces the civil violence rate linearly over time, which sometimes approaches zero by the end of the simulation. This can be interpreted through violent agents' behavior, who would avoid visible cameras but have no means of escaping hidden cameras. Therefore, they are removed from the simulation more frequently, leading to a sudden dip in civil violence, before it starts rising again. A higher number of cameras does not mean that civil violence can be suppressed more easily, especially in the very early stages. Instead, they seem to cause stronger fluctuations

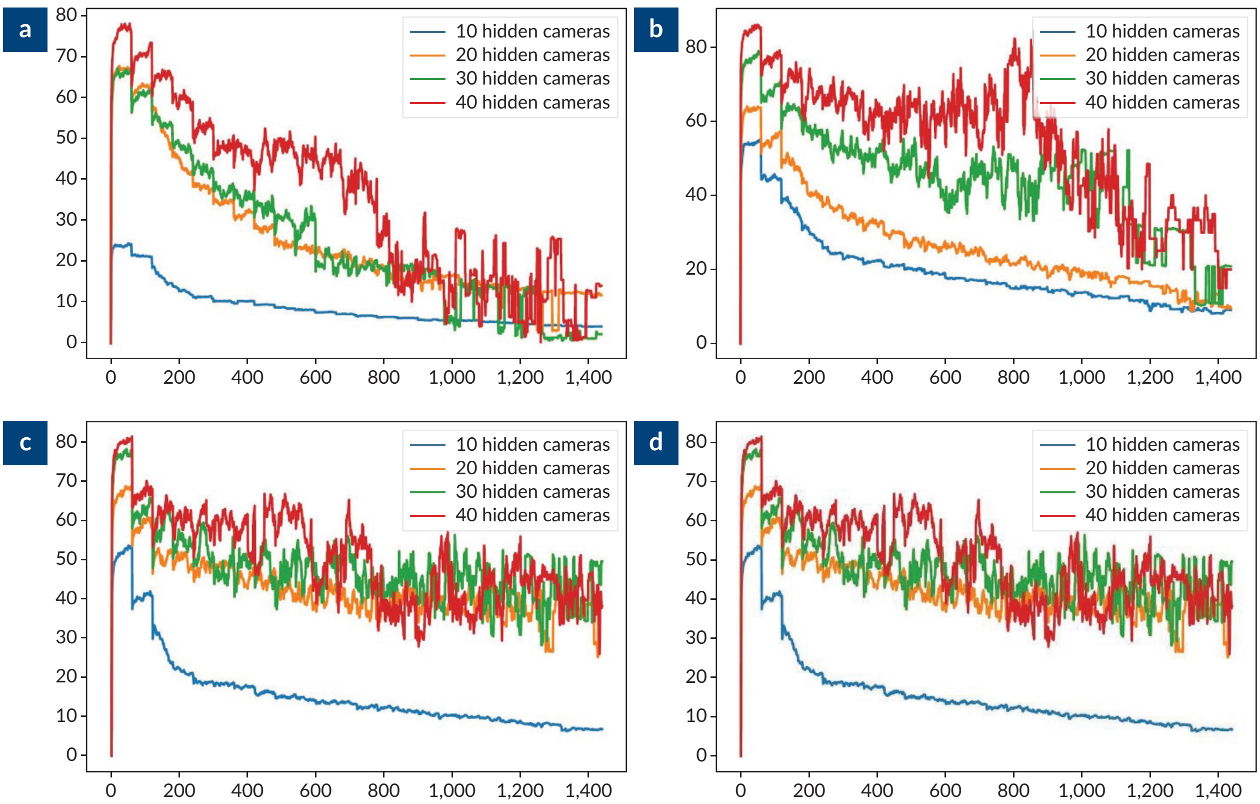

Figure 1. Effect of mixed camera types on the sum of agitated and violent agents divided by the total number of agents over the course of four hours with (a) 10 visible cameras, (b) 20 visible cameras, (c) 30 visible cameras, and (d) 40 visible cameras.

in the civil violence rate. As more agents turn violent due to the high surveillance level, more of them will be removed due to the cameras detecting them. In conclusion, it appears that a low number of hidden cameras are more effective at suppressing civil violence than visible cameras, though they also produce more general unrest, as the number of violent agents is in constant flux. Combining hidden and visible cameras demonstrates that, depending on the ratio, the characteristics of each type may dominate the cumulative effect. For instance, we observed that the higher the number of visible cameras, the lower the civil violence rate. At 40 visible cameras (Figure 1d), this rate seems to grow constant as the simulation pursues. Meanwhile, at 10 visible cameras (Figure 1a), the civil violence rate sinks monotonously as hidden cameras mostly dominate. According to the simulation, the most effective method appears to be a low number of hidden and visible cameras.

In terms of using exclusively visible cameras, the results show that the drop in civil violence rate is roughly 20–30% and the higher the number of visible cameras, the less effective they are (Figure 2a). (Smart) CCTV systems are widely studied in the literature and many authors advocate the little influence they have on public disorder offenses, becoming less effective over time and introducing significant challenges for the use of public spaces and individual rights (Fontes & Lütge, 2021; Fontes & Perrone, 2021; Kostka et al., 2021).

The involvement of police introduces a nigh oscillating behavior. If more policemen are involved, the civil violence rate decreases (Figures 2b and 2c). Indeed, a very large number of police officers, coupled with heavy surveillance, are necessary to keep the civil violence rate at a relatively low level (Figure 2c). When compared to the use of hidden cameras alone, the simulation shows that police involvement would render less effective.

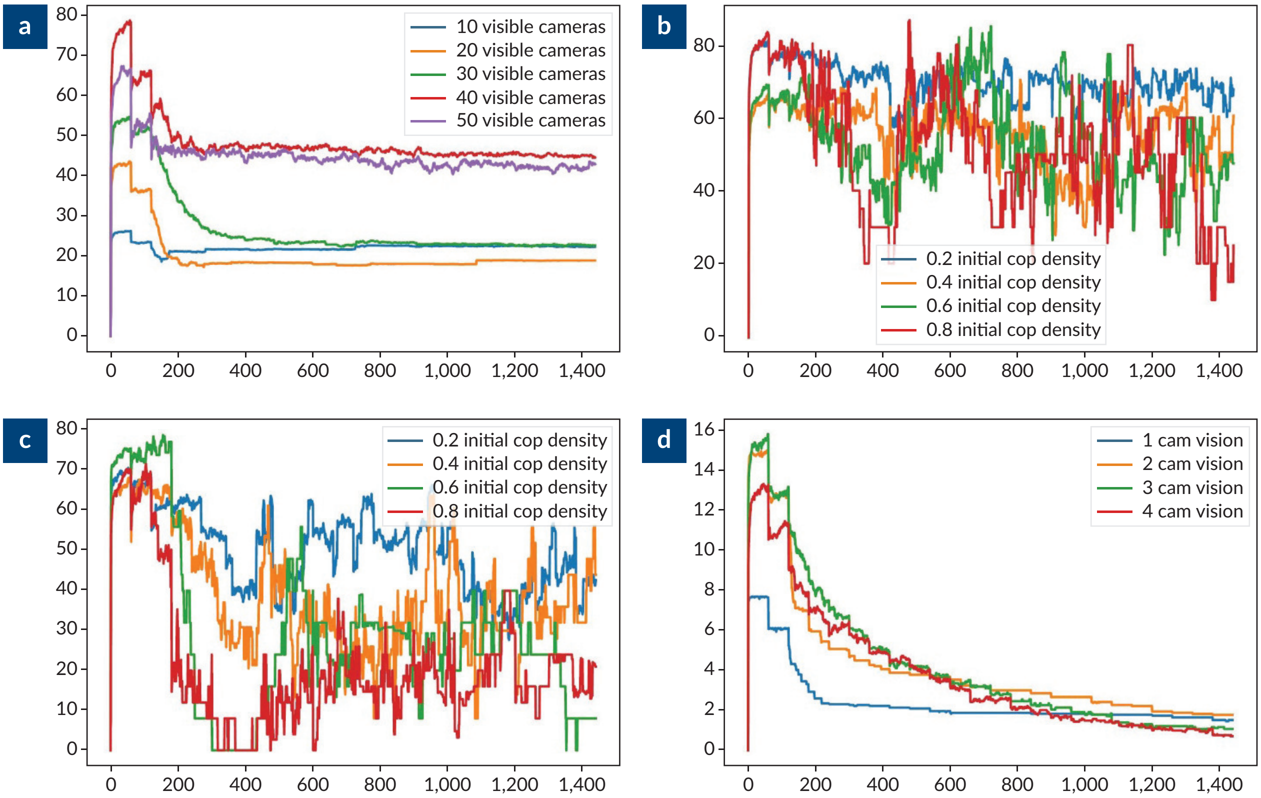

Figure 2. Effects of varying the conditions of the experiment: (a) effect of visible cameras on the sum of agitated and violent agents divided by the total number of agents over the course of four hours; (b) effect of police officers on the sum of agitated and violent agents divided by the total number of agents over the course of four hours for a fixed number of mixed type cameras with 20 visible and 20 hidden cameras; (c) effect of police officers on the sum of agitated and violent agents divided by the total number of agents over the course of four hours for a fixed number of mixed type cameras with 40 visible and 40 hidden cameras; and (d) effect of the cameras' range of vision on the sum of agitated and violent agents divided by the total number of agents over the course of four hours for 10 visible and 10 hidden cameras.

In terms of the range of vision, the more effective solution seems to be a smaller range of vision for a combination of hidden and visible cameras, although the results show that it is only significant for cam-vision = 1 (Figure 2d), implying that deterrence has little to do with the actual technical capabilities of the cameras. Indeed, CCTV systems do not even have to be operational in order to achieve a deterrence effect.

3.3.2. Effect of Coveillance

Additionally, we investigated the effect of coveillance (as defined in Table 2) on suppressing civil violence. For this purpose, we run several experiments (Figure 3), modeled according to the following rules:

- Varying the strength of coveillance within a range of [0,3] in steps of 1, to investigate the influence of coveillance on the number of violent agents;
- Varying the level of people inflow within a range of [1,4] in steps of 1 to observe the civil violence rate over time;
- Varying the agent vision radius within a range of [1,3] in steps of 1 to observe the civil violence rate over time;

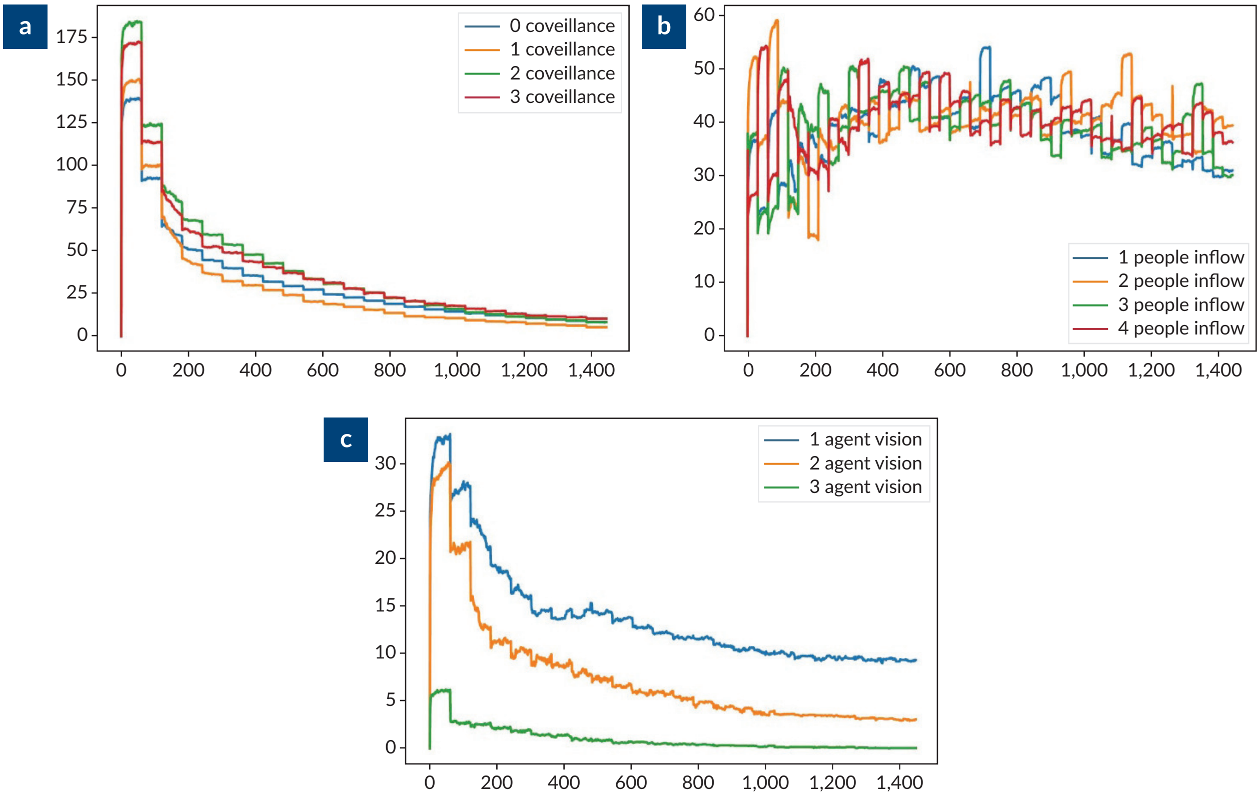

Figure 3. Effects of varying the conditions of the experiment: (a) effect of coveillance on the number of violent agents over time; (b) effect of people inflow on the civil violence rate over time; and (c) effect of the agents' range of vision on the civil violence rate over time.

- In all cases, we added 10 visible and 10 hidden cameras, building on the results of the previous experiments.

The conceptualization of coveillance is based on people inflow, i.e., how many new agents are entering the grid, and agent vision, i.e., an agent's range of vision, mimicking for the experiment the dynamics of public space and casual surveillance (see Table 2). The results show that coveillance can reduce the number of violent agents exponentially, although the employed strength makes little difference (Figure 3a). Figure 3b shows how increasing population inflow does not have an effect on the civil violence rate. However, a larger range of vision for agents seems effective at reducing it (Figure 3c). In the simulation, the agent's range of vision determines its range of movement within a single time step, which corresponds to the speed at which an agent moves across the grid. Therefore, the simulation leads us to conclude that quickly moving about and having a large range of vision is more effective than having a high number of agents. The results also refer to the importance of who is watching, as the range of vision was deemed insignificant for surveillance cameras but highly important for population agents.

3.3.3. Effect of Selfveillance Combined With Smartphone Interference

Next, we investigated the effect of selfveillance (as defined in Table 2) combined with smartphone interference. For this purpose, we run several experiments (Figure 4), modeled according to the following rules:

- Varying the strength of selfveillance within a range of [0,3] in steps of 1 to explore its effect on the number of violent agents;
- Varying the strength of selfveillance within a range of [0,3] in steps of 1, while setting phone jamming to values in a range of [0.1,0.3] in steps of 0.1. Since phone jamming tends to yield high, constant civil violence rates, we tested whether selfveillance is effective in the face of a particularly strong civil violence outbreak.

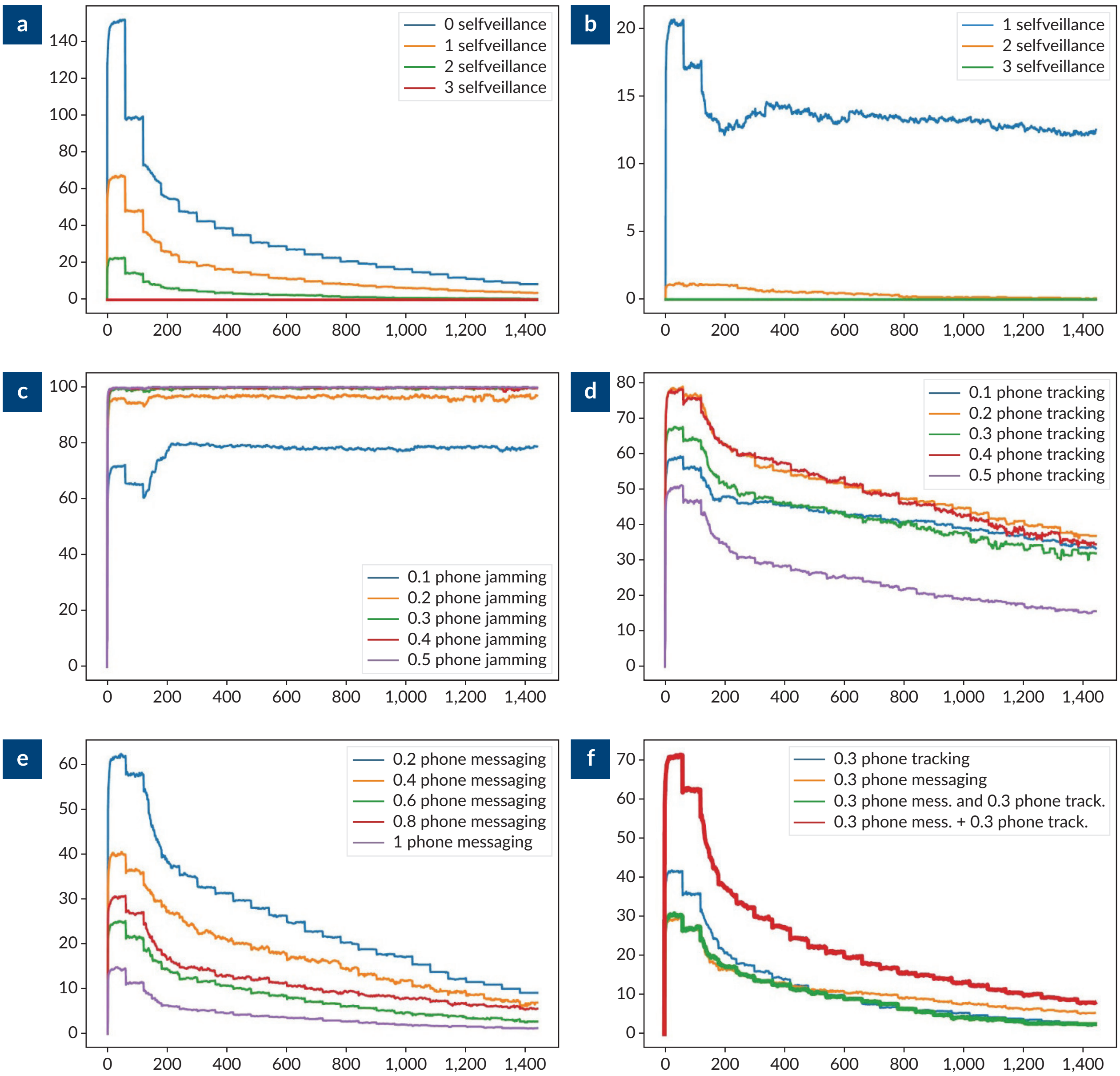

Figure 4. Effects of varying the conditions of the experiment: (a) effect of selfveillance on the number of violent agents over time; (b) effect of selfveillance in conjunction with 0.2 phone jamming on the civil violence rate over time; (c) effect of phone jamming on the civil violence rate over time; (d) effect of phone tracking on the civil violence rate over time; (e) effect of phone messaging on the civil violence rate over time; and (f) effect of phone tracking combined with phone messaging on the civil violence rate over time.

We also looked into the effects of smartphone interference alone by:

- Varying the level of phone surveillance within a range of [0,3] in steps of 1;
- Varying the level of phone tracking within a range of [0.1,0.5] in steps of 0.1;
- Varying the strength of phone jamming within a range of [0.1,0.5] in steps of 0.1;
- Varying the level of phone messaging within a range of [0.2,1.0] in steps of 0.2;
- Observing whether any synergetic effects appear when employing multiple phone-based actuators (i.e., phone messaging and phone tracking, both at level 0.3) at once;
- In all cases, we added 10 visible and 10 hidden cameras.

As the level of selfveillance increases, the results show an exponential decay of violent agents (Figure 4a), rendering selfveillance highly effective, similar to what we have seen with coveillance. The simulation also showed that 0.2 phone jamming and low selfveillance can significantly reduce the civil violence rate (Figure 4b). However, only phone jamming at 0.2 yields a 90% rate of civil violence (Figure 4c). If we increase the level of selfveillance, the rate of civil violence tends to zero (Figures 4a and 4b). Although unlikely that civil violence can ever be fully eradicated, the results indicate that selfveillance has great potential and its value might have been underestimated, at least until the recent event of the Covid-19 pandemic, as seen in the case of contact tracing apps (Fontes et al., 2022). Moreover, according to the results of the experiments, in comparison to other methods such as phone jamming, phone tracking, and phone messaging (as forms of centralized surveillance and nudging citizens), selfveillance can be more effective in suppressing civil violence (Figures 4c–4f).

We also explored whether a combination of phone-based actuation techniques could work in synergy, but results showed that they do not compound additively. For instance, employing both phone tracking and phone messaging does not yield better results than using the latter alone (Figure 4f).

4. Potentials and Limitations: A Socio-Technical Approach to ABMs for UDTs and Urban Surveillance

4.1. Key Takeaways of an ABM and Potential Integration Into a UDT

The results described in the previous section seem promising and encourage further research and testing in closer to real environments. Indeed, UDTs can provide the context data for the set-up environment of an ABM and together they can be employed to explore and experiment in a simulation environment before implementing policies and measures in practice.

However, while ABMs are useful for exploring emergent behavior and mainly valuable for understanding trends and relationships, they cannot be trusted for quantitative measurements. Additionally, complex ABMs may yield difficult and less reliable interpretations of cause–effect relationships. ABMs' potential to assist decision-makers lies in the enabled simulations and predictions, which can be complemented and tested using other methods and approaches (namely empirical and leveraging urban big data). As we have demonstrated, the use cases and experiments enabled by these models are numerous. Another advantage lies in the fact that simulation environments are considered safe spaces to conduct experiments before exposing communities to greater risks and potential harms.

According to this simulation's results, we can present the following takeaways, which could guide future research and inform policymaking.

- A low number of visible and hidden surveillance cameras are most effective at suppressing civil violence.
- Surveillance cameras do not require a high range of vision to be effective. Conversely, a heightened range of vision renders citizens more effective at reducing civil violence through coveillance.
- Selfveillance can be highly effective at suppressing civil violence.
- The simultaneous use of multiple phone-based actuators does not yield better results than the individual measures.

We emphasize that despite the promising results, embarking on intrusive surveillance and ubiquitous data collection in public spaces raises significant ethical concerns that should be addressed and assessed to ensure that such policies work in the best interest of impacted communities. The use of AI for law enforcement, as well as other critical activities that overlap with urban planning, and considering nudging as a means to govern societies, are not without a toll on individuals and communities. Below, we explore some of the implications.

4.2. Ethical Implications for Individuals and Society

Surveillance and tracking systems have been moving away from humans-in-the-loop towards fully automated intelligent systems associated with many socio-technical challenges that currently prevent a full realization of their potentials. For instance, robust computer vision cannot be taken for granted, while misclassifications of abnormal crowd behavior can have severe consequences (Wang et al., 2012). Additionally, a demand for real-time processing and communication coupled with a large amount of data yields high computational costs, requiring intensive resources and underscoring the importance of creating a general framework for distributed surveillance systems (Kumari et al., 2023; Valera & Velastin, 2005). Such technical limitations render highly autonomous surveillance systems infeasible for now. Nonetheless, researchers are identifying ways to navigate and overcome such problems and autonomous surveillance systems are quickly becoming more robust, reliable, and ubiquitous. In terms of actuation, it is worth mentioning that the smart city paradigm often considers humans as an integral part of the system (see for instance Fontes et al., 2024). When it comes to complex tasks such as surveillance and crowd control, the value of human input is not diminished by the automation of surveillance systems. As the simulation confirmed, nudging and self-nudging can be an integral part of social control assisted by technology-based systems. Additionally, there are social and cultural aspects in terms of how power structures interact with surveillance practices, which cannot be underestimated lest that efficiency is undermined by lack of trust and acceptance or lead to the erosion of democratic values (Fontes et al., 2022; Wood, 2009). Indeed, even in the scenario of intelligent autonomous surveillance systems, humans will somehow remain in the loop; the question is whether they are in control or controlled by technology.

In parallel, UDTs are evolving and integrating data from several sources. Indeed, ubiquitous surveillance is not only focused on physical spaces but also on digital social spaces. However, despite the advancements in crowd characterization using social media data (Duan et al., 2020; Gong et al., 2020), current UDTs are still mainly used to model physical space and a few specific activities taking place there (often related to mobility). The convergence between physical and cyberspace further complicates complex systems (Fontes & Dubey, in press), deeming the full realization of UDTs difficult to accomplish due to data gaps or the underestimation of the impact of social media on crowd behavior.

We also underscore that the social implications of autonomous surveillance systems for individuals and society are beyond technical feasibility and the overall performance limitations of a system. Surveillance is a means of bestowing power on the watcher over the watched. When conducted as mass surveillance, it can deepen existing or create new power imbalances, as exposed by the surveillance capitalism theory (Zuboff, 2023). Moreover, it allows profiling and identification of individuals and can lead to exploiting certain vulnerabilities while employing behavioral nudging techniques, sometimes hardly distinguishable from manipulative practices (Fontes et al., 2022).

Public authorities may have plausible arguments to justify mass surveillance, namely to suppress civil violence. According to some studies, people may actually accept being exposed to intrusive surveillance technologies in some cases (Kostka et al., 2021). Nonetheless, acceptance and trust in public authorities do not efface risks related to fairness, transparency, and proportionality. Individual consent might not prevent abusive use of personal data, if prerequisites such as individual autonomy and transparency are overlooked in the first place (Fontes et al., 2022). In extension, some of these systems may be beyond the rule of law (Ogasawara, 2022; Van Brakel, 2021), pose a threat to fundamental and human rights (Pauwels, 2020), or lead to the undermining of democratic values due to a potential chilling effect (Barkane, 2022; Selinger & Hartzog, 2020) and self-censorship (Büchi et al., 2022). They can also impact accessibility and the expectation of anonymity in public spaces, thereby promoting the exclusion of disproportionately affected vulnerable groups (Fontes & Lütge, 2021; Hirose, 2016). Mass and automated surveillance of individuals and modeling crowd behavior in a realistic and holistic manner may radically change the way society functions by trivializing the use of personal data, leading to a paradigm shift in the perception of privacy in relation to personal data (Fontes et al., 2024).

On the other hand, the empowerment of public authorities over citizens may result in coercing populations into accepting a restriction of rights, which resonates with how authoritarian regimes and autocratic forms of exercising power. Thus, mainstreaming surveillance governed by autonomous systems may widen the rift between citizens and public authorities. Raising awareness among public authorities and populations about the impacts of autonomous systems should be a priority, namely when discussing holistic forms of twinning reality through UDTs and human digital twins, which might as well become agents of ABMs not only inspired on real cities but run on their digital replicas (Fontes et al., 2024).

5. Conclusion

While the contextual data UDTs aggregate could be leveraged to inform more realistic ABMs for simulations on urban surveillance and security, consequently yielding more sophisticated interpretations to support urban planning and management, the implications of mass surveillance are serious for individuals and society. Therefore, instead of being lured into creating a holistic model of the real world with the purpose of rendering all events predictable and undesirable outcomes preventable, we should question how technology is replacing humans when it comes to interpreting the world. We should investigate how such models can incept values in communities that may be in tension with existing values and norms. Moreover, surveillance invokes a paternalistic conception of caretaking and being taken care of. If UDTs will have the ability of transforming physical space to manage crowds and urban life, we need to ask on behalf of whom. Democratic systems entail changes in the structures of power and social mobility.

As demonstrated, simulations can hint at ways of leveraging surveillance in many forms to nudge behavior and control crowds. However, the assumption that autonomous surveillance systems can be run through simulations represents a turning point for society. There is the need for more research and impact assessments in order to find a balance at the intersection of simulation-based environments and holistic data models in relation to the automation of decisions affecting real cities and citizens.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

Data can be made available upon request.

Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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ARTICLE

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In Praise of Diversity in Participatory Heritage Planning Empowered by Artificial Intelligence: Windcatchers in Yazd

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Abstract

Heritage planning is changing, in both theory and practice. There is greater attention to the cultural significance (values and attributes) conveyed to a heritage property, rather than focusing on the property alone. Identifying and revealing this cultural significance has become a critical step in heritage planning. Moreover, international guidelines increasingly encourage public participation in defining the cultural significance of heritage sites. However, effectively involving diverse stakeholders and capturing the cultural significance they attribute to heritage remains a challenge, particularly when dealing with extensive datasets and multiple stakeholders. Although automated methods have shown potential in fields like digital humanities, their application in heritage planning is still limited. This article explores the innovative use of artificial intelligence (AI), particularly text classification analysis, to analyze unstructured textual data (e.g., policy documents, literature, and social media) to uncover the cultural significance of built heritage. Focusing on Yazd, Iran, and specifically on windcatchers—a key cultural attribute recognized for its "outstanding universal value" by UNESCO—this study integrates AI to enhance both urban and socio-cultural planning. This article, as the concluding piece of a broader research project, synthesizes the project's findings to highlight AI's potential for inclusive heritage planning, referencing related publications of the same project to provide context while remaining concise. The research is structured in three phases: first, a literature review on AI applications in participatory heritage planning and value-based heritage planning; second, the methodology for data collection and analysis, including coding and comparing values and attributes of windcatchers conveyed by different stakeholders; and third, findings on the values and attributes, and their interrelationships as revealed through the data. The results confirm that while there are both conflicts and alignments in the cultural significance attributed to windcatchers in Yazd among various stakeholders, the theoretical framework presented here offers a valuable tool for heritage planning. By decoding and measuring cultural significance from diverse perspectives, this framework aids in identifying conflicts and alignments and in better aligning stakeholder perspectives. This model can be adapted to other key attributes in Yazd and other case studies, offering broader applications in heritage planning. Additionally, the

findings underscore the potential of AI to evaluate the legislative framework's effectiveness in enhancing public engagement.

Keywords
artificial intelligence; cultural heritage; cultural significance; Iran; public participation; Yazd

1. Introduction

Heritage studies are shifting from a focus on the heritage property alone to its cultural significance (Silva & Roders, 2012). Cultural significance includes what motivates the listing of a particular resource as heritage (attributes) and why these resources are listed as heritage (values). In parallel, a value-based approach to heritage planning is introduced, which considers heritage planning as a "dynamic process of change management" (ICOMOS Australia, 1987). Accordingly, a city is addressed as a "living heritage" with dynamic associative values that differ based on the time period and the different perspectives of stakeholders (Ginzarly et al., 2019; Poulios, 2014).

This dynamic approach to heritage planning acknowledges that each community and its members can convey different meanings to heritage as a whole, even if some attributes or values overlap (Bonet et al., 2020). Even the same community—due to aging and growth of knowledge and experiences—could evolve in their perspective of heritage. Given this diverse character of heritage, the participation of varied stakeholders, experts, and non-experts in determining heritage cultural significance has been strongly recommended, both in academia (Bonet et al., 2020; Ginzarly et al., 2019; J. Li et al., 2020; Palma & Díaz-Puente, 2024; Rêgo & Almeida, 2022; Yung et al., 2017) and by international recommendations (e.g., UNESCO, 2011, 2016). However, what happens when communities disagree on what is significant and why? How could then the cultural significance of heritage be defined? Through a broader statement, even if potentially contradictory, returning to the tradition of one narrative, only including what met consensus? Or no statement at all, as full consensus could not be reached?

Participatory practices applied to heritage planning also aim for consensus-building on the cultural significance of heritage (Den, 2014; García et al., 2019; Harmon & Viles, 2013; Rêgo & Almeida, 2022; UNESCO, 2011; Van Assche & Duineveld, 2013; Zhou et al., 2018). Consensus and conflict are intertwined concepts and cannot be addressed without each other in an inclusive decision-making process. Varied literature considers conflict as a challenge of consensus-building yet to be solved (e.g., Kaya & Erol, 2016; Lin & Geertman, 2015; Raynor et al., 2017; Rêgo & Almeida, 2022), and that further research discussing the issues, reasons, and conflict resolution methods (e.g., mediation, facilitation, negotiation, collaboration, and consensus-building) is needed.

Still, few scholars argue that conflict is as important and beneficial as consensus in participatory practices because conflict contributes to the generation of new ideas and solutions (Bailey et al., 2011; van Ewijk, 2011). This controversy about heritage may contribute to the formulation of more sustainable urban development and management practices (Antweiler, 1998; Corburn, 2005; Skoglund & Svensson, 2010). Accordingly, a balance between consensus and conflict is considered essential. It is the role of leaders and policymakers to demonstrate a genuine commitment to participation by embracing community diversity and conflict (Fahmi et al., 2016; Maginn, 2007; Purbani, 2017).

Some studies explore and cherish stakeholders' conflicts to reach a consensus. Yu et al. (2019) organized interviews with key stakeholders, reviewed project documents, used a model to analyze stakeholders' conflicts, and developed action schemes accordingly. Besides, García et al. (2019) presented a methodology to consider the majorities and consensus, as well as the minorities and controversial interests, to construct a holistic but integrated decision, in which all values are considered as equally important. As such, it is important to holistically understand the views of various types of stakeholders, to make integrated decisions.

Currently, studies that explore public participation in heritage planning are using various manual conventional methods (e.g., Bonet et al., 2020; J. Li et al., 2021). Nevertheless, this process can be costly and time-consuming, especially on built heritage, when many stakeholders are involved (J. Li et al., 2020; Morrison & Xian, 2016). While the automation of methods has proven to mitigate such restrictions in fields such as digital humanities (e.g., Bouzguenda et al., 2019; Horgan & Dimitrijević, 2019; Melica et al., 2018), their application in heritage planning, practice, and theory is still scarce. Hence, this research aims to investigate the potential of artificial intelligence (AI) models (e.g., multi-label text classification analysis) in analyzing available unstructured textual data from multiple sources (e.g., policy documents, literature, and social media), to reveal values and attributes conveyed to built heritage by different stakeholders, to build a foundation to align various values for making integrated decisions.

By comparing the different stakeholders' perspectives, discovered using an AI approach from multiple unstructured data sources, this research develops an approach to reveal alignments and conflicts between academic experts, policymakers, and users to shed light on the conflicts and alignments embedded in the multi-stakeholder setting and as a step further towards inclusive data-supported heritage planning. To provide empirical evidence of such an approach, this research explores various stakeholders' perspectives on the cultural significance conveyed to a specific case study, the city of Yazd, Iran. The focus of research is on windcatchers, which are Yazd's key attributes conveying outstanding universal value (OUV), as inscribed on the UNESCO World Heritage List (UNESCO, 2017). This research discusses alignments and conflicts in the attributes and values, by comparing the perspectives of policymakers, users, and academic experts. Based on the analysis, a critical reflection on the changes expected in heritage planning is discussed.

This article is part of a broader research project, with its findings contributing to a series of related publications. Throughout the text, we reference these works to offer readers additional context and in-depth analyses, allowing the article to remain concise while including essential information. As the concluding article, it synthesizes the findings from the other sections of the project to highlight the potential of AI for inclusive heritage planning. This study offers a comprehensive methodology with a customized AI-supported tool to detect alignments and conflicts in participation processes applied to heritage planning. Besides, this study reveals a critical gap that requires more reflection on the changes expected in heritage planning, by considering how different stakeholders may grow in their contribution to the definition of cultural significance in heritage planning, given the rising importance of public participation. Considering the increasing significance of public participation, Section 2 delves into the concepts explored in this research, such as value-based heritage planning practices, the definition of cultural significance, and how AI has been applied in participatory heritage planning.

2. Literature Review

2.1. Value-Based Heritage Planning and Cultural Significance

A value-based heritage planning process recognizes heritage as a whole that can be defined differently by various stakeholders (Bonet et al., 2020). Given this dynamic character of heritage, the participation of multi-disciplinary stakeholders, beyond experts, has been strongly recommended to determine heritage cultural significance (e.g., Bonet et al., 2020; Ginzarly et al., 2019; J. Li et al., 2020; UNESCO, 2011; Yung et al., 2017).

Value-based management processes are recommended to start with a cultural significance assessment (with a statement of cultural significance as outcome), followed by policy development, policy management, and vulnerability assessment of cultural significance (Clark, 2001; ICOMOS Australia, 1987; Kerr, 2013). As such, in the entire process of value-based heritage planning, the statement of cultural significance becomes the key reference (ICOMOS Australia, 1999). Specifically, the Statement of Outstanding Universal Value (UNESCO, 2008) is the statement of cultural significance detailing the cultural significance of OUV conveyed to heritage properties, justifying the selected criteria and supporting the process of the properties' nomination for inscription in the UNESCO World Heritage List (UNESCO, 2005). As stated in the 2005 operational guidelines, the OUV and the conditions of authenticity of the properties should be maintained or enhanced from the time of inscription onwards (UNESCO, 2005). This value-based management process has been extensively applied in practice in countries such as Australia and the United Kingdom, either by changing the legislation or drafting new conservation guidelines (Silva & Roders, 2012).

As mentioned earlier, cultural significance includes what motivates the listing of a particular resource as heritage (attributes) and why these resources are listed as heritage (values). The theoretical frameworks of cultural significance used in this study are composed of (a) values, as developed by Pereira Roders (2007), and (b) attributes, as developed by Veldpaus (2015). Value classes presented by Pereira Roders include eight primary values and sub-classes (Silva & Roders, 2012). The attributes framework consists of tangible attributes (asset-related, societal, process) and intangible attributes (asset, area, all).

2.2. AI in Participatory Heritage Planning

AI has emerged as a valuable tool for participatory heritage planning, especially for analyzing available data sources (e.g., social media platforms), as evidenced by previous studies (e.g., Abeysinghe et al., 2018; Afzaal et al., 2019; Qiu & Zhang, 2021). Using these tools for public participatory heritage planning has been gaining significant attention from both researchers and practitioners, in line with UNESCO's recommendations (UNESCO, 2011).

For instance, Abeysinghe et al. (2018) introduced a social media analytics platform that utilizes machine learning techniques and a visualization tool to identify discussion pathways, aspects, and their corresponding sentiment and deeper emotions. This platform enables decision-makers to gain valuable insights into the most talked-about topics related to a particular entity. Additionally, the analysis of associated sentiments and emotions assists in identifying feedback related to these topics. Similarly, the research of Afzaal et al. (2019) distinguishes the opinions or sentiments of people about heritage properties. Furthermore, Qiu and

Zhang (2021) conducted a study that explored the structure and connections between cognitive elements associated with intangible cultural heritage tourism. They analyzed data from Weibo, a prominent social media platform in China, employing matrix construction, dimension classification, and semantic network analysis as the primary analytical processes. These scholars highlighted the potential of social media for engaging citizens and gaining insights into their emotional attachments to the urban environment.

However, the exploration of social media and AI for participatory heritage planning is still in its nascent stage. Existing literature lacks heritage-specific tools that specifically address the cultural significance of built heritage and the explicit connection between attributes and values (Bai et al., 2021). Furthermore, previous studies have often focused on broader geographical scales, such as countries, cities, or neighborhoods, rather than delving into specific attributes within a city, such as windcatchers (e.g., Ginzarly et al., 2019; van der Hoeven, 2020). Therefore, the present study aims to investigate the potential of available data sources and employ AI methods for data analysis to uncover individuals' perspectives regarding the cultural significance (values and attributes) of built heritage on the scale of the building element, the windcatcher.

3. Case: Windcatchers in Yazd

A windcatcher is a traditional building element that has been used for passive cooling/natural ventilation in buildings, over time and place. Windcatchers are widely used in North Africa and West Asia. Iran and other countries around the Persian Gulf have used windcatchers for the past 3,000 years (Saadatian et al., 2012). Windcatchers rely on local weather and microclimate conditions, and their design is often adapted to the local context (Ford, 2001) in shape, size, and direction. Windcatchers can be circular, octagonal, polygonal, square, or oblong. They can be unidirectional, bidirectional, or multidirectional (Movahed, 2016). In different climate zones, six types of windcatchers have been identified (see Figure 1).

Windcatchers are usually vertical shafts with vents above the roof of the main room(s) in a building. The main goal is to enable passive cooling/natural ventilation, by channeling the desired wind to the interior of the living spaces, where air often passes over a pool of water (acting as a humidifier) and provides thermal comfort to the building users (see Figure 2). Other elements such as windows and doors are also important elements of this ecosystem, contributing to the wind circulation, together with the windcatcher (Movahed, 2016).

Yazd is called the "city of windcatchers" because the city has the highest number of windcatchers among cities in Iran (Saadatian et al., 2012). The windcatcher is selected as a case study as it is an important attribute for various stakeholders, from Yazd and beyond. The windcatcher is an important element for locals, as many

Figure 1. Various types of windcatchers in different climate zones. Source: Jomehzadeh et al. (2017).

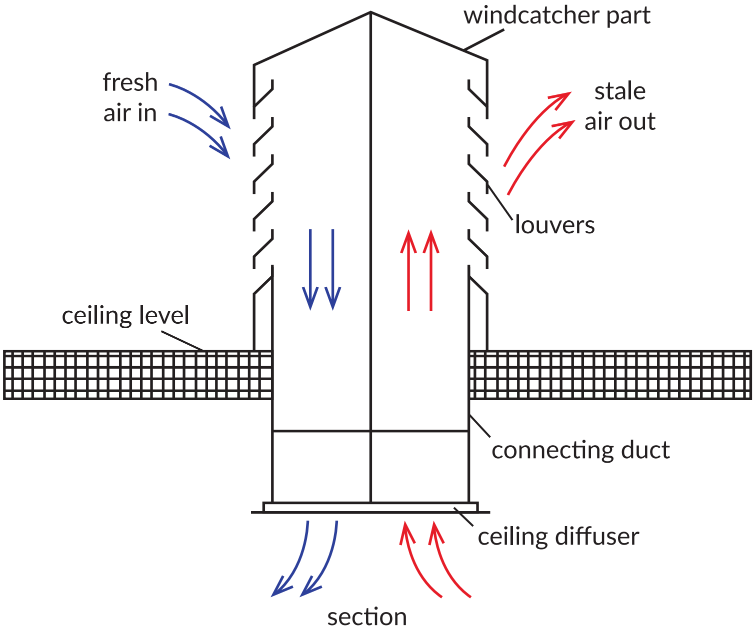

Figure 2. Section view to demonstrate the structure and mechanism of windcatchers. Source: L. Li and Mak (2007).

houses in the historic city of Yazd have at least one windcatcher. Tourists often write about windcatchers since they are unique building elements that can be seen from everywhere in the historic city of Yazd, due to their height difference within the urban context, acting as landmarks in the urban landscape. Scientists have done much research on windcatchers, mainly due to their main goal of natural ventilation, exploring ways to redesign and develop traditional windcatchers for the modern era (e.g., Moghaddam et al., 2011; Zafarmandi & Mahdavinejad, 2021). Lastly, windcatchers are mentioned in various local, national, and international policy documents as an attribute conveying cultural significance.

4. Methods

The process followed in this research entails three steps, namely data acquisition, data pre-processing, and data analysis (see Figure 3).

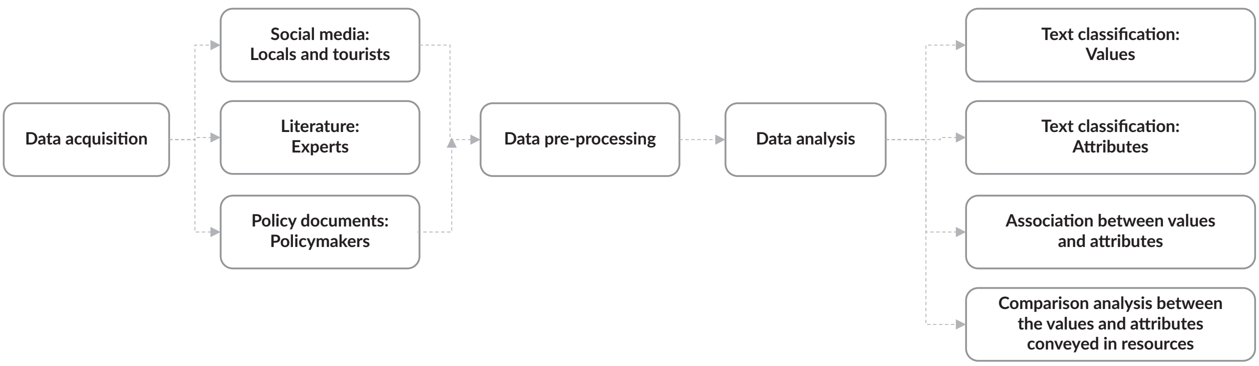

Figure 3. Overview of the methodological framework.

4.1. Data Acquisition

This study reveals and compares the cultural significance conveyed by three stakeholder groups to the windcatchers. These groups are academic experts, policymakers, and users, based on the theoretical framework by Pereira Roders (2019). The relevant resources for each stakeholder were collected from various sources (Table 1). They are, respectively, the literature, policy documents, and social media posts (only Instagram and Twitter) referring to windcatchers and Yazd. All the paragraphs in these documents referencing the windcatchers of Yazd were collected and analyzed. All the data were collected manually, except for the social media data which was retrieved using the WebHarvy web scraping software due to its large volume.

All sub-national, national, and supra-national policy documents related to the city of Yazd addressing windcatchers in any part of the whole document were collected as data sources. Overall, seven documents were used as datasets: three sub-national, one national, and three supra-national policy documents. All the paragraphs in these documents addressing windcatchers were elicited, structured, and analyzed. Additional insights into policy makers' perspectives on the windcatchers of Yazd are provided in Foroughi (2023).

Three peer-reviewed academic databases—Scopus, ScienceDirect, and SID (Iranian Scientific Information Database)—were initially selected as primary data sources for their comprehensive coverage, relevance, and regional insights. However, these databases may not include all journals or languages, potentially introducing bias. To expand the search, the snowball method was employed, using references from identified papers (e.g., Asadi et al., 2016; Vahdatpour & Ariaei, 2020). In total, two book chapters and 92 papers were identified (Foroughi et al., 2024), and all sentences mentioning windcatchers were extracted for analysis. Future research should consider additional databases like Google Scholar and JSTOR to ensure a more thorough review and reduce regional or linguistic biases. Additional insights into experts' perspectives on the windcatchers of Yazd are provided in Foroughi et al. (2024).

Social media platforms commonly used in Iran during this research, specifically Instagram, Twitter, Facebook, and LinkedIn, were also evaluated as potential data sources. After an initial review, Instagram and Twitter were identified as the primary platforms containing relevant posts. Consequently, posts related to the windcatchers of Yazd were automatically mined using WebHarvy, a paid tool capable of extracting text, HTML, images, and URLs from various websites and saving the data in multiple formats. A total of 23,899 posts were mined, including information such as usernames, post content, publication time, and users'

Table 1. The stakeholders and relevant resources.

Stakeholders	Definition	Resources
Policymakers	Those developing the plans and tools to manage local resources	Relevant local, national, and international policy documents
Academic experts	Those working in academia, e.g., researchers	Academic databases: Scopus, ScienceDirect, and SID
Users	Community in general, e.g., local, regional, and national population, tourists, educators	Social media: Instagram and Twitter

Note: SID is the Iranian Scientific Information Database.

biographies. However, demographic characteristics of the users were not captured. Ethical considerations were prioritized by only processing hashtags and comments related to heritage values and attributes, without storing any sensitive personal data. Personal information was not disclosed at any stage of the research, and users' identities were kept anonymous unless explicit permission was obtained. To further ensure anonymity, usernames were altered (e.g., user1, user2) and posts were rephrased to make the data untraceable. Additional insights into public opinions on the windcatchers of Yazd shared on social media are provided in Foroughi et al. (2023).

4.2. Data Pre-Processing and Data Analysis

In order to facilitate data analysis, data pre-processing was conducted. All variations of "windcatcher" and "Yazd" were normalized to "windcatcher" and "Yazd" (both in Persian and English, e.g., "Yazd," "yazd," "یزد"). Moreover, unnecessary data including stop words, references, punctuation marks, and website links were removed. After data cleaning and pre-processing, the dataset was ready for text analysis. To reveal the cultural significance conveyed in texts, two theoretical frameworks were used to decode the attributes and values conveyed in the literature, policy documents, and social media (see Figure 4). The theoretical frameworks of cultural significance used in this study are composed of (a) values, as developed by Pereira Roders (2007), and (b) attributes, as developed by Veldpaus (2015).

Overall, the analysis of attributes and values was undertaken using Python libraries, including Numpy (for performing statistical computations) and Pandas (used for data manipulation and analysis on data frames). Each sentence was analyzed and assessed through quantitative content analysis and qualitative categorical analysis. The quantitative analysis revealed the most and least frequent attributes and values, and identified patterns of the relation between attributes and values. The qualitative categorical analysis showed the categories of values and attributes addressed in the texts.

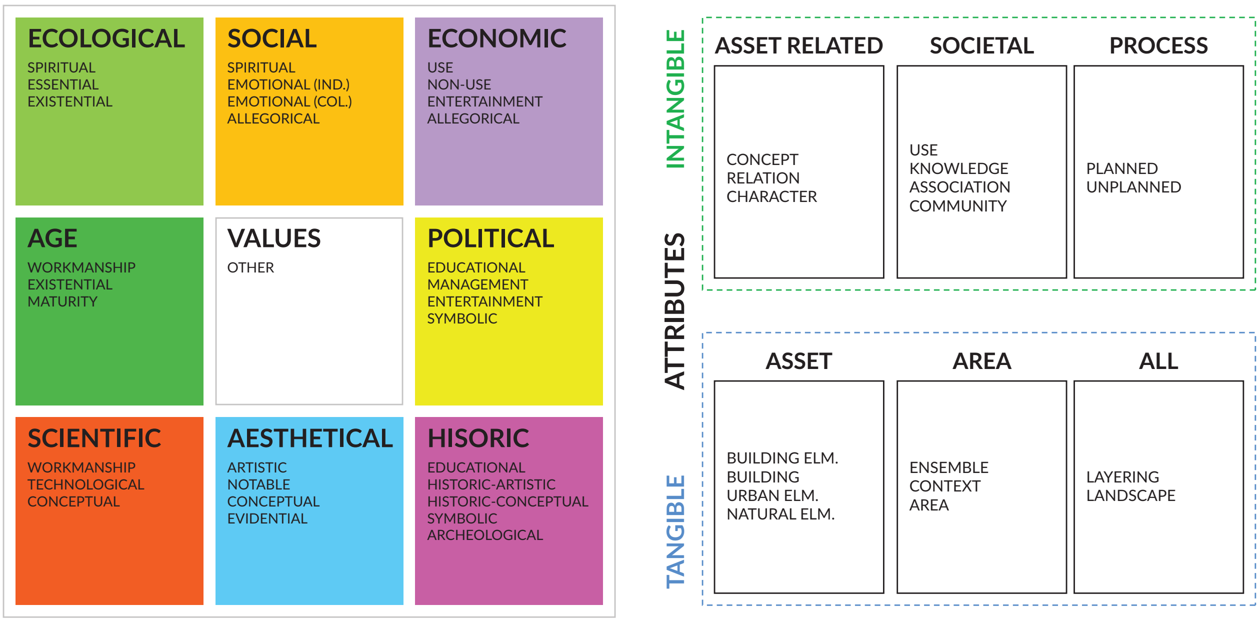

Figure 4. Theoretical framework on culturally significant values and attributes. Sources: Pereira Roders (2007) and Veldpaus (2015).

The qualitative analysis in this research is a multi-label text classification task used in natural language processing where the goal is to assign multiple labels to a given text document. In this research, each label represents a specific class of values or attributes that the document can belong to. We trained the BERT (bidirectional encoder representations from transformers) model to perform multi-label text classification. The objective was to predict the relevant labels, which represent either values or attributes, based on a given input text.

The BERT model is an influential pre-trained language model developed by researchers of Google (Devlin et al., 2018). BERT has revolutionized the field of natural language processing with its innovative bidirectional approach to language understanding and generation. Unlike previous models that rely on unidirectional processing, BERT leverages a bidirectional context understanding by considering both preceding and following words simultaneously. This unique capability allows BERT to capture comprehensive contextual representations of words and sentences, leading to a deeper understanding of language semantics (Devlin et al., 2018).

To measure the similarity between the words used in the sentence and the classes of values (social, historical, aesthetic, etc.), cosine similarity was applied. Cosine similarity measures the similarity between two vectors by calculating the cosine of the angle between them. Higher cosine similarity indicates greater similarity between the pairs of sentences (B. Li & Han, 2013). A higher cosine similarity indicates a stronger association between the sentence and the corresponding value class, facilitating the classification process. Data analysis and modeling are conducted using Google Colaboratory (Colab), an online platform for collaborative coding and computation. Lastly, the performance of the model was evaluated using accuracy, precision, recall, or F1 score metrics.

Overall, after acquiring the relevant data related to the three stakeholder groups, the values and attributes conveyed by these groups were revealed and analyzed. Consequently, a comparative analysis between the data sources was conducted based on the results found using the above methods and frameworks. This analysis reveals the conflicts and alignments between the perspectives of the stakeholder groups on windcatchers' cultural significance (values and attributes).

5. Results

5.1. Cultural Significance Analysis

As explained in Section 2, cultural significance is analyzed using two frameworks for both values and attributes. This section compares the frequency of mentions of values and attributes in all three types of sources. The reliability of the multi-label text classification model developed was tested and confirmed by the methods mentioned in Section 3 (accuracy: 94%; precision value: 77%; F-measure: 76%).

5.1.1. Values of Windcatchers in Yazd

Concerning the cultural significance of the windcatchers in Yazd, and in particular the values, the data sources referenced all eight categories of values. The most referenced are the economic values (24%), followed by age (15%), ecological (15%), historic (12%), social (11%), scientific (11%), aesthetical (10%), and political (3%) values (see Figure 5). Still, there are some differences and similarities in the most and least addressed values, per data source. While economic and ecological values are the most conveyed values in both literature (academic experts) and policy documents (policymakers), age and historic values are the most addressed values in social media (users). Political values are the least conveyed values in all data sources.

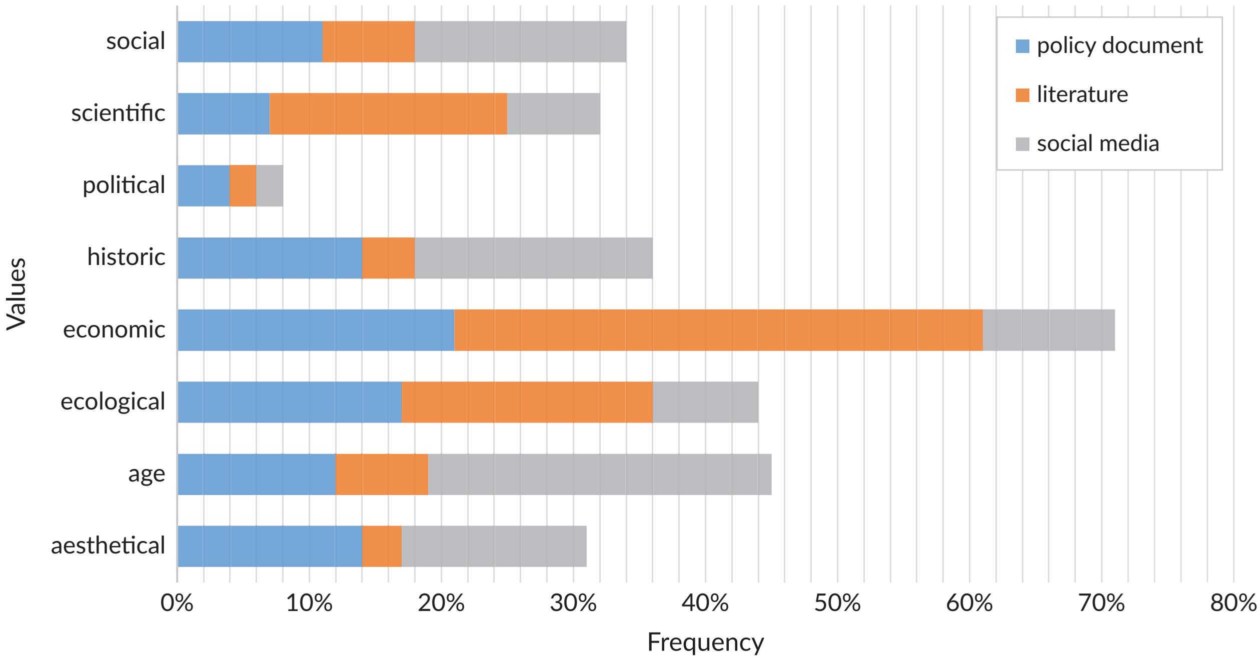

Figure 5. The frequency of values conveyed in different data resources.

5.1.2. Attributes of Windcatchers in Yazd

While all the data sources address all eight categories of values, only a few categories of attributes were found conveying these values. Results reveal that the tangible attributes were referenced more frequently than the intangible attributes (see Figure 6). Respectively, the most frequent tangible attributes belong to the asset class, namely the building (e.g., house, building), the building element (e.g., room, window, roof), and the natural element (e.g., garden, courtyard).

Nonetheless, also intangible attributes were addressed, including more generic attributes such as architecture and design. Social media data convey the most intangible attributes, followed by the literature, and lastly the policy documents. The referenced intangible attributes mostly belong to the asset-related

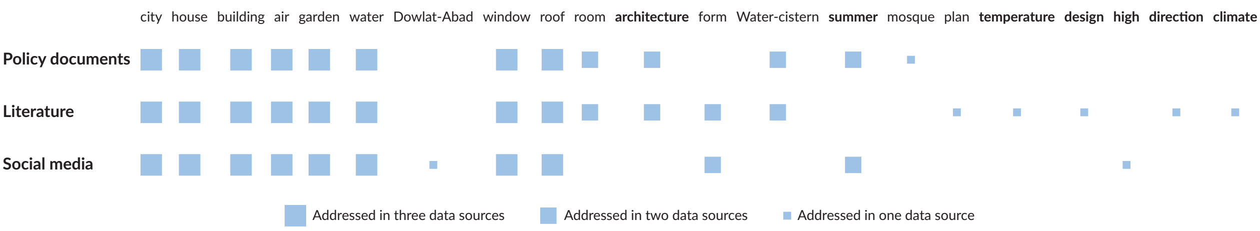

Figure 6. The 20 most frequent attributes in each of the data sources. Notes: The frequency decreases from left to right; tangible: normal font style; intangible: bold font style.

class, which includes the character (e.g., summer, heat, temperature), concept (architecture, design), and relation (e.g., direction, high). To be more precise, temperature, climate, summer, and heat are natural elements and not attributes but they convey the intangible character of windcatchers. They are used in sentences addressing the windcatchers' intangible character that makes a pleasant microclimate in a hot and arid climate in summer by decreasing the indoor temperature.

Among the 20 most frequent attributes in each data source, there are seven common attributes, namely city, house, building, water, air, garden, window, and roof. This shows the importance of the relationship between the windcatchers and their buildings (houses), as well as the city, according to all the stakeholders. Besides, the close relationship between the windcatchers and water, air, garden, windows, and roofs is often mentioned, by all the stakeholders (see Table 2).

Still, some attributes are only frequently mentioned by specific stakeholders. The intangible attributes of windcatchers making a pleasant microclimate (e.g., temperature, climate) and the windcatchers' design concept and plan are mainly discussed by academic experts. The relation of windcatchers with other building elements as per the height difference (and their role in the skyline of the city) is only addressed by users. Besides, only users mention explicit buildings with windcatchers, namely Aghazadeh and Dowlat-Abad buildings.

Table 2. Exemplary quotes.

Reference	Exemplary quote
Conservation Plan of the Historic City of Yazd	*Windcatchers* are closely connected to the *main room*, *porch*, *pool*, and *basement*, creating a condition for the *air* to *ventilate* the *building*, and while the air passes by the *moisture*, elements like the *pool*, *garden*, *tree*, and *basement's wall* compensate the lack of moisture in the *earth* and create a pleasant environment in *hot summer* days for residents.
Windcatcher: Iranian Engineering Masterpiece	*Evaporative cooling* is an important function of *windcatchers*. In Yazd, usually there is a *water pond* in one of the *rooms*, with a *windcatcher* on top of that. This *water pond* contributes to *evaporative* cooling (Bahaodori Nejad & Dehghani, 2018).
Numerical simulation of cooling performance of wind tower (Baud-Geer) in hot and arid region	This figure shows that, by using the logical amount of *water* in the *evaporating system* of the *windcatcher*, the *temperature* decreases a lot and the relative *humidity* increases, both of which are suitable *for hot and dry regions* of a city like Yazd in Iran (Kalantar, 2009).
ID_Post 895	This *room* receives the *air* from the *windcatcher* above it, which pushes *air* from the surrounding environment down to the *pool*, *cooling* it. This *cooled air* is then circulated into the surrounding *rooms*, bringing the *temperatures* down. These *rooms* are beautifully decorated with coloured glass *windows* and *doors* and some of them have their own little *pools*. The *colored lights* streaming from these *windows* get reflected in these *pools* and create a visual experience that is just spellbinding.
ID_Post 4739	Small beautiful *windows* for *air circulation*, facing away from the *sun*. *Windcatchers* are designed in combination with traditional *water reservoirs* on lower levels, capable of storing *water* at near-freezing *temperatures* during *summer*. These are the reasons that made living in the desert possible. This *cooling system* effect is strongest in the *driest climate* and they have done it in the most beautiful way.

Table 2. (Cont.) Exemplary quotes.

Reference	Exemplary quote
ID_Post 1606	…The *windcatcher* operates according to the condition of the *wind* and *sun radiation* in the region. In ancient times and in traditional *buildings* in *arid and dry regions*, the *windcatcher* functioned like the modern *air conditioning system. A windcatcher* is like a chimney whose end is in the underground and the top is set over a specific height on the roof and is built at the entrance of the *house* over *underground water reservoirs* or *ponds* built inside the *house*. The *dry and warm air* passes over a *pond* with a *fountain* and gets *cool* and *wet* through *evaporation*. The *windcatcher's material* plays another role. Due to the high fluctuation of *temperature* differences between day and night in this *climate* and nighttime coldness, a *windcatcher* which is made with *mud-brick* gets *cool* by *radiation* and *convection*.
ID_Post 4	The ancient *city* of *wind catchers*, Yazd, located in central Iran, is one of the great *adobe cities* of the world. Poking high above many of the *buildings*, the tower-scaled *windcatchers* in Iran are designed to *cool* the inside of *homes* by directing the *air* down and inside the *homes*. There are usually small *ponds* of *water* below the *windcatchers* to further help them act as *air conditioners*, as Yazd is one of the *driest cities* in Iran.

5.2. Comparative Analysis

Among the 20 most frequent attributes in each data source, there are seven common attributes addressed by all the stakeholders, namely city, house, building, water, air, garden, window, and roof. Nevertheless, the stakeholders associated different values with these attributes.

Figure 7 highlights the relation between values and these most frequent attributes concerning windcatchers in Yazd. Various stakeholders not only convey a great diversity of values to windcatchers but also illustrate the relation between these values and specific attributes. The case study confirms that cultural significance is defined by a combination of tangible and intangible attributes and values and that its cultural significance is better understood when perceived as an ecosystem. For example, some tangible and intangible attributes (e.g., climate character of Yazd, garden, water, openings) work together with windcatchers to ventilate the air in a building to create a microclimate, to passively provide thermal comfort for the users, and also to protect the building from earthquakes (ecological and economic values of windcatchers). As such, preserving only windcatchers rather than the ecosystem as a whole could endanger the relevant values.

Academic experts highlight fewer attributes, mainly related to certain values, namely economic, ecological, and scientific. Nevertheless, policymakers and users refer to a broader range of values and attributes. As such, while some attributes and values were already conveyed by all stakeholders, the other values and attributes mentioned by only one or two groups of stakeholders are more complementary than contradictory. For example, only users frequently refer to special buildings with unique windcatchers, namely the Aghazadeh and Dowlat-Abad buildings. Together with the policymakers, users highlight the landscape of the historic city of Yazd, created by the urban ensemble punctuated by landmarks such as windcatchers, turquoise domes, and minarets. Lastly, the significance of decoration and decorative materials (e.g., plaster and tile) and their social values are referenced by policy documents.

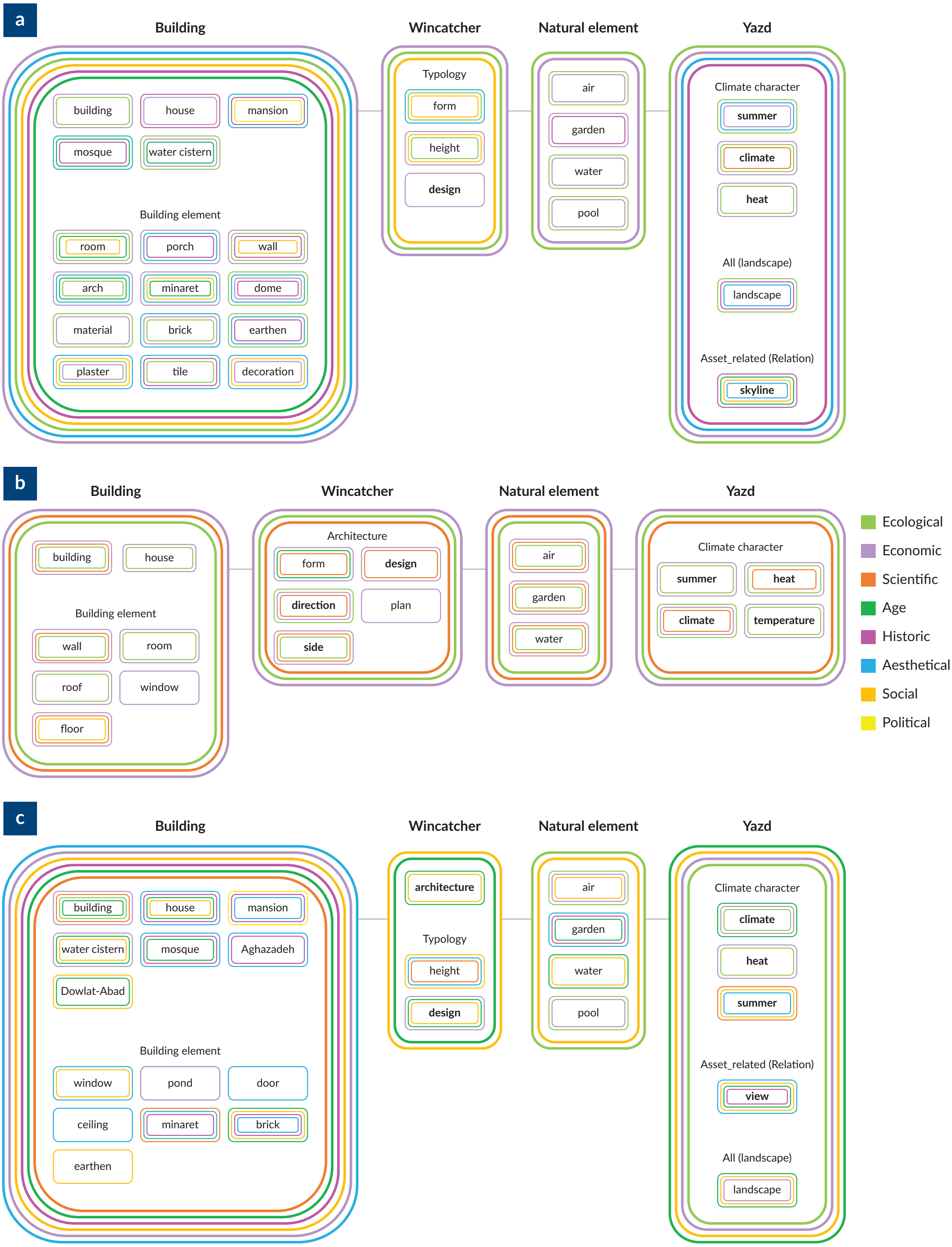

Figure 7. The relation between values and the most frequent attributes concerning the windcatchers in Yazd, with data from (a) policy documents, (b) literature, and (c) social media. Notes: Colorful lines show the values as illustrated in the legend; tangible: normal font style; intangible: bold font style.

6. Discussion

Inclusive heritage planning is crucial for accommodating the diverse cultural significance conveyed by various actors to built heritage. Understanding and acknowledging these values, similarities, and differences is essential to foster inclusive discussions and decision-making. However, the sheer volume of data generated by these actors makes manual analysis time-consuming and impractical. To address this challenge, digital humanities and technologies such as AI offer promising solutions by streamlining the analysis process and potentially uncovering new insights.

This work introduces an innovative methodology for heritage planning that provides deeper insights into the perceptions of policymakers, experts, and users on the heritage values of windcatchers in Yazd, Iran, using social media data, academic literature, and policy documents. AI was applied to analyze the data sources—policy documents, literature, and social media posts—and facilitate the exploration of similarities and differences among the actors. The findings highlight the existence of both similarities and differences, shedding light on the various aspects of values they prioritize. This empirical foundation provides a more robust basis for inclusive discussions and facilitates the inclusive nature of the heritage planning process.

This research challenges the notion that users have little interest in windcatchers, revealing that many users hold positive values toward them. While a small number of posts expressed negative values related to their practicality in modern life, there is a consensus on the positive cultural and social values associated with windcatchers. However, further research is needed to explore if there are additional negative values held by residents. The different perspectives on windcatchers' significance among stakeholders can lead to conflicts over the future of built heritage. Taking into account both positive and negative values can contribute to a more inclusive and democratic approach to heritage governance and planning. Decision-makers and experts need to consider negative values as a complement to the official heritage discourse, representing diversity and multiculturalism and addressing heritage controversies and various interests. This comprehensive understanding can guide heritage managers in their efforts to conserve the cultural significance of windcatchers effectively.

We acknowledge the role that social media can play in empowering the users' community. Social media helps to materialize and foster public engagement, especially when the community is active. This research confirms the potential role that social media can play in broadening the current understanding of the cultural significance of built heritage and in allowing greater inclusiveness in heritage planning. Besides, AI makes it possible to automatically analyze stakeholders' perspectives with great speed and minimum cost.

While this study demonstrates AI's potential to enhance the recognition and planning of cultural heritage, it is important to address several challenges. AI may struggle with contextual understanding, potentially missing nuances in the history and culture of heritage sites that human experts can capture. Furthermore, biases in training data can lead to skewed representations of cultural aspects. Additionally, the complexity of AI algorithms can hinder transparency and accountability, making it difficult to explain decision-making processes to policymakers and potentially eroding trust in the technology. Addressing these challenges is essential for maximizing AI's effectiveness in heritage planning. Besides, AI relying on available data sources including social media data may not fully represent all stakeholder perspectives or demographic information. The methodology's limitations include a focus on official policy documents, academic literature, and social media, potentially overlooking other policymaker, expert, and user groups.

Additionally, the findings from this study, which are based on the analysis of windcatchers in Yazd, Iran, offer valuable insights into the diverse cultural values and perspectives of users, experts, and policymakers. However, to enhance the applicability of these results, future research should focus on a more detailed examination of how these findings can be generalized and applied to other cultural heritage contexts. This involves evaluating how the methodology used here can be adapted to different geographical locations, cultural settings, and heritage types. By extending the analysis to other case studies and comparing results across various contexts, researchers can assess the broader relevance and adaptability of the proposed approach. Such exploration will contribute to a deeper understanding of how stakeholder perspectives can be integrated into heritage planning processes on a global scale, ensuring that the methodologies developed are robust and versatile for diverse heritage scenarios.

7. Conclusion

This research confirmed the assumed benefit of analyzing and comparing various available data, illustrating different stakeholders' perspectives on heritage properties with the support of AI models, to identify and interpret heritage cultural significance (values and attributes). It confirmed the relations between diverse cultural significance (attributes and values) conveyed to the windcatchers of Yazd. The research illustrated the importance of considering an ecosystem and the relations multiple between attributes and values, rather than just the relation of one attribute/value with other attributes/values, researched in isolation. This approach avoids neglecting attributes, tangible and intangible, that are highly related to each other, even when stakeholders omit their relation and highlight only some of the attributes and values of the ecosystem. An innovative aspect of this work consists of the methodology developed, which can be applied to other case studies and different scales in heritage planning studies. Such methodologies using AI and available data sources (e.g., social media) can provide necessary information for heritage managers to enhance legislative frameworks.

Although international organizations such as UNESCO recommend greater public participation, the implementation of participation remains critical. Future studies could illustrate how heritage planning is growing in inclusiveness by using AI and available data sources (e.g., social media). Besides, it is important to investigate the exchange of heritage knowledge (cultural significance conveyed by different stakeholders) between policymakers, academic experts, and users in an inclusive heritage planning system, which can lead to a shared understanding of the cultural significance of heritage and, when needed, help reach consensus among different stakeholders.

Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The data are available at https://data.4tu.nl/datasets/5e55cf64-7912-4b07-8b8e-c2afb067c3e7/2

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ARTICLE

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Simulating Complex Urban Behaviours With AI: Incorporating Improved Intelligent Agents in Urban Simulation Models

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Abstract

Artificial intelligence is a transformational development across multiple research areas within urban planning. Urban simulation models have been an important part of urban planning for decades. Current advances in artificial intelligence have changed the scope of these models by enabling the incorporation of more complex agent behaviours in models aimed at understanding dweller behaviour within alternative future scenarios. The research presented in this article is situated in location choice modelling. It compares outcomes of two multi-agent systems, testing intelligent computer agent decision-making with selected behavioural patterns associated with human decision-making, given the same choices and scenarios. The majority of agent-based urban simulation models in use base the decision-making of agents on logic-based agent architecture and utility maximisation theory. This article explores the use of cognitive agent architecture as an alternative approach to endow agents with memory representation and experiential learning, thus enhancing their intelligence. The study evaluates the model's suitability, strengths, and weaknesses, by comparing it against the results of a control model featuring commonly used logic-based architecture. The findings showcase the improved ability of cognitive-based intelligent agents to display dynamic market behaviours. The conclusion discusses the potential of utilising cognitive agent architectures and the ability of these models to investigate complex urban patterns incorporating unpredictability, uncertainty, non-linearity, adaptability, evolution, and emergence. The experiment demonstrates the possibility of modelling with more intelligent agents for future city planning and policy.

Keywords

agent-based modelling; artificial intelligence; cognitive agents; complexity; household location choice; intelligent agents; market dynamics; planning tools; urban simulation

1. Introduction

Urban planning aims to increase the efficiency of a city and maintain its constant development rate, avoiding periods of stagnation (Bettencourt et al., 2007), while balancing social, environmental, and economic aspects in dynamic relation. However, according to Batty (2008), the concept of achieving and maintaining the equilibrium in an urban system is flawed. Urban systems are far from the equilibrium, existing in a state of tension as different opposing forces build up and break down across a range of spatial and temporal scales, resulting in an array of urban forms and functions (Batty, 2017). The complexity of future scenarios cannot be fully understood as linear and predictable. Within urban studies, cities have begun to be viewed as complex adaptive systems (Sengupta, 2017). Urban dynamics are driven by collective behaviour, where many urban actors' decisions build upon previous decisions made by other urban actors (Portugali, 2006, 2018; Portugali & Haken, 2018).

These complex behaviours and patterns are also exhibited in the housing markets (Marsh & Gibb, 2011). Residential location choice holds significant importance in urban planning due to its impact on social outcomes, showcased in the Netherlands' Housing Memorandum and discussions on new urbanism, as well as smart growth in the USA (Clark et al., 2006). Historic, personal, and collective influences are important to the explorations enabled through the specification of bottom-up, agent-based, and simulated urban models.

Within the realm of urban simulation, researchers create digital representations that mimic the behaviour of entities known as agents (Davidsson & Verhagen, 2013), facilitating experimentation and exploration of large-scale consequences arising from localised interactions (Axelrod, 2007). Urban simulation serves multifaceted purposes within the urban planning domain, ranging across prediction, proof, education, and discovery. These simulations are useful tools for planners, enhancing policymaking processes by providing insights into the potential impacts of various interventions (Batty, 2008; Harris, 1965).

Residential location choice models, primarily created using agent-based modelling (ABM), offer insights into household preferences. Rooted in urban economic theory, these models reveal how diverse attributes influence households' location decisions, impacting employment, economic development, social structure, spatial segregation, and transportation systems (Jin & Lee, 2018; Waddell & Ulfarsson, 2003; Wang & Waddell, 2013). Understanding and accurately modelling residential location choice behaviour are paramount for urban planners, policymakers, and researchers alike (Schirmer et al., 2014).

ABM represents a form of artificial intelligence (AI) that simulates the actions and interactions of autonomous agents within a predefined environment (Brafman, 1997; Crooks et al., 2014; Jennings, 2000; Russell & Norvig, 2021; Wooldridge & Jennings, 1995). It integrates weak and strong notions of intelligence, allowing agents to adapt their behaviour based on rules and objectives (Wooldridge, 2009; Wooldridge & Jennings, 1995). Regarding the latter, AI is primarily concerned with rational action, where an intelligent agent makes the best possible decision in a given situation, considering uncertainties and benefits to humans (Russell & Norvig, 2021). Intelligent agents represent a range from simple programs solving specific problems to complex entities like human beings or organisations. There are several types of intelligent agents: simple reflex agents, which act based on current conditions without any history; model-based reflex agents, which use stored models of the world to operate in incomplete environments; goal-based agents, which have desirable outcomes and strive towards achieving/realising them; utility-based agents, whose actions are guided by a utility function measuring desirability (a rational utility-based agent chooses the action that maximises what the agent expects to derive by comparing different outcomes); and learning agents, equipped with a learning element to adapt their behaviour over time through memory representation and experience (Russell & Norvig, 2021).

Current adaptations of residential choice models, based on McFadden's discrete choice modelling, utility maximisation, and expected utility (utility-based intelligent agents; Acheampong & Silva, 2015; Iacono et al., 2008; Silva & Wu, 2012), fail to capture the complexity of decision-making in the housing markets, as evidenced by critiques of the theory in the wider literature (Camerer et al., 2004; Davidson, 1991) and field evidence from behavioural economics (DellaVigna, 2009). Theories such as Simon's concept of "bounded" rationality (Simon, 1972) and the notion of costly optimisation (Conlisk, 1988) offer more nuanced insights into decision-making processes in complex and uncertain environments like residential mobility. They highlight the need for a more subjective rationality to be employed to better reflect the dynamics of urban residential choice seen in real-world decision-making. This call is also echoed in the field of urban simulation, as a number of identified shortcomings point to skewed distributions of demand-let price for land arising due to calibration issues (Rosenfield et al., 2013), limitations on the reliance of empirically-derived relationships (Verburg et al., 2002), lack of impact of demographic changes on demand for dwellings (Ettema, 2011), and lack of cognitive agents capable of adjusting their behaviour to simulate housing search and choice in a dynamic context (Ettema et al., 2005). Both urban economics and urban modelling fields seek to employ new methods that better incorporate dynamics resulting from the complex nature of cities and human-level behaviours driving them.

By employing new ABM architecture and agent theories, residential location choice models can introduce cognitive elements, enabling them to address increasingly complex questions relevant to urban planning. This article aims to explore the integration of strong notions of intelligence into a residential location choice simulation model, leveraging artificial environments to compare novel cognitive agents against industry-standard utility agents. Section 2 below looks into the relevant literature for both the state of the art and the issues around modelling complex behaviour. Section 3 describes the methodology for the creation, running, and analysis of results for the novel cognitive agent models created as part of this research. Section 4 describes the results from the analysis and Section 5 discusses the relevance of these results to the fields of urban planning and modelling.

2. Literature Review

Recently, there has been an increase in policymakers' interest in the housing market processes and outcomes in an attempt to support urban planning (Maclennan & O'Sullivan, 2012). Understanding and modelling residential location choice is invaluable to urban planners as it aids in understanding the impact of planned interventions (Batty, 2008; Harris, 1965; Schirmer et al., 2014). These types of models have evolved over time, with current iterations featuring disaggregated ABM techniques with the decision-making of agents being based upon economic theories and models (Acheampong & Silva, 2015; Heyman et al., 2018; Iacono et al., 2008; Klabunde & Willekens, 2016; Lopes et al., 2019; Silva & Wu, 2012). However, these models are mostly based on McFadden's discrete choice modelling, utility maximisation, and expected utility approaches (Acheampong & Silva, 2015; Iacono et al., 2008; Silva & Wu, 2012). Despite their dominance, models based upon rational choice and optimizing behaviour have notably failed to explain observed behaviours (Cho, 1996; Karunarathne & Ariyawansa, 2015; Koklic, 2009; Koklic & Vida, 2011; Meen, 2008).

This failure motivates an interest in alternative theoretical approaches, in an attempt to account for the disparity between true and observed utility (Train, 2003). Within the literature, there is a strong critique of expected utility models based on neoclassical economics with a call to shift towards behavioural economic theories (Dunning, 2017; Marsh & Gibb, 2011).

Current neoclassical economic models are based upon assumptions, such as the ability of households to achieve or approximate utility maximisation in decision-making (Dunning, 2017). According to these models, a dwelling location has the ability to reflect the optimal balance between household preferences, housing characteristics, financial constraints, and market prices (Dunning, 2017), showcasing perfect knowledge of the market, a somewhat contested concept (Simon, 1972). The neoclassical economic perspective often overlooks the significance of the search process in housing decisions, presuming that outputs explain preferences and markets trend towards equilibrium (Dunning, 2017). Yet, urban systems, as argued by Batty (2008), exist in a constant state of flux rather than achieving a static equilibrium. This view is supported by urban studies, highlighting cities as complex adaptive systems shaped by collective behaviours (Batty, 2017; Portugali, 2006, 2018; Portugali & Haken, 2018; Sengupta, 2017).

Within the alternative behavioural economics framework, the search process is far more significant as actors in markets do not possess perfect knowledge (March, 1978; Rosser & Rosser, 2015; Simon, 1972). There is a need for information to be gathered, organised, and evaluated, potentially leading to suboptimal decisions (Dunning, 2017). In adopting an approach rooted in institutional and behavioural economics, there's a need to question the level of abstraction in theorising and modelling housing market behaviour. The complexity inherent in housing choices challenges conventional abstractions, emphasising the need for economic models to incorporate uncertainty, complexity, and the role of expectations (Marsh & Gibb, 2011). Marsh and Gibb (2011) argue this level of complexity can be achieved by integrating micro-foundations of bounded rationality and simple decisional rules. This is echoed by findings from Wolfram's Cellular Automata models (1994) and other modellers denoting that simple agent interactions can give rise to complex behavioural patterns (Batty, 2009; S.-H. Chen, 2012; Y. Chen et al., 2012; Wolfram, 1994). Therefore, a model need not be complex but be able to exhibit, through the interactions of rule-following agents and their social dynamics, the complex aggregate housing market behaviours required.

Categories of behaviours, also known as dynamics, that exist in housing markets range widely, as mentioned in the wider urban economic literature (Dunning, 2017; Paraschiv & Chenavaz, 2011; Simon, 1972; Tsai et al., 2010; Whittle et al., 2014). This article has compiled a relevant list of such behaviours, evidenced in the literature, in Table 1. The selection is not exhaustive, but it is sufficient to frame the results of this article's created models and judge their ability to showcase dynamic behaviours that link to urban theories framed in complexity.

Considering new publications in the field, it is evident there is ongoing research into decision-making mechanisms for agents within residential location choice models with attempts to incorporate subjectivity in agent decision-making. Fatmi and Habib (2018) have recently proposed a new prototype for the integrated transport, land-use, and energy model (Habib & Anik, 2021; Habib & McCarthy, 2021) that incorporates how life circumstances of agents affect their location choices. The model is based upon the theory of residential stress, suggesting residential stress triggers a household's migration—generated by changes in life stages, dwelling characteristics, and neighbourhood attributes (Fatmi et al., 2017). The approach integrates a "fuzzy"

Table 1. List of market dynamics, their literature citations, complexity patterns, and price indicators.

Categories of Behaviour/Market Dynamics	Cited in Literature	Related Complexity Patterns	Price Indicators
Sacrifice/Satisficing	Simon's theory challenges the notion that consumers aim to maximise utility. Instead, he proposes that they satisfice due to bounded rationality, making decisions that are "good enough" rather than meticulously calculating optimal choices (Russell & Norvig, 2021; Simon, 1972).	Unpredictability and uncertainty are both patterns in housing markets. People making choices may not be optimal but satisfactory given cognitive limitations.	Uncertainty results in an unprecedented increase in demand for sub-optimal choices which in turn lead to higher overall prices for lower valued houses.
Shifting Preferences	Dunning (2017), in his paper outlining competing notions of home search, regards households with the ability to change preferences based on new information.	Preferences are dynamic and can shift with new information, often revolving around broader aspirations such as comfort. This is indicative of complex adaptive patterns that can be viewed as unpredictable with demand having no equilibrium but existing on the edge of chaos.	Unpredictable consumer shifts in preferences result in volatile changes in prices, with increased frequency of demand and varied pricing for both high and low valued homes.
Contradicting/ Varied Preferences	Dunning (2017), in his paper outlining competing notions of home search, describes contradicting and varied demands exhibited by consumers. Preferences in housing can be contradictory, with individuals desiring attributes like larger space while also seeking intimacy or homeliness.	These patterns of behaviour are characterised by uncertainty in consumer decision-making leading to the dynamic self-organisation of market choices. This reveals patterns of plural taste and preferences at once.	Plurality leads to varied preference behaviours with distinguishable price bands for houses and multi-modal distribution of demand showing different demand groups.
Existence of Price Bubbles	Research on a range of outcomes from the 2008 crash and critics on neoclassical theories suggests the existence of price bubbles arising from consumer behaviour in real-estate markets (Stephens, 2012; Whittle et al., 2014).	This type of market dynamics is reminiscent of cumulative and evolutionary complex patterns. A lack of equilibrium that sees competition being the driving force for emergent price hikes that defy the global/system optimal.	Lack of adherence to the system optimal manifest as market prices reaching higher than expected peaks.

Table 1. (Cont.) List of market dynamics, their literature citations, complexity patterns, and price indicators.

Categories of Behaviour/Market Dynamics	Cited in Literature	Related Complexity Patterns	Price Indicators
Herd Behaviour	Research by Tsai et al. (2010) and others point to households exhibiting herd behaviour in real-estate markets (Whittle et al., 2014). Biased price expectations lead to speculative activities causing volatility in prices and greater demand when prices are higher.	Housing demand is influenced by herd behaviour, which is cumulative and evolutionary in nature. Consumers self-organise and adapt their behaviour in accordance with what other consumers believe, leading to non-rational patterns of behaviour.	The volatility of fluctuating prices and the strengthening of demand at times when the product price is high indicates collective anticipatory behaviour.
Loss Aversion	Loss aversion has been observed in studies by Paraschiv and Chenavaz (2011) on homeowner selling and buying activity in real-estate markets. Loss aversion among homeowners leads to reluctance in selling properties at nominal losses.	Loss aversion behaviour is a non-rational optimisation behaviour. It allows the system to have variations leading to non-linearity and unpredictability in patterns that never reach equilibrium but strive towards a moving one. This challenges the assumed global/system optimal.	What is observable is a gradual price increases especially for lower valued homes as a resultant outcome of this non-rational behaviour.

logic-based location search model within the integrated transport, land-use, and energy framework, utilising a multinomial logit model to handle utility equations and incorporate evolving coefficients reflecting life-stage changes, thereby blending subjectivity into decision-making while retaining a logic-based foundation rooted in neoclassical economic theories. Other attempts feature egalitarian bargaining, Nash bargaining, and utilitarian principles (Yao & Wang, 2021) that incorporate group decision-making within household location choice dynamics. This features a latent-class-discrete choice modelling approach incorporating personality traits for agents that have a higher or lower tendency towards egalitarianism in collaborative decision-making (Yao & Wang, 2021). Other attempts seek to improve on a classic utility maximisation location choice model with the addition of reference-dependent theory (Li et al., 2020). It is evident that the field is attempting to evolve its economic theoretical basis for agent decision-making to improve the potential of urban simulations and their usefulness to urban planners.

However, many of these and previous attempts still rely heavily on neoclassical principles of rationality as agents are modelled as being rational. This has led to a number of identified shortcomings that point to the lack of spatial attributes in determining location choice with skewed distributions of demand-let price for land arising due to calibration issues (Rosenfield et al., 2013), limitations on the reliance of empirically-derived relationships (Verburg et al., 2002), lack of impact of demographic changes to demand for dwellings (Ettema, 2011), and a lack of calibration methods for parameter values to ensure best fit of model (Kii & Doi, 2005). These all add to a call for more advanced behavioural agents (Vorel et al., 2015). Furthermore, there is a lack of cognitive agents capable of adjusting their behaviour, agents for simulating housing search and choice while incorporating negotiation between developers and potential buyers in a dynamic context (Ettema et al., 2005). The literature clearly indicates researchers in the field of urban simulative models are seeking to harness the advantages of disaggregated behavioural approaches (Vorel et al., 2015). However, to the best of the authors' knowledge, currently there are no urban applications of advanced cognitive behaviours and architectures (Heppenstall et al., 2016). This article seeks to demonstrate how the use of alternative agent decision-making theories and cognitive-based intelligent agents can lead to the incorporation of different types of dynamic behaviours in residential location choice models.

3. Methodology

The methodology section outlines the approach employed in the research. It explains the creation of two distinct models featuring two different types of intelligent agents (AI) engaging in residential dwelling demand and exchange within a simulated virtual urban location choice environment, reduced with essential qualities that the intelligent agents can respond to.

3.1. Overview of the Methodology

This follows a four-step process (Figure 1). Step 1 involves the creation of a virtual environment, an abstracted real-estate market featuring household agents competing to live in houses located in different neighbourhoods, each with their own attributes. The agent's choice is focused on satisfying the seven criteria outlined in Table 2. Step 2 involves the creation of the decision-making mechanisms for each of the two distinct simulations created, exploring the implications of different types of intelligent agents on the ability to exhibit dynamic behaviours within the housing markets. Step 3 runs both models for 30 turns and

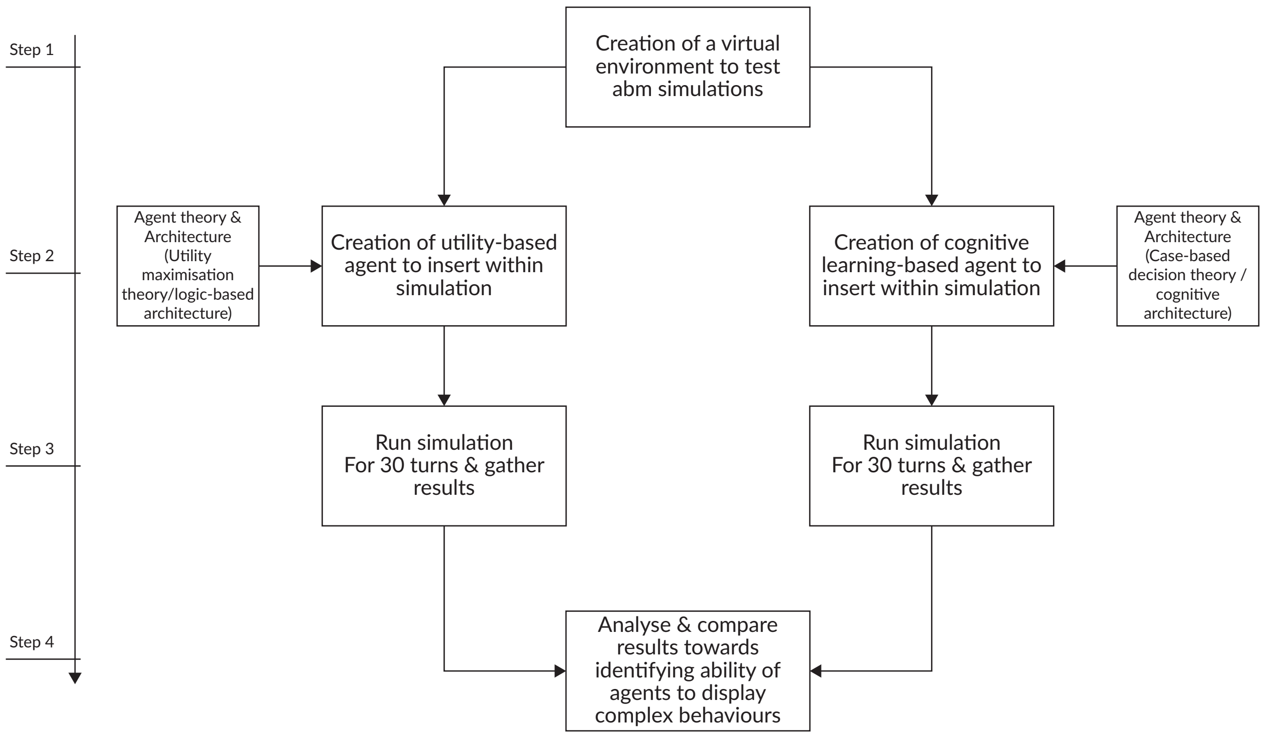

Figure 1. Diagram of methodology steps.

their results, the evolution of price for each of the houses, are collected. Step 4 is the analysis and comparison of the results using two statistical analyses. The primary objective of the analyses is to investigate the ability of these two simulations to exhibit dynamic behaviours through diverse price fluctuation patterns as outlined in Table 1.

Table 2. Simulation parameters.

Input Type	Parameter Setting
Number of household agents	24
Number of houses	12
Number of neighbourhoods	3
Household attributes	ID, Income, Number of children, Current house
House attributes	ID, Neighbourhood, Near a park, Near a school, Near work, Initial price, Current price, Number of rooms
Neighbourhood attributes	ID, Houses contained, Park, Work, School
Criteria that households strive to achieve when choosing a house	7 (Live in a house, Suitability, Affordability, Safety, Live near a park, Live near a school, Live near work)
Dynamic criteria influenced by other/collective household choices	2 (Affordability, Safety)
Simulation outputs	Price evolution over the course of 30 turns for each house

3.2. Step 1: Creation of a Virtual Environment with Entities, State Variables, and Scales

The models consist of 12 dwellings and 24 household agents competing for occupancy, with standardised attributes across entities. Dwellings are spread across three neighbourhoods offering distinct amenities like parks, schools, and work proximity (see Figure 2). Agents aim to meet the seven criteria, including living in a suitable, affordable, and safe house near parks, schools, and work. Safety rating and house prices are dynamic, influenced by collective agent decision-making with safety being a measure of relative income levels within the neighbourhoods. Houses and agents possess the unique core attributes outlined in Table 2.

3.3. Step 2: Data Inputs and Simulation Run Overview

As conceptual models, the research does not require real-world data for input with entity (i.e., neighbourhoods, houses, agents, etc.) attributes determined through calibration and parameter-sweeping experiments, ensuring a controlled environment for effective comparisons between the models.

The simulations run for 30 turns, with each turn consisting of a sequence of seven stages (Figure 3). The first stage involves gaining a perspective, with household agents setting objectives for the round. In the cognitive architecture, agents establish preferences, while in the industry standard model with utility agents preferences are pre-set, aiming to maximise utility. The second stage is the housing search, with agents exploring the market based on their demands. Selection criteria differ: Cognitive-based intelligent agents consider updated preferences, while utility-based intelligent agents prioritise improvements in specific utility aspects. The third

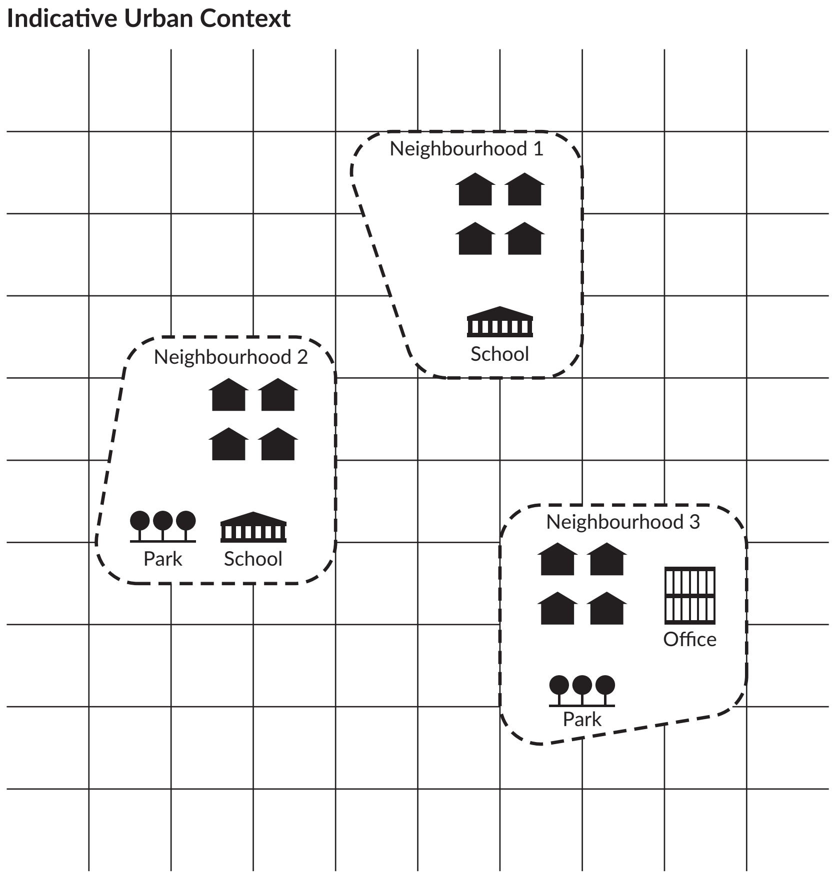

Figure 2. Simulation virtual environment.

stage involves registering an interest in the shortlisted houses, impacting market values. The fourth stage adjusts house prices based on accumulated demand. A linear relationship between interest (demand) for a house and price shift is established, represented by the following equation:

$$pc = pi \times [1 + (ti \times 0.05)]$$

Where *pc* is the new current house price, *pi* is the initial house price, and *ti* is the total amount of interest (demand) for the house in a turn. In the fifth stage, agents decide between available houses, using lexicographical methods. The sixth stage varies: Cognitive-based intelligent agents update preference rankings, while utility-based intelligent agents assess utility scores. Finally, the satisfaction level in the seventh stage determines the agents' continued activity in the housing market, assessing their satisfaction with their current choice.

3.4. Step 3: Model Theories/Architecture

3.4.1. Model 1: Logic-Based Agent Architecture

Model 1 employs utility maximisation-based intelligent agents with a logic-based architecture. Normally, agents would use a utility maximisation equation to determine the best alternative. In this case, due to these models being conceptual and therefore lacking empirical data by which to derive the utility values, a preference list of utility featuring each housing attribute is created. It utilises ordinal utility (Hicks & Allen,

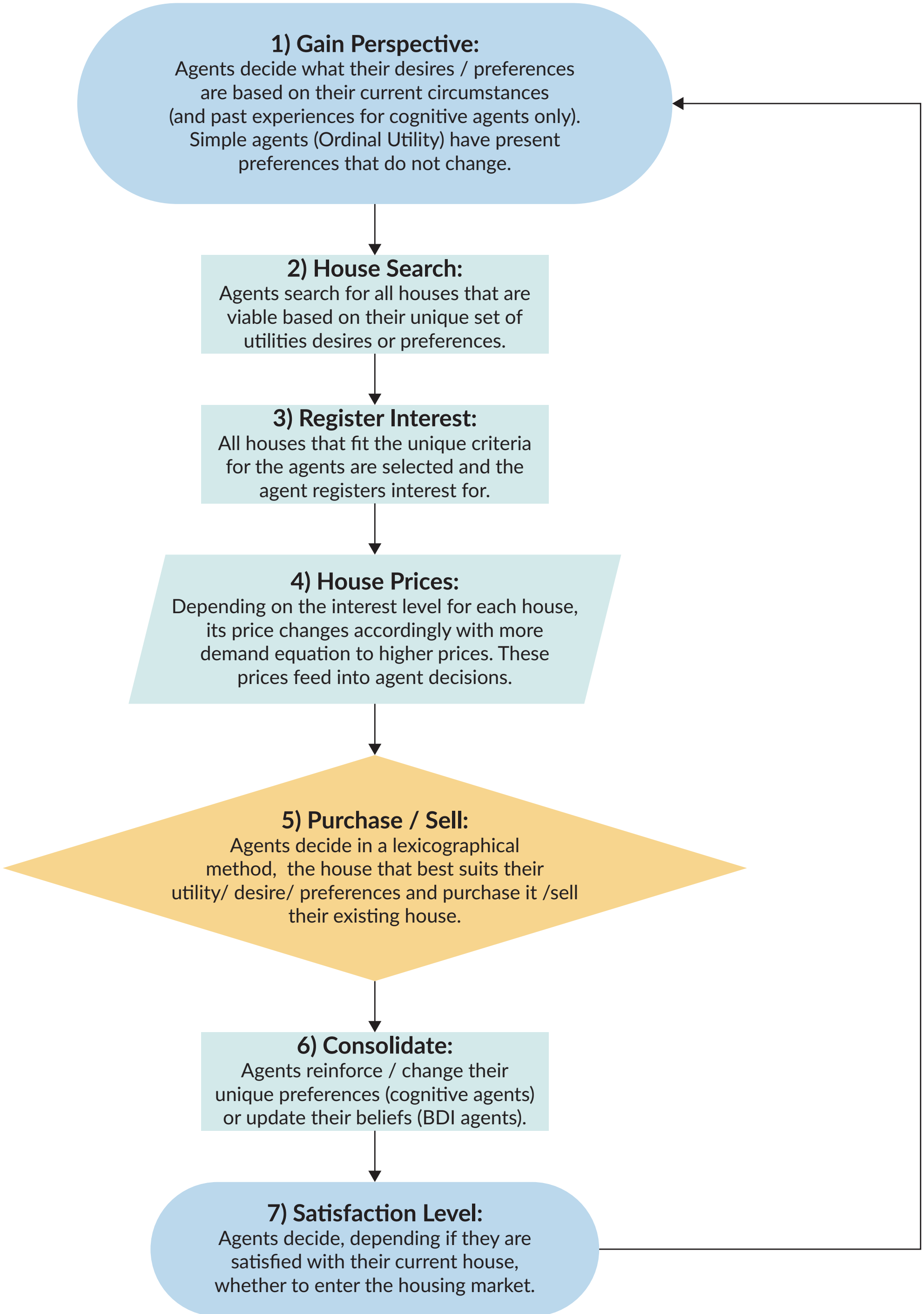

Figure 3. Overview of the seven-stage process run at each turn of the simulation.

1934) to enable agents to make logic-inferred decisions under certainty. The ordinal utility function, like utility maximisation, ensures the U value of a preferable alternative (U_n) is greater than that of an alternative (U_m) as seen in the equation below (Batley, 2008, p. 7):

$$\hat{U} - n \geq \hat{U}_m \, iff \; x_n \geq x_m$$

where $\hat{U} = f(U)$, and f is a strict monotone of U.

This is achieved without the need to empirically calibrate the utility of each attribute using empirical data, but still maintaining set utility values throughout the simulation, a characteristic of utility maximisation-based models.

The list of prioritisation of the criteria in terms of their utility, with the first on the list being the most preferable (highest utility) and the last item on the list being the least preferable (least utility), as well as the decision-making process at each turn, is outlined in Figure 4.

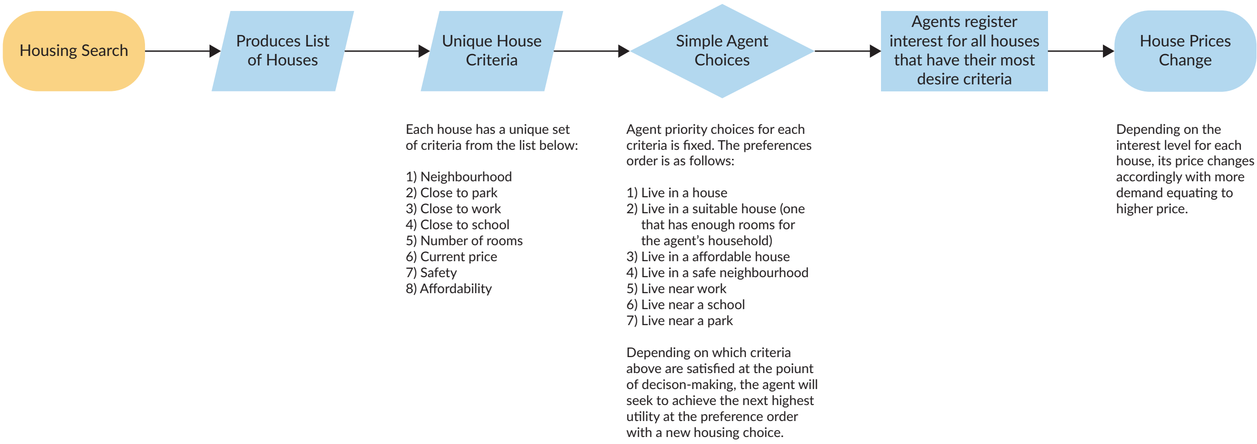

Figure 4. Diagram outlining the decision-making process for simple agents (logic-based architecture).

3.4.2. Model 2: Cognitive Agent Architecture

Model 2 introduces cognitive-based intelligent agents with memory storage and representation capabilities. This model enables agents to learn from past experiences and prioritise housing attributes based on subjective preferences. The core algorithms are inspired by the case-based decision theory and consumer behaviour theory. The case-based decision theory has agents use past experiences to make current decisions, where each memory comprises a situation, action, and result (Gilboa & Schmeidler, 1995). In this model, an agent's actions are their prioritisation of criteria in a given situation and the results of those actions are recorded as experience, which in turn influences further actions. Experience results in a utility constant number (c) that gets added or subtracted from the memory's numerical representation of total utility for any given criterion depending on whether the agent had a positive or negative experience with it. This ensures all decisions are based on previous decision prioritisation outcomes and agent taste and preferences evolve as they experience different things. These total utility representations for each criterion are as follows:

1. self.esuit = esuitable : Agent's utility function for suitability;
2. self.eaffo = eaffordable : Agent's utility function for affordability;
3. self.esafe = esafe : Agent's utility function for safety;
4. self.ework = ework : Agent's utility function for living close to work;
5. self.escho = eschool : Agent's utility function for living close to school;
6. self.epark = epark : Agent's utility function for living close to parks.

The housing choice sequence for cognitive-based intelligent agents involves assessing experiences (Figure 5). For example, if an agent who is physically active lived in a house close to a park and had a positive experience

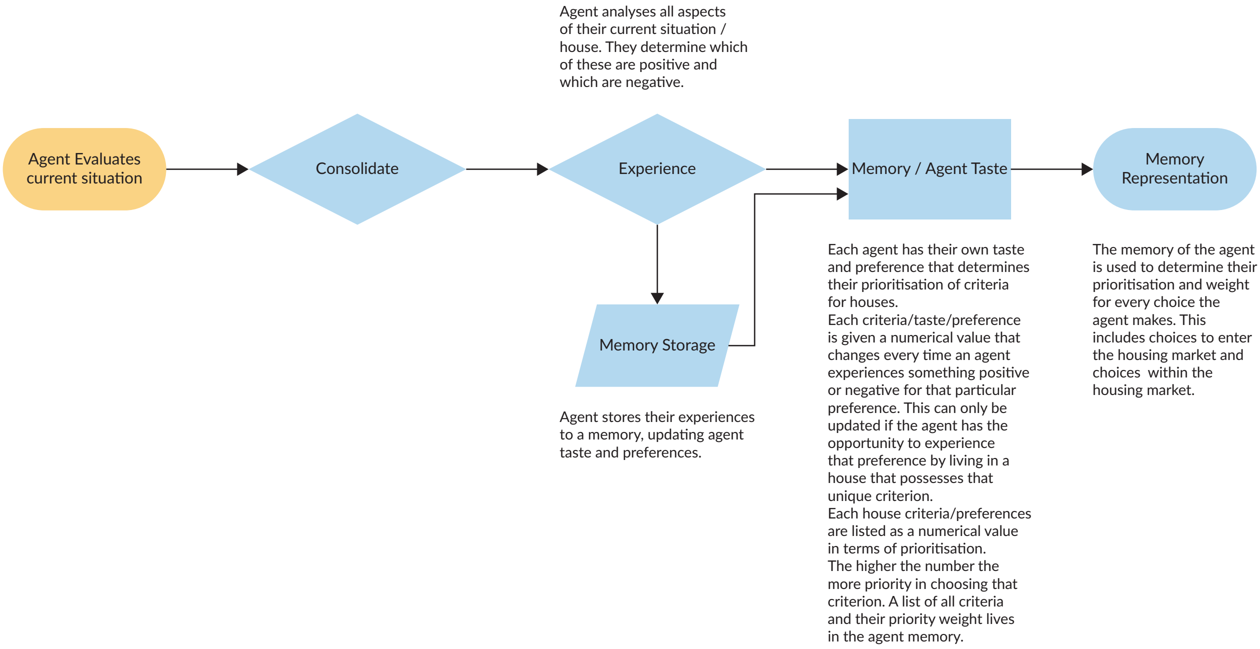

Figure 5. Cognitive agents' overview of inputs to and from memory through experience.

as a result of it, their total utility representation for that criterion (epark) would be updated with the equation epark = epark + c. Cognitive agent choice sees them prioritise housing criteria in a lexicographical way, where the criterion with the highest total utility representation number is used to cull the list, removing all alternatives that do not possess that criterion. For example, out of the 12 houses, if the agent's prioritised criterion is to live close to work, all houses that do not have that attribute are removed from the choice list for that turn. This continues with the second-highest utility value criterion which culls the list further and then the third, and so on, until a single option is left that consists of the agent's choice of house for that turn. After the set choice, at the end of the turn, the agent evaluates their experience with that choice which results in changes to memory representations of each criterion's utility number which leads them to change and refine their tastes and preferences. Whether something is seen as a positive or negative experience depends on both the agent's attributes (such as income level, family situation, etc.) and if the house meets their needs.

3.5. Step 4: Analysis and Comparison of the Results

The output of the simulations is a series of price fluctuations for each house resulting from changes in demand patterns at each of the 30-turn simulation runs for each model. Two statistical analyses (decomposition analysis and histogram with normal distribution fit) are used to identify and compare the capacity of each model to exhibit each of the six identified categories of behaviour. The authors chose to use the multiplicative time series decomposition analysis to identify trends and fluctuations in individual house prices across different value spectrums. This method allows for the detailed examination of how demand and price change over time, highlighting seasonal and trend components (Prema & Rao, 2015). It provides insights into the variability and predictability of demand through metrics like the mean absolute deviation (MAD). This approach is effective for understanding the subjectivity in the agents' decision-making patterns and the overall alignment of computational simulations with real-world dynamic behaviours.

The research utilised histogram analysis with a normal distribution fit to examine the frequency of house prices and demand levels over 30 rounds. This method reveals demand distributions and standard deviations for houses in different price brackets. It helps identify how agents perceive house value, showing decision-making differences by highlighting skewed, normal, or multi-modal distributions. The analysis also compares deviations at various price points, indicating the agents' interest patterns and their rationality. By disregarding outliers, the study ensures the results represent the majority of agent behaviours, providing insights into how computational agents' demand patterns align with real-world dynamic behaviours.

Table 3 summarises what types of dynamic behaviours are visible through each of the analysis and their details.

Table 3. Types of analyses and the dynamic behaviours they reveal.

Type of Analysis	Dynamic Behaviour Represented	Details
Decomposition analysis with a seasonal period of five turns	Shifting Preferences, Herd Behaviour, Loss Aversion, Existence of Price Bubbles	Shifting Preferences: High fluctuation of demand and lack of defined cyclical shape in seasonal fit indicate evolving decision patterns. Herd Behaviour: High fluctuation in demand and multiple differently valued peaks within a seasonal cycle indicate collective decision-making patterns. Loss Aversion: Positive overall trend in demand suggests agents reluctant to sell at a loss, leading to gradual price increases. Existence of Price Bubbles: Irregular and high amplitude and frequency of price fluctuations suggest subjective decision-making and potential formation of price bubbles.
Histogram with normal distribution fit	Contradicting/Varied Preferences, Herd Behaviour, Price Bubbles, Sacrifice/Satisficing	Contradicting/Varied Preferences: Multi-modal distribution indicates diverse preferences among agents, leading to varied demand patterns. Herd Behaviour: High frequency of prices for high-valued homes suggests collective decision-making and herd behaviour. Price Bubbles: High frequency of prices for high-valued homes suggests herd behaviour and potential formation of price bubbles. Sacrifice/Satisficing: Even deviation across all price points indicates strong demand for sub-optimal choices, reflecting the agents' willingness to make sacrifices for specific preferences.

4. Results

4.1. Utility-Based Intelligent Agent Results

In the decomposition analysis, these agents show a high MAD value (Observation 2 in Figures 6, 7) for high-value homes, but a low one for lower-valued homes, partly indicating shifting preferences. In high- and low-value houses, utility-based intelligent agents have a low-steep downwards trend (Observation 3 in Figures 6, 7) which does not indicate loss aversion behaviour. In both high- and low-valued housing, agents maintain relatively low amplitudes of price fluctuations (Observation 5 in Figures 6, 7). In low-valued house analysis, the amplitude of price fluctuations is regular after turn 5 (Observation 5 in Figure 7). Spikes in prices occur regularly every 3 rounds in high-valued houses (Observation 4 in Figure 6) while more irregular in low-valued houses (Observation 4 in Figure 7). Furthermore, the seasonal fit pattern for utility-based intelligent agents in high-valued houses is smooth and irregular in lower-valued houses (Observation 1 in Figure 7). This partly indicates the existence of price bubbles but not herd behaviour.

In the histogram analysis, the agents achieve a skewed distribution to the right (Observation 1 in Figure 8) with their highest occurring frequency of price for a single house being in the lower end at 110,000. This shows a relative lack of varied/contradicting preferences in utility-based intelligent agents and a lack of herd behaviour. Utility-based intelligent agents see their *StDev* increase as house values increase (Observation 2 in Figure 8), meaning they compete more for higher-valued homes and do not settle easily for less optimal choices, showcasing the existence of price bubbles (but not behaviours of sacrifice/satisficing).

4.2. Cognitive-Based Intelligent Agent Results

In the decomposition analysis, cognitive-based intelligent agents achieve a higher MAD value on both high- and low-valued houses (Observation 2 in Figures 6, 7). Thus, they exhibit greater patterns of shifting preferences and herd behaviour than their utility counterparts. In high-value houses, they have a low-steep downwards trend (Observation 3 in Figure 6), however, in low-value houses, they maintain an upwards trend (Observation 3 in Figure 7). This means they exhibit loss aversion behavioural patterns when dealing with low-valued housing. They show high irregular amplitudes of price fluctuation in both high- and low-valued houses (Observation 5 in Figure 7) while also maintaining irregular frequencies of price spikes and irregularly shaped seasonal fit patterns (Observations 1, 4 in Figures 6, 7). This showcases shifting preferences and price bubbles.

In the histogram analysis, these agents exhibit a multi-modal distribution (Observation 1 in Figure 8) with high points at 180,000 and 125,000. Therefore, they split themselves into different groups with contradicting/varied preferences and have the most frequency of prices occurring on the far right of the graph, indicative of herd behaviour, demand increases as price increases, and price bubbles. They also have an even *StDev* distribution across the spectrum (Observation 2 in Figure 8). This means they exhibit complex behaviours of sacrifice as they maintain strong demand for sub-optimal choices, evident also in their multi-modal distribution of price frequencies.

Table 4 summarises the results of the analysis for each of the two computational models. It is evident that a change in the decision-making mechanisms of the intelligent agents (AI) has a profound effect on their actions in a real-estate market and their ability to showcase emergent price patterns that are indicative of dynamic market behaviours. Their performance in that aspect is outlined in Table 4, which clearly indicates that cognitive-based intelligent agents, with their ability to learn and adjust their taste and preferences as they gain experience, showcase more patterns of complex behaviours.

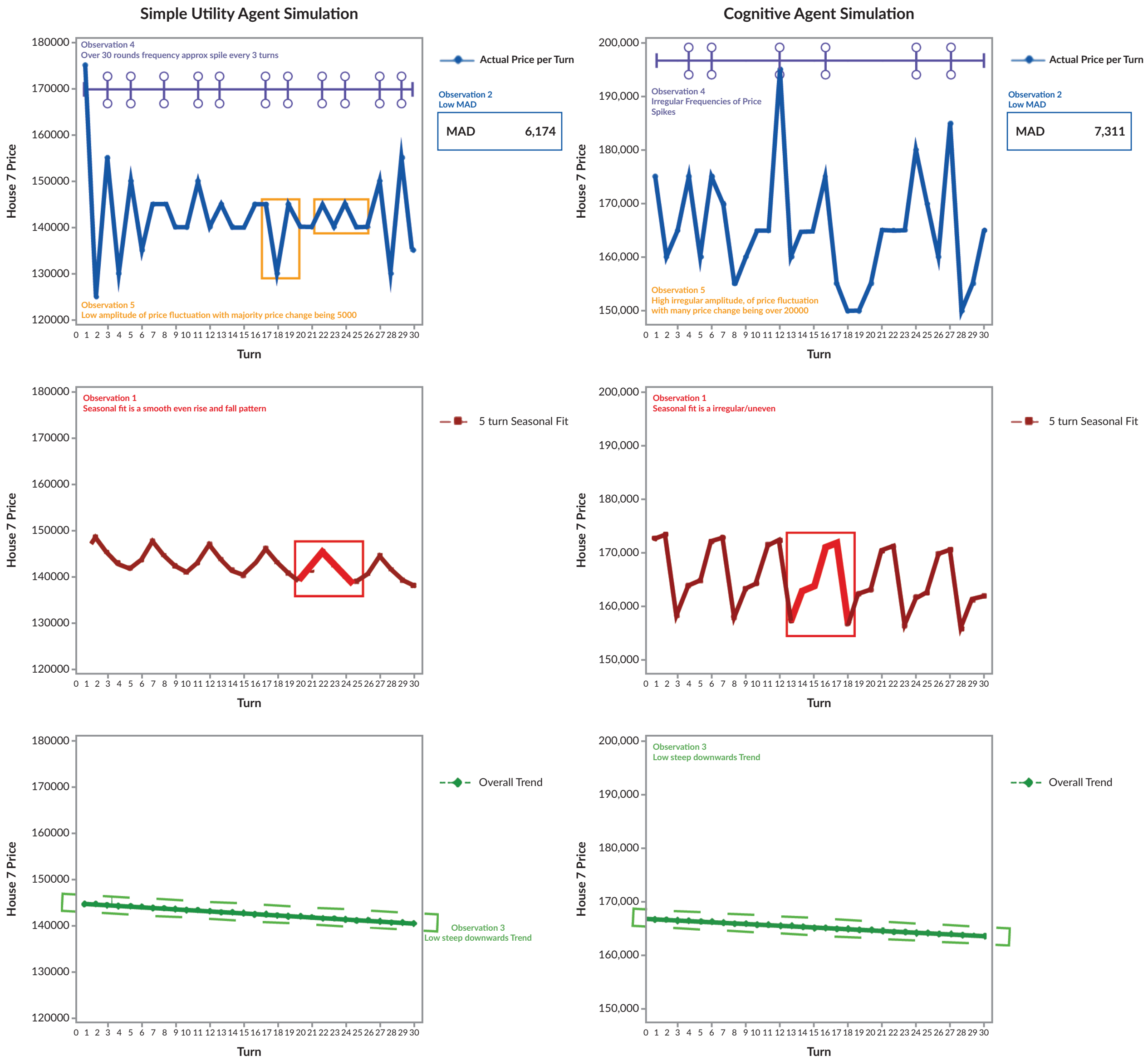

Figure 6. High-value house decomposition analysis results with five turn seasonal fit for utility-based agents vs cognitive agents.

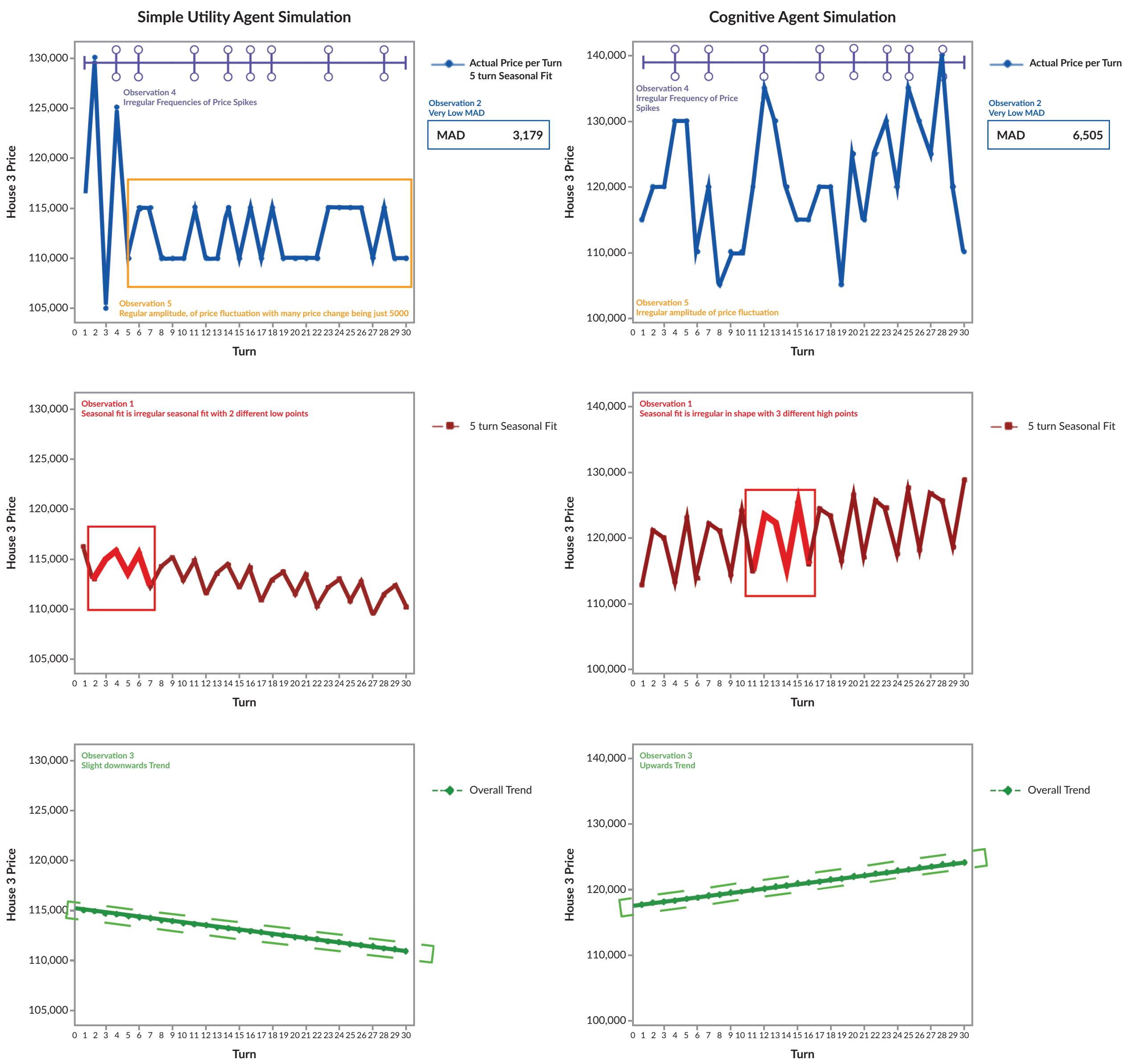

Figure 7. Low-value house decomposition analysis results with five turn seasonal fit for utility-based agents vs cognitive agents.

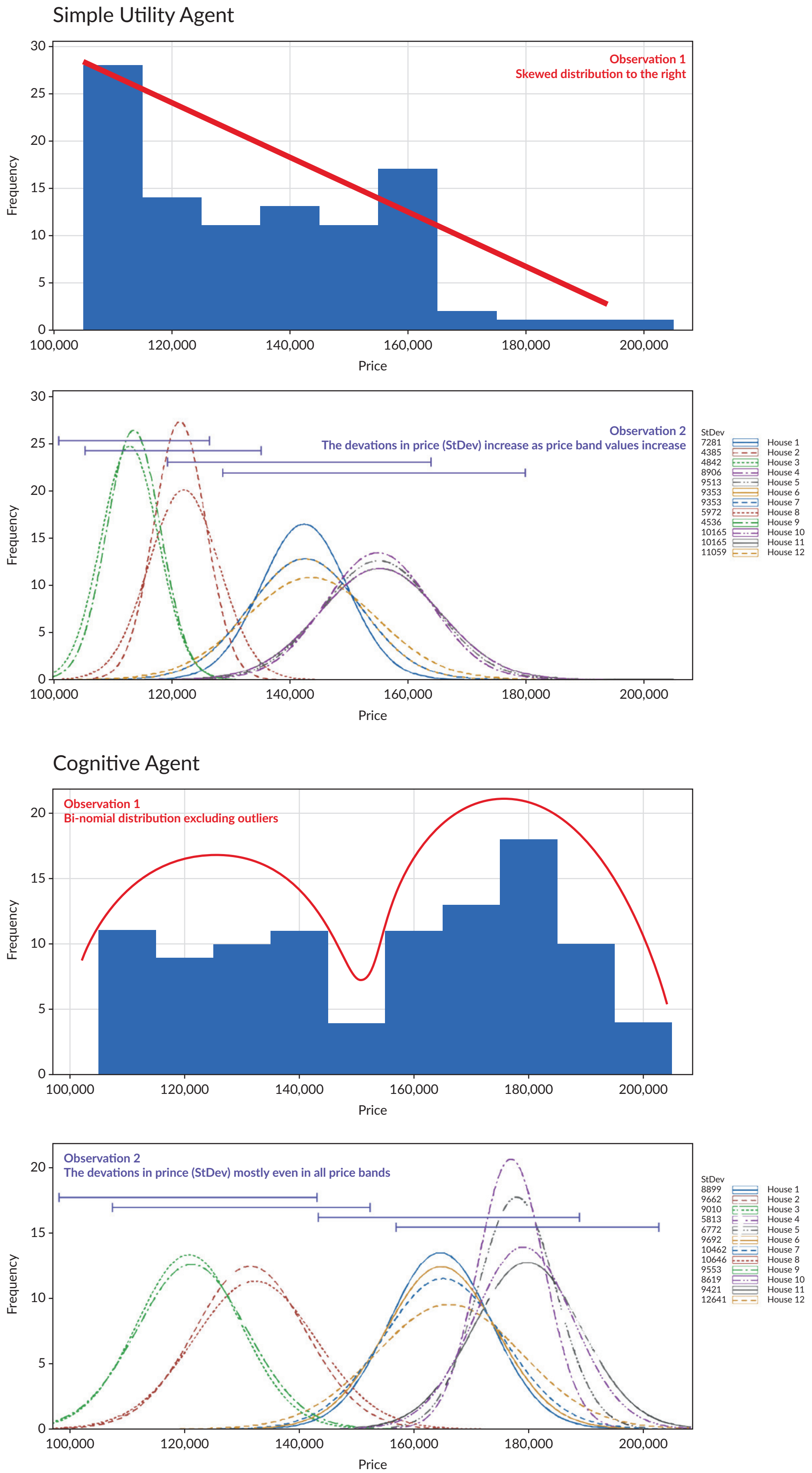

Figure 8. Histogram analysis with normal-distribution for simple utility-based agents vs cognitive agents.

Table 4. Results of analyses for each simulation and ability of simulations to display dynamic behaviours.

Model	MAD	Trend	Amplitude and Frequency of Price Spikes	Seasonal Fit	Frequency Distribution	Standard Deviation	Complex Behaviours Exhibited
Utility	Lower	Low-steep downwards trend	Low amplitude with a mix of regular (high-valued homes) and irregular (low-valued homes) frequency of price spikes	Smooth, even rise and fall	Skewed distribution to the right	Increases as house values increase	1. Shifting preferences 2. Existence of price bubbles
Cognitive	Higher	Low-steep downwards trend (high value), Upwards trend (low value)	High irregular amplitudes, irregular frequency spikes	Irregularly shaped seasonal fit patterns	Multi-modal distribution	Even distribution across the spectrum	1. Sacrifice / satisficing 2. Shifting preferences 3. Contradicting / Varied preferences 4. Existence of price bubbles 5. Herd behaviour 6. Loss aversion

5. Discussion

Studies in housing markets (Dunning, 2017; Paraschiv & Chenavaz, 2011; Simon, 1972; Tsai et al., 2010; Whittle et al., 2014) reveal that residential demand patterns exhibit dynamic and evolving behaviours rather than linear and predictable trends (see Table 1). This study highlights various categories of behaviours observed in the housing markets. These behaviours underscore the intricate nature of decision-making processes and the need for models to account for uncertainty, complexity, and social dynamics (Paraschiv & Chenavaz, 2011; Tsai et al., 2010; Whittle et al., 2014). This is in line with Batty's (2008) challenge to traditional notions of equilibrium in urban systems, suggesting that cities are in a constant state of flux rather than reaching a stable equilibrium. They are on the edge of chaos brought about by stakeholder actions that seemingly defy notions of rationality. Yet, urban simulation tools for planners continue to rely on neoclassical notions of rationality to aid in strategic decision-making. The findings of this study critique these types of models as they fail to exhibit such an array of dynamic behaviours (Table 4).

The route to improvement is not purely one of changing the economic theoretical basis for intelligent agents, as seen in recent advancements in the literature (see Section 2). It requires changing the types of intelligent agents (AI) and their respective architecture. Despite advancements in ABM, there remains a lack of cognitive-based intelligent agents capable of adjusting their behaviour and simulating a housing search and choice in dynamic contexts (Ettema et al., 2005). The construction of cognitive-based intelligent agents in this study addresses this gap by showcasing their superior ability at exhibiting dynamic behaviours (Table 4).

By utilising AI featuring cognitive learning intelligent agents, planners can gain a deeper understanding of housing, transportation, and living environments. This development contributes to the planners' ability to investigate urban patterns of complexity aligning with unpredictability, uncertainty, non-linearity, adaptability, evolution, and emergence, as shown by the ability of cognitive-based intelligent agents to showcase all dynamic behaviours and complexity patterns (outlined in Table 1). These insights have the potential to inform more effective policy interventions aimed at addressing various urban challenges (Batty, 2008; Harris, 1965) forming the basis for improved versions of tools for planners.

The findings of this study therefore underscore the usefulness of AI and cognitive-based intelligent agents, to better capture the complexities of decision-making processes (Cho, 1996; Karunarathne & Ariyawansa, 2015; Meen, 2008). The ability of cognitive-based intelligent agents to display complexity patterns in housing markets is evident in their unpredictable and adaptive behaviour. Their choice of sub-optimal houses led to increased demand for these choices and subsequently drove up overall prices for lower-valued houses. The unpredictability of their decision-making is further reflected in volatile changes in prices, with shifts in agent preferences resulting in varied pricing. They displayed non-rational patterns of herd behaviour, characterised by cumulative and evolutionary shifts in preferences, contributing to fluctuating prices and strengthening of demand. This constant movement towards the equilibrium and non-rational optimisation behaviour challenges traditional notions of rationality in the housing markets and further perpetuates price evolution, highlighting the cumulative nature of their behaviour. The findings prove that, by incorporating subjective rationality into intelligent agent (AI) frameworks, researchers can develop models that better capture the diverse and often irrational behaviours exhibited by human populations. The findings reveal that cognitive-based intelligent agents demonstrate subjective reasoning through their utilisation of inductive reasoning, which is distinct from the deductive reasoning employed by their logic-based counterparts (Russell & Norvig, 2021). Inductive reasoning, from a philosophical perspective, involves drawing plausible conclusions based on past experiences rather than inferring absolute truths from logical premises. This reliance on past experiences introduces an element of subjectivity, as decisions made may not always align with factual depictions of future outcomes, but instead stem from an acknowledgment of imperfect knowledge and individual biases. These intelligent agents (AI) prioritise plausibly good decisions based on their past experiences, which may lead to sub-optimal choices in certain situations. This can be observed through the results as cognitive-based intelligent agents display patterns of sacrifice/satisficing which are behaviours observed by economists (Dunning, 2017; Simon, 1972) in real-estate markets. Therefore, they embrace a more nuanced approach to decision-making, one that accounts for the complexities of real-world scenarios and the inherent uncertainty of future outcomes. This development addresses current urban studies and planning theory critiques that view cities as complex adaptive systems shaped by the seemingly irrational collective behaviour of the entities that comprise them (Batty, 2017; Portugali, 2006, 2018; Portugali & Haken, 2018; Sengupta, 2017). The incorporation of subjective rationality into intelligent agents (AI) contributes to knowledge by enhancing the potential of residential location models to better reflect the complexities of decision-making processes in the housing markets (Conlisk, 1988; Simon, 1972).

Researchers are increasingly recognising the importance of advanced cognitive architectures in urban simulation models (Ettema et al., 2005; Vorel et al., 2015). This study created a simple virtual environment with intelligent agents of limited sophistication with only a few variables and rules governing their decision-making mechanisms. Yet despite the lack of sophistication, the intelligent agents (AI) managed to display a remarkable array of emergent complex patterns and dynamic market behaviours. This validates

Marsh and Gibb's (2011) claim of reduced sophistication in model creation which could make cognitive-based intelligent agent models easier to compute, use, and research. Therefore, both the performance and ease of use of this study's model highlight the opportunities and benefits of incorporating new AI and cognitive architectures into urban simulation frameworks. However, this is only an initial step towards creating such AI-based models as tools for planners. A potential concern with cognitive agents is the issue of computational cost. Cognitive agents require increased computation due to the algorithms of memory and experience that dictate decision-making. As you scale up the environment and amount of agents, computational cost increases exponentially. Further research is also required to develop widely acceptable indicators that link positive and negative perceptions of experiences to population attributes for this type of model.

6. Conclusion

We have presented an experimental development in location choice modelling and more widely urban simulation. The experiment demonstrates that cognitive decision-making agents within an agent-based urban simulation can contribute to at least three times the variety of observable complex dynamic behaviours compared to the current widely used logic-based agents built on utility maximisation theory. We present the findings in the context of existing critiques in urban theory, simulation, and behavioural economics literature, and the lack of alternative options. The construction of alternative agent architectures is an applied development of intelligent agents from the field of AI, endowing agents with memory representation and experiential learning within urban simulation. The findings are relevant towards demonstrating the utility of cognitive agent architectures and their use in investigating urban phenomena through a complexity lens incorporating unpredictability, uncertainty, non-linearity, adaptability, evolution, and emergence. The experiment—while being an initial step with much future research to be done on issues surrounding scalability, computational cost, and development of widely acceptable indicators—emphasises the possibilities of constructing and using intelligent agents for alternative explorations of urban phenomena towards improved urban planning and policy.

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Conflict of Interests
The authors declare no conflict of interests.

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ARTICLE

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A Machine Learning Approach to Adapt Local Land Use Planning to Climate Change

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Abstract

The impacts on living conditions and natural habitats deriving from planning decisions require complex analysis of cross-acting factors, which in turn require interdisciplinary data. At the municipal level, both data collection and the knowledge needed to interpret it are often lacking. Additionally, climate change and species extinction demand rapid and effective policies in order to preserve soil resources for future generations. Ex-ante evaluation of planning measures is insufficient owing to a lack of data and linear models capable of simulating the impacts of complex systemic relationships. Integrating machine learning (ML) into systemic planning increases awareness of impacts by providing decision-makers with predictive analysis and risk mitigation tools. ML can predict future scenarios beyond rigid linear models, identifying patterns, trends, and correlations within complex systems and depicting hidden relationships. This article focuses on a case study of single-family houses in Upper Austria, chosen for its transferability to other regions. It critically reflects on an ML approach, linking data on past and current planning regulations and decisions to the physical environment. We create an inventory of categories of areas with different features to inform nature-based solutions and backcasting planning decisions and build a training dataset for ML models. Our model predicts the effects of planning decisions on soil sealing. We discuss how ML can support local planning by providing area assessments in soil sealing within the case study. The article presents a working approach to planning and demonstrates that more data is needed to achieve well-founded planning statements.

Keywords

GIS analysis; machine learning; nature-based solutions; spatial analysis; spatial planning

1. Introduction

Municipal planning is crucial for climate adaptation and mitigation (e.g., Measham et al., 2011; Storbjörk, 2010). Local governments in Austria, through mayors and councils, use various informal and formal instruments for spatial planning. Spatial planning involves balancing diverse interests and strategic coordination with planning goals and policies at the regional, national, and international levels. One area receiving increased political attention is the preservation of soil as a resource in order to arrive at nature-based solutions (NBS) and mitigate climate change as well as adapt to it (Seddon et al., 2020). NBS are broadly defined as solutions to societal challenges that are inspired and supported by nature (European Commission, 2015). In contrast to many engineered solutions, NBS have the potential to address both climate mitigation and adaptation challenges at relatively low cost while delivering multiple additional benefits for people and nature (Seddon et al., 2020). While urban areas are often beneficiaries of NBS (e.g., urban greening), in smaller regions and municipalities the relevance of unsealed soil as a resource and the application of NBS are often overlooked. At the municipal level, there is often a lack of data and expertise for NBS in planning, resulting in shortcomings in addressing climate change and biodiversity loss locally, as pointed out by recent studies (Boehnke et al., 2023). There is therefore an urgent need to plan strategically for more efficient NBS use in settlement development and create transparency based on sufficient and good-quality data. Machine learning (ML) and automated analysis offer a potential solution. Spatial planning research is exploring artificial intelligence, including ML, to aid data collection, processing, and interpretation. A survey of the literature, however, reveals a gap: While ML is used for predicting land use changes based on time series or extracting imaging landscape elements and features, possible correlations and patterns with underlying planning regulations have not so far been analyzed.

A main aim of this study is to support the development of simulations for the review of planning regulations relevant to the preservation of soil as well as the implementation of NBS and the actual planning decisions taken based on a case study in Austria. The study targets smaller municipalities with limited capacities that often overlook broader implications. In order to develop a robust concept and database for impact analysis as a basis for NBS assessment within an existing regulatory framework, we pursue a methodological approach to building ML models towards the goal of making unsealed soil more visible as a resource and analyzing areas with NBS potential. The prediction of planning decisions on soil sealing is tested via three ML models (k-nearest neighbors [KNN], random forest, and support vector machines). Backcasting planning information and developing qualitative area categories for NBS provides the training dataset for the ML model. Our study provides insights into linking data on planning regulations and decisions to data on the physical environment in Upper Austria.

Following a literature review outlining the research gap (Section 2), the article details the five-step method design (Section 3) and implementation of Steps 1–3 with results (Section 4). The concluding discussion (Section 5) and outlook (Section 6) provide an interpretation of the results and offer directions for further research.

2. State of the Art and Conceptual Framework

2.1. The Role of Municipalities in the Preservation of Soil/Land for Climate Change Adaptation and NBS

At the local level, immediate and directly tangible climate change impacts converge with concrete opportunities for action and local knowledge about vulnerabilities (Radinger-Peer et al., 2015). Local governments are, on the one hand, confronted with multiple global crises (e.g., climate crisis, financial crisis, biodiversity crisis) plus the overarching pressure on land as a valuable resource for multiple purposes, and, on the other hand, with the day-to-day challenges in their place-specific local context (Haase et al., 2018). They often lack the ability to track the consequences of sealing resulting from their planning regulations and decisions and thus overlook the opportunities for climate change adaptation and mitigation as well as preservation of biodiversity (Raymond et al., 2017). Unsealed soil is a key resource for climate change adaptation. In order to strategically minimize climate change impacts, unsealed land is needed to strategically position and connect NBS (Seddon et al., 2020). Particularly in small- to medium-sized municipalities, soil sealing is happening with increasing velocity, counteracting climate change adaptation and mitigation. At the same time, small- and medium-sized municipalities and their role in climate change adaptation, mitigation, and biodiversity conservation remain surprisingly under-researched (Fünfgeld et al., 2023). Many planning processes lack systematic integration of NBS based on strategies for preservation of soil and strategic planning of adaptation measures.

One central aspect that hinders municipalities is limited (institutional) adaptive capacity, owing to limited resources, knowledge, and political will (Buschmann et al., 2022; Fünfgeld et al., 2023). Further barriers on the municipal level include the difficulty in understanding climate science (Fünfgeld, 2010), lack of staffing capacity (Bierbaum et al., 2013), and limited financial resources (Vringer et al., 2021). As a consequence, small- and medium-sized municipalities are characterized by much greater pragmatism in their planning decisions as opposed to strategic planning approaches (Bardt, 2018). Oijstaeijen et al. (2022) point out that smaller municipalities are more affected by knowledge gaps and, therefore, planning decisions that do take NBS and green infrastructure into account are almost solely cost-driven and fail to recognize the full range of benefits (Brokking et al., 2021). Unrecognized benefits of NBS include increased climate resilience, quality of life for inhabitants, as well as biodiversity (Pan et al., 2021). In summary, there is a significant gap in both practice and research on how small- and medium-sized municipalities can be supported in making informed decisions based on transparent data and how planning regulations and subsequent decisions affect opportunities to implement NBS for more resilient land use planning.

2.2. Artificial Intelligence and ML in Spatial Planning

Artificial intelligence and ML offer many possibilities for planning and decision-making, from test automation and simulation to uncovering patterns in data. ML algorithms, including random forest, support vector machines, and neural networks, are used in land use planning and have proven suitable for developing predictive models based on soil data and environmental variables (Chaturvedi & de Vries, 2021). These models are often trained on time series and time-lapse analyses of remote sensing data, segmented to identify/classify objects like roads, buildings, and vegetation (Dornaika et al., 2016; Shorter & Kasparis, 2009; Zhou & Chang, 2021), or classify urban functional areas (Chen et al., 2021). Automatic (Karila et al.,

2023) and manual labeling (González-Collazo et al., 2023) of remote sensing data provides the ground truth for quantitative evaluation of the trained model. If available, it would still be preferable to use already vectorized data with attribute information. ML methods can serve as a fallback option to fill gaps in the vectorized data needed for our project. In Austria and EU countries, land use plans are already available in digital formats, e.g., via the INSPIRE interface (Directive of 14 March 2007, 2007). However, there is no generalized, comprehensive information available for zoning plans and building regulations. For landscape features, vectorized data is partially available through OpenStreetMap, and open government data (OGD) and at small scales via INSPIRE, such as CORINE Land Cover (Büttner et al., 2004). Higher resolution data in the form of point clouds (e.g., LiDAR or terrestrial laser scans) is available but complex to analyze due to the need for attribution and feature extraction.

Nagappan and Daud (2021) show that while ML models are used to identify land-use or land-cover patterns from various data/time series, possible correlations with planning regulations are not analyzed. In their 2022 study, Takouabou et al. (2022) argue that static models are inadequate for understanding the complex urban dynamics of contemporary cities. They proposed that ML algorithms could offer a more effective approach to data processing, facilitating the reorganization of urban planning processes. This is also true for rural areas. The pressing need for planning support for accurate estimation of decision outcomes and interactions is essential for robust and sustainable development in rural areas. A review of the existing research reveals a lack of case studies and practical ML applications in spatial planning, soil quality and land use analysis, and natural structures serving as NBS. Nor do they establish a link to the underlying planning regulations.

Analyzing open spaces in connection with underlying planning regulations is the innovative part of creating the datasets. This article critically discusses the opportunities such a model offers and the need to embed it in additional methodological approaches. As an initial conceptual study, we discuss the feasibility of ML application in spatial planning at the community level, using open data to train the model. We also identify the conditions necessary for NBS to foster climate change adaptation and biodiversity preservation and examine the likely impact of an ML-supported model in planning practice.

3. Case Study and Methodology

The article focuses on a case study of single-family houses in Hörsching, Upper Austria, chosen for its transferability to other regions. It covers 10 ha, chosen because single-family homes constitute 64% of residential buildings in Austria (Statistik Austria, 2023). This dominance is notable in the outskirts of large cities like Vienna, Graz, and Linz.

Figure 1 shows the settlement structure and key spatial regulations of the zoning plans for the use case area, provided by representatives of Hörsching. The settlement database represents planning regulations for different development phases (from west to east and from the 1980s to the present). Additionally, municipal strategic planning documents were examined, including the local development concept and sectoral development concepts for traffic, building land, and green space.

This section describes the classification process and the development of the ML training data and model. The MLbase4NBS method (see Figure 2) presented in this article is part of our five-step concept (ML4Nature) for the automated assessment of NBS potentials. To quantitatively assess NBS potentials on

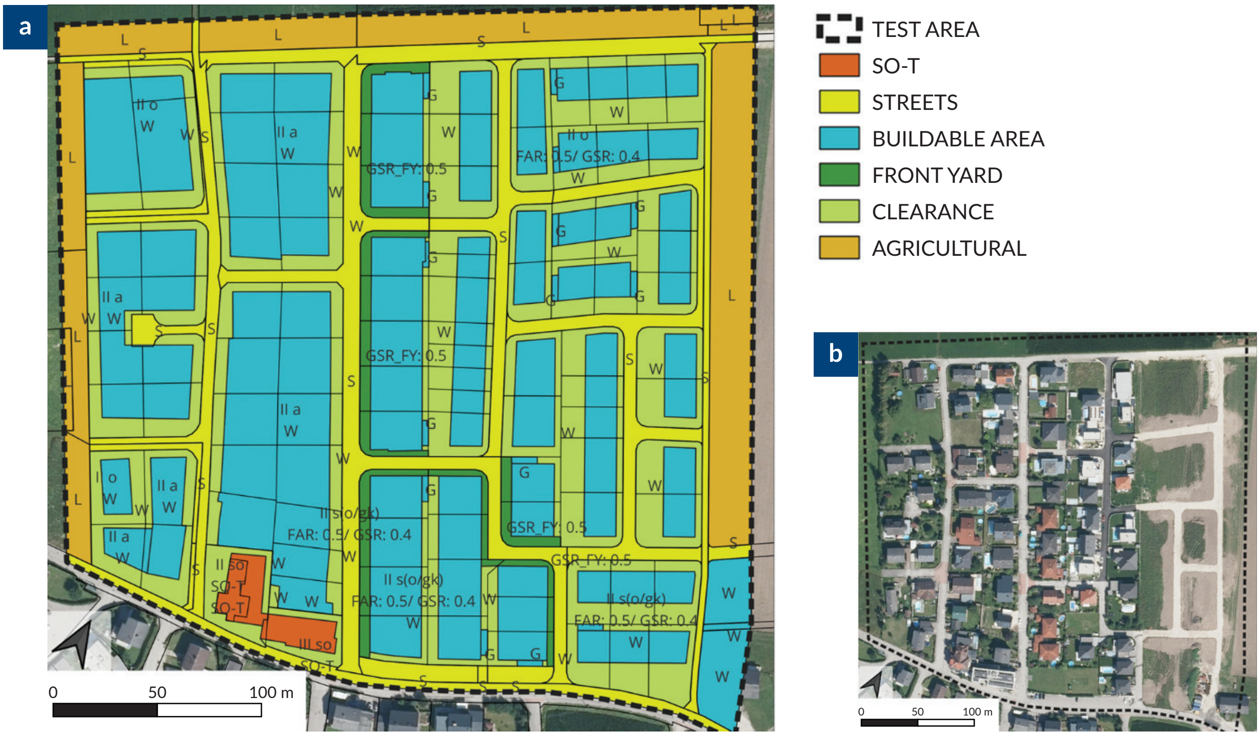

Figure 1. Use case area for the presented method including (a) zoning plan and (b) aerial view. Source: Adapted from the digital cadastral map (BEV, 2023) and map data (Geoland, 2024).

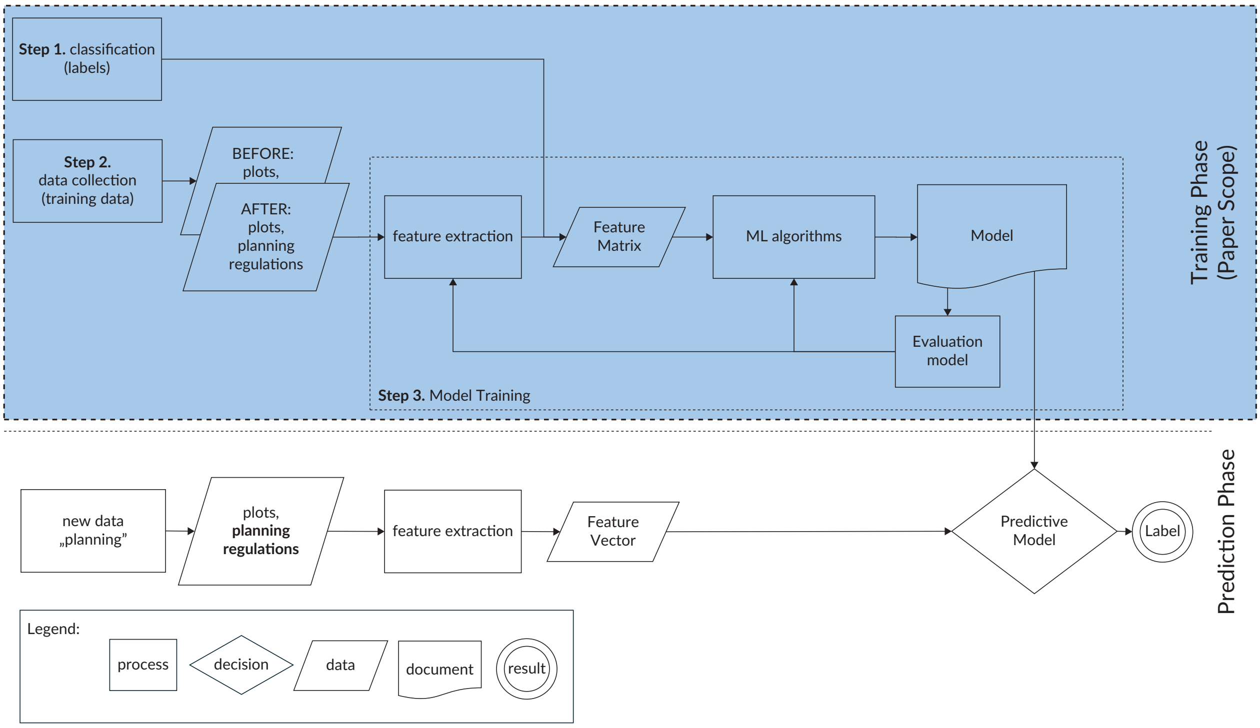

Figure 2. MLbase4NBS method: Training Phase (Steps 1–3, paper scope) and Prediction Phase.

properties, the analysis divided and classified properties into qualitative subareas (Steps 1 and 2). The ML model was then trained on these subareas along with building and planning regulations (Step 3). This model predicts qualities of subareas on new plots based on proposed planning regulations (Step 4), enabling quantification of NBS potentials (Step 5). The cumulative potentials are derived from the expected effects of the subareas, considering their features, size, and location (see data structure in Figure 3).

3.1. Step 1: Elaborating the Classification Model

By analyzing past and current planning regulations of the research area, past planning decisions can be processed for detailed backcasting and measure evaluation. The backcasting information is processed as a learning/training dataset for future decisions, measures, and actions. This process builds the inventory of "spatial" NBS, based on orthophoto mapping and site visits to derive different area category attributions for computer-aided processing.

Initially, all categories of different areas on a parcel must be defined and elaborated, considering their impacts on environment, habitat, and climate. These areas are categorized according to criteria such as biodiversity indices, evaporation and infiltration potential, or sealing. The classification model is intended for use in an automated evaluation process for NBS.

Figure 3 outlines the process: Specific quantitative and qualitative properties were collected for different areas. These include general information on location, geometry, and formal use, such as the natural green space characteristics, which were distinguished into ML4Nature (surface) categories and ML4Nature (areas) equipment (see Table 1).

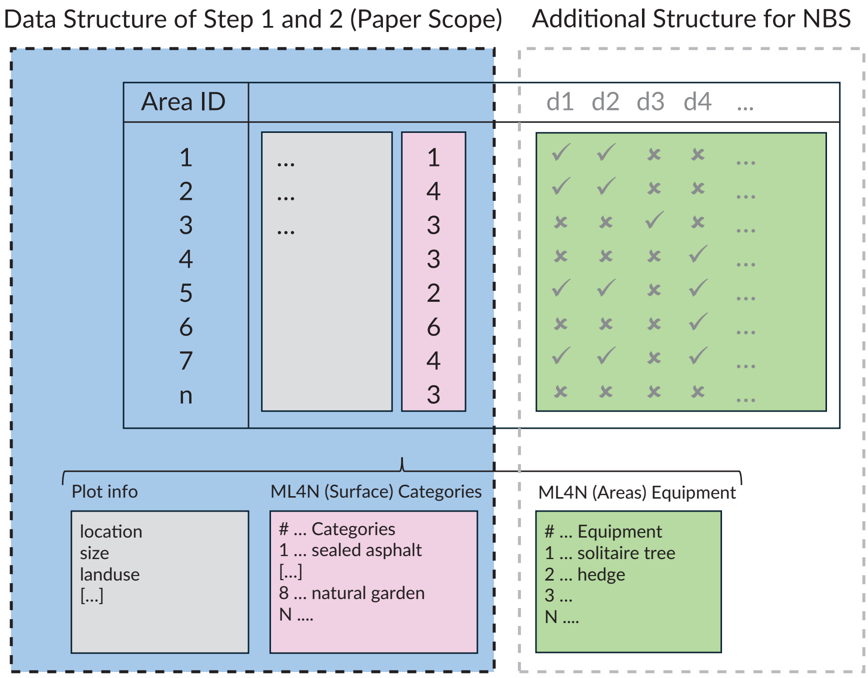

Figure 3. Data structure concept: surface-related properties (paper scope) and NBS equipment of areas.

Table 1. ML4Nature surface categories within the settlement structure.

ML4Nature_CAT_ID	ML4Nature Surface Category	Drachenfels Category
1	Sealed asphalt, dark concrete	
2	Sealed asphalt, light-coloured concrete	
3	Sealed water pool	
5	Fruit and vegetable garden	12.6.2
6	Home garden with large trees	12.6.3
7	Modern ornamental garden	12.6.4
8	Natural garden	12.6.5
9	Heterogeneous home garden area	12.6.6
[…]	[…]	[…]
60	Agricultural area, field	
99	Buildings	

The ML4Nature categories were based on Drachenfels (2021) after screening several categorization schemes. They refer to structures common in small- to medium-scale municipal settlement areas such as the sub-group “vegetation-determined biotope complexes and types of use in green spaces.” They were supplemented by additional areas (sealed surfaces, buildings) not defined as “green spaces,” which were preeminent in the first analysis presented in this article as they are a pre-requisite of many NBS to climate change adaptation next to structures attached to buildings themselves. ML4Nature equipment holds key features of green spaces (based on Drachenfels, 2021) with a minimum set of facilities by area (see Figure 2).

General plot information supplemented by Categories and Equipment form the basis for the automated and rule-based evaluation of open spaces. They constitute the starting point for NBS analysis: The NBS potentials (potentials for cooling, evaporation, infiltration) are defined for the different area categories. These depend on the vegetation and soil characteristics of the area.

3.2. Step 2: Development of Training Dataset

To predict the distribution of areas on parcels based on planning regulations with ML, a geospatial training dataset was developed, containing digital planning regulations categorized for impact analysis. Pre-trained models for roads, buildings, and swimming pools can assist in the preparation and pre-classification of spatial features within the dataset. Data can be sourced from established databases, GIS, and OGD platforms such as:

- National cadastre-info (https://data.bev.gv.at) on land;
- Federal GIS DORIS (https://www.doris.at);
- National open data (https://data.gv.at);
- European initiatives like Copernicus (https://www.copernicus.eu/en);
- Various GitHub repositories (https://github.com/zhouenbo/awesome-satellite-imagery-datasets).

ML algorithms can be created and tested using Python-based open-source tools like Tensorflow (https://www.tensorflow.org) and Pytorch (https://pytorch.org), which offer pre-trained models for image segmentation and object detection, applicable to aerial image analysis and land cover classification.

The preparation of our datasets included the preparation of GIS data at parcel level, as well as the extraction and digitization of building regulations. The resulting dataset contained information on past and existing land use and land cover distributions, and the planning regulations that influence them. Additional planning information and parcel-specific details (terrain, height, orientation, geometry/form) were then added.

Establishing the ground truth for the training data involves various methods of collection, calculation, and classification of areal features per building plot. Geoprocessing tools based on OGD, pre-trained models for certain features (e.g., buildings, water areas, streets), and manual identification and labeling of open and green spaces according to defined quality criteria and categories are used for pre-processing and classification.

3.3. Step 3: Model Training

Finding an optimal model that neither overfits nor underfits requires an iterative approach. This is why a supervised learning model is preferable to an unsupervised model, as it can represent individual decisions more clearly. The quality of an ML project depends on three important factors: data collection, data pre-processing, and data labeling. Accurate labeling is essential for robust results.

The dataset (split into training and validation data) is used to train an ML model. The dataset allows qualifying which regression procedure or decision tree/forest fits best. The ground truth enables quantitative evaluation of the tested models and selection of the best fitting model according to evaluation criteria. The trained model can forecast future scenarios based on planning regulation settings, estimating the distribution of areas on parcels and climate impact based on the areal share.

When selecting a model for a relatively small dataset with less than 1,000 samples and no linear relationship between features, models that handle non-linear relationships were considered. KNN is intuitive and effective for simple, small datasets. Random forest, based on multiple decision trees, prevents overfitting and handles non-linear relationships well. Support vector regression (SVR) uses kernel tricks to model complex relationships but requires careful parameter tuning. Within this methodological approach, the ML model was selected based on cross-validation to determine the best fit for the data's characteristics.

The selection of ML models for testing this use case was based on the following considerations:

- KNN: The idea behind KNN is that similar data points in the data space will have similar target values, assuming that soils and areas/points in similar regions have similar characteristics. The basic premise of the model is that where most features are similar, a similar result is likely to occur.
- Random forest: This model is robust to overfitting and can handle complex non-linear relationships between input features and target values. In our application, the relationships between input values are non-linear, making random forest an appropriate choice. In general, both KNN and random forest are good models for prediction scenarios where the relationships between values are unclear or how parameters affect outcomes is not well defined.
- SVR: Particularly suitable when the data are not linearly separable or the relationships are non-linear. SVR is robust to outliers, making it a strong candidate for dealing with diverse and complex datasets where standard linear models fail.

Our study empirically tested the prediction of area categories (classification problem) and the rate of sealed area on plots (regression problem). Utilizing planning data, cadastral data, aerial photographs, and on-site inspections, an evaluation with these two target variables appears feasible and realistic.

3.4. Step 4: Prediction Phase, and Step 5: Integration and Consideration of Structures Serving as NBS

As shown in the lower part of Figure 2, the prediction (Step 4) of area properties and the area category forms the basis of the automated investigation of NBS potentials for future building developments based on existing zoning regulations. The specific implementation of this link (Step 5) was not part of this study. For example, the degree of sealing of properties does not yet allow specific conclusions to be drawn about the infiltration capacity of areas. The challenge of assessing the climate impact of open spaces thus remains unresolved in this article. By collecting the spatial and green space defining characteristics of the properties, a future assessment of the NBS potential can be implemented based on quantitative data and on prediction of the area category through a set of statistical rules (depending on size, location, and presence) together with a larger dataset. The accuracy of the data does not allow for property-specific assessments, but it does allow for the estimation of potential within ranges for different planning alternatives in advance.

4. ML Implementation and Results (Steps 1–3)

This section describes the execution and implementation of the MLbase4NBS method illustrated in Section 3 (Steps 1–3) and the results of the iterative process of model training (see Section 4.2).

4.1. Set-Up of a Training Dataset and Related Opportunities and Limitations (Steps 1 and 2)

4.1.1. Data Sources and Quality

The base data for analysis are development and zoning plans, which were georeferenced manually. As GIS base, orthophotos of varying recency and sources (Geoland, 2024; Google Maps) are used. Further, cadastral shape data from the Federal Office of Metrology and Surveying (BEV, 2023) are added. Among key spatial information in the plans, the following points were homogeneously regulated for the entire study area:

- Green space percentage on the properties (min. 40%);
- Floor area ratio (0.5);
- Max. 2 floors (in the special designation for tourism max. 3 floors);
- Open or semi-detached construction within the polygons declared as building areas;
- Building setback of 3–5 meters from the street;
- Areas specifically designated as front gardens with separate minimum greening requirements.

Furthermore, regulations in textual parts of the zoning plans necessary for NBS potentials of the areas are included:

- The mandatory greening of flat roofs > 50 m² (although there are numerous exceptions);
- The requirement for car parking in designated areas to be grassed rather than paved;
- Special regulations for enclosures;

- The requirement to infiltrate stormwater on the properties themselves.

For the case study, the different areas were manually assigned to the ML4Nature categories by subdividing the cadastral base areas (see Figure 4a). Next, eight zoning plan documents were digitally uniformized (see Figure 4b). Via intersection, different subareas were created; they form the basis for the training dataset (Figure 4c).

4.1.2. Processing of Planning Regulations and Their Implications on the Existence of NBS

The challenges of combining textual and geometric planning regulations (Sections 3 and 4.1) were due to the difficulty of extracting common regulations from regulation plans and translating textual planning regulations to parcels. Therefore, the textual regulations and the regulatory plans were processed in parallel. By geoprocessing and assigning certain areas from the plan to the parcels, the identified findings were attached to the individual objects via attributes. A triangulation of the following methods was used to prepare the base data for supervised ML and a practicable categorization of open spaces: GIS analysis, systematic literature review, historical document analysis, orthophoto mapping.

The 1,404 different subareas were assigned to 10 different ML4Nature categories (see Table 1) and ML4Nature equipment features were examined for the areas. The equipment has not yet been included in the ML questions tested here. Overall, more than 47% of the total case study area is sealed, either by buildings, roads, or other sealed surfaces.

4.1.3. Training Data (Limitations and Opportunities)

National and federal OGD data sources (attributed vector data, orthophotos) were used to carry out the method on this use case and were updated and supplemented by visiting the site. Here it also became apparent that an attempt is being made to answer two specific questions based on the small sample: a classification problem and a regression problem.

4.1.3.1. Classification Problem

Figure 4 shows that the combined information on open space and development regulations form the attributes for the classification problem. Table 2 shows the 24+2 attributes identified in the model.

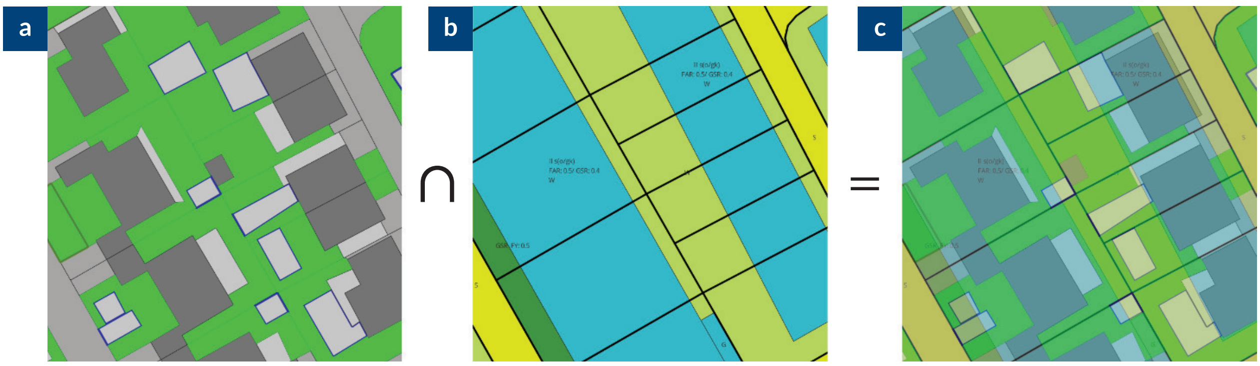

Figure 4. Intersection of ML4Nature categories with development plan as base for the training dataset.

Table 2. Overview of tested ML problems.

ML Problem	# Features	Attributes	Target Value
Classification	$n = 1{,}404$	26 attributes: size of plot, perimeter area ratio ($Z = A \times 100 / P^2$), [Previous State:] (overall) use category from Austrian land register, use categories as list from Austrian land register, share of building area on plot, share of sealed area on plot, land use/zoning category, front yard (t/f), sealed surface (t/f), [Development Plan:] number of floors on plot, floor area ratio, building eaves height on parcel, building ridge height on parcel, special regulations for front yard (t/f), special regulation for building clearance/side setback (t/f), dedicated land use/zoning category for plot parts (e.g., outbuildings), number of floors on plot part, special building arrangement for plot part, min. green space ratio on plot, floor area ratio for plot part, min. green space ratio for front yard plot parts, [Location:] point x, point y	ML4Nature-CATEGORY OF PLOT PART
Regression	$n = 132$	15 attributes: size of plot, perimeter area ratio ($Z = A \times 100 / P^2$), [Previous State:] (overall) use category from Austrian land register, use categories as list from Austrian land register, share of building area on plot, share of sealed area on plot, land use/zoning category on plot, overall dedicated land use/zoning category for plot, [Development Plan:] building arrangement (e.g., open, closed, or semi-detached construction) for whole plot, number of floors on plot, floor area ratio, building eaves height on plot, building ridge height on plot, share of dedicated building clearance areas on plot, share of dedicated front yard areas on plot	RATE OF SEALED AREA ON PLOT

In addition to the general property attributes and the attributes describing the previous state of the areas, there are attributes containing development regulations. Attributes 25 and 26 (as X and Y coordinates for a point grid) are included because the dataset is subsequently artificially enlarged (see Figure 5b).

Table 2 (row 1) attributes show which open space ML4Nature (surface) category (Table 1) is predicted for an area by the classification model.

4.1.3.2. Regression Problem

In order to predict the proportion of sealed area on a plot, the plot level attributes were collected. Table 2 (row 2) shows the 15 attributes used for the prediction.

Figure 5 shows the current rate of building on plots as an analysis step during data collection (Figure 5a) and the rate of sealed areas on plots (Figure 5b). The rate of sealed area on plot (Table 2, row 2) is the target for the regression model. The model predicts the rate of sealed areas per plot based on the plot data collected. Table 3 shows the attributes selected for the regression model. The training datasets are small. A total of 1,404 different subareas were identified on 132 plots.

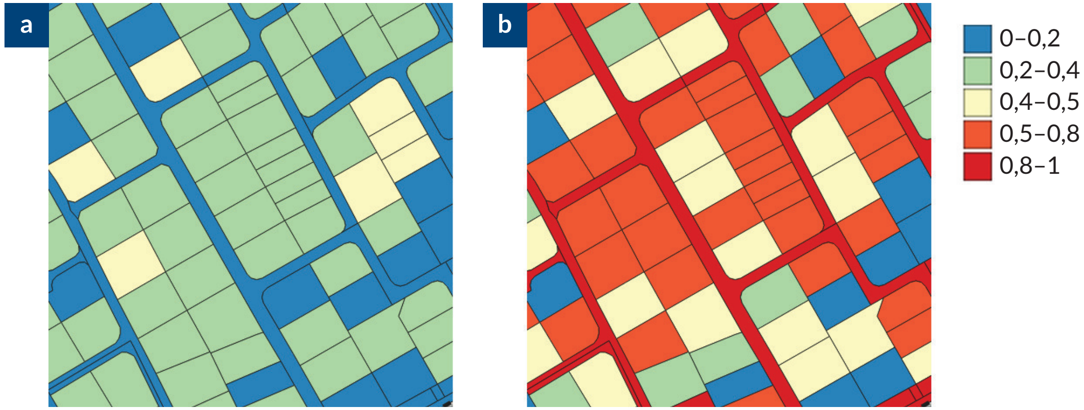

Figure 5. Rates of (a) building areas on plots and (b) sealed area on plot.

Table 3. Accuracy classification of ML4Nature category.

	Polygons (*N* = 1,404, test-size 30%, 24 features)		Point Grid (*N* = 24,703, test-size 30%, 24 features)		Point Grid Without Streets (*N* = 20,682, test-size 30%, 24 features)	
Classifier Model	Accuracy	Parameter	Accuracy	Parameter	Accuracy	Parameter
KNN	0.38388625592417064	5 neighbors	0.9666711644852247	3 neighbors	0.9618049959709911	3 neighbors
Random Forest	0.3818683026279804	n_estimators: 50 max_depth: None CV = 3	0.9830557483229239	n_estimators: 200 max_depth: None CV = 3	0.9825242372382754	n_estimators: 200 max_depth: 100 CV = 3

4.2. ML Model Training (Step 3) and Results

4.2.1. Prediction of Category (Classification Problem)

In the following, the selected models for classification (prediction of area category on subareas of features) are presented and the results are compared. Table 3 shows the accuracy classification of the ML4Nature category of polygons, point grid, and an alternative of point grid analysis with removed road surfaces.

The polygon-based analysis shows that the accuracy of KNN and random forest are approximately equally poor. The accuracy ranges from 0 to 1, where 1 would indicate overfitting of the model. With 10 possible categories in the training dataset, a rate of 38% is better than chance (10%), but still far from an accurate prediction. This is most likely due to the small training dataset.

To check if the prediction works better with a larger dataset, a point grid (2m) was placed over the polygons, with each individual point receiving the information of the area on which it lies. This immediately gave us a test dataset of over 24,000 records (see Figure 6b). Using the point-grid dataset, the accuracy of both models jumped to almost 1, indicating strong overfitting. This is because the algorithm is too well trained on the training set, which is certainly also due to the small number of different initial values, resulting in too little noise in the model.

In particular, road surfaces (which make up about 20% of the area of the test site) can probably be predicted very well on the basis of the input variables. When road surfaces are completely removed from the training dataset, as expected, the accuracy drops slightly, but this suggests that the input variables were not badly chosen and that the model could work quite well with a larger sample.

Overall, the small datasets are challenging and need to be extended to larger samples with higher variance. Strategies for automatically increasing the variance of the data or artificially enriching and enlarging the test data are discussed in Section 5.1.

4.2.2. Prediction of Sealed Area (Regression Problem)

For the prediction of sealed areas, KNN and random forest were used. Additionally, the results of the SVR were examined. The results are compared in Table 4. Streets with high accuracy were removed from the training dataset.

Test A, a test run with a very small plot dataset (N = 132), shows that the accuracy value of KNN cannot be trusted. It jumps significantly with each new calculation. SVR and random forest have a similar range of values, which could indicate a lack of quality in the dataset, most likely only in its size.

Therefore, the extension via a point grid of 2m, as in the classification problem, was chosen to increase the dataset. The enlarged training dataset (N = 24,709) leads to an accuracy of 1 in all three models, due to massive overfitting of the larger but still simple dataset of low complexity.

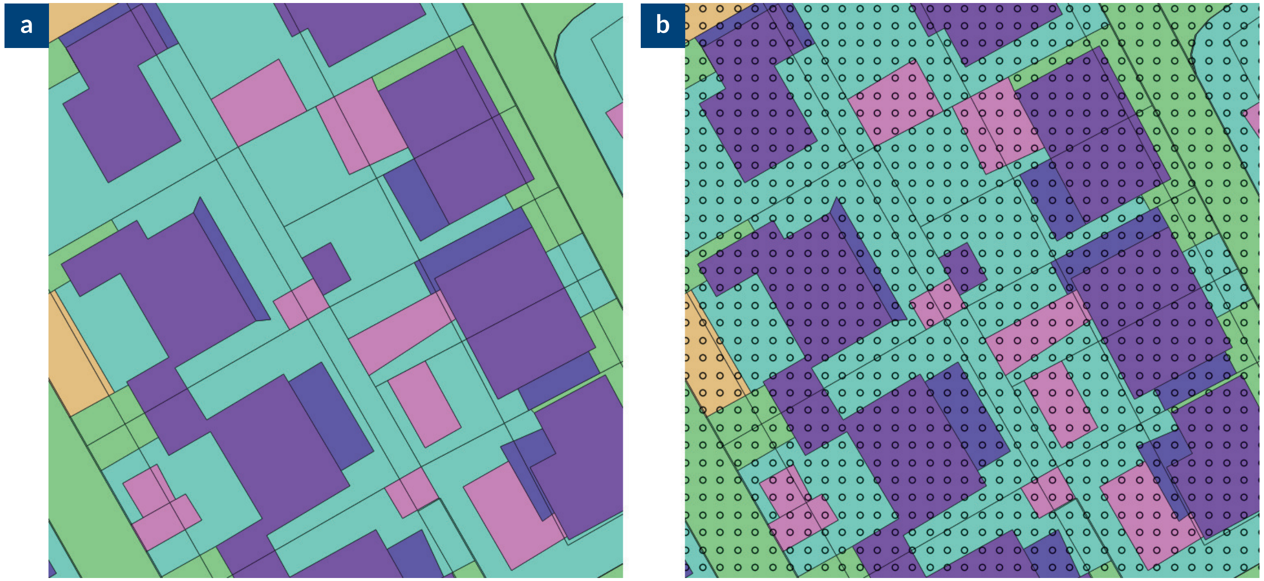

Figure 6. Extending the training dataset by using a point grid (b) instead of the polygon layer (a).

Table 4. Accuracy of the regression models: Test comparison.

	Test A (*N* = 132, test-size 30%, 15 features)		Test B (*N* = 495, test-size 30%, 15 features)		Test C (*N* = 495, test-size 30%, 15 features)	
Regression Model	Accuracy	Parameter	Accuracy	Parameter	Accuracy	Parameter
KNN	0.541316	5 neighbors	0.869972	5 neighbors	0.810307	5 neighbors
Random Forest	0.3423376622194893	n_estimators: 50 max_depth: 5 CV = 5	0.9072332695334303	n_estimators: 100 max_depth: 15 CV = 3	0.8612529237675896	n_estimators: 150 max_depth: None CV = 3
SVR	0.35775595006039373	C = 1.0, epsilon = 0.2	0.7140296158996142	C = 1.0, epsilon = 0.2	0.744826052468326	C = 1.0, epsilon = 0.2

Test B in Table 4 shows that reducing the number of points ($N = 495$) by considering only the 50th largest point leads to more variation in the dataset and more reasonable results.

To further improve the training dataset, the variance of the examples was increased by adding noise to certain features by randomly increasing and decreasing the feature size by +/– 5%. The ratio describing the relationship between area and feature perimeter was also randomized by +/– 5%. Noise was also added to the target variable (SEAL_PERC). Test C shows the expected changes in the accuracy of the models.

5. Discussion

This article has presented a conceptual approach to classifying subareas and predicting soil sealing on areal plots. The methodological approach provides a planning tool for estimating categorization probabilities based on planning rules. With more features in the training dataset and additional variables (e.g., NBS equipment of the areas), target variables can be predicted in detail, and linking regulations with implications on soil sealing as well as NBS is possible.

5.1. Feasibility and Limitations in the Set-Up and Application of the ML4Nature Concept

There is potential bias in data and parameter settings during training: Selecting hyperparameters based on best-fit criteria is tempting but can lead to overfitting. Consistency in predictions must be ensured for small data samples. The validity of cross-validation depends on the quality of the subsets, which small samples cannot guarantee. Extending test datasets reduces overfitting tendencies, indicating that the proposed method can provide conclusive results. The ML model predicts area distributions of previously classified areas.

There are challenges owing to incomplete data: While all current planning data was available for our small use case, evolutionary steps and initial data were not fully available. On a larger scale, data is likely to be incomplete. Missing data can be substituted with assumptions for initial testing, but this can lead to distortions. Techniques like iterative imputation estimate missing values based on existing data, reducing the impact of gaps. Leveraging local expertise and historical land maps can provide preliminary insights and help make educated guesses about missing data. This strategy addresses immediate challenges and sets a pathway for continuous improvement, enhancing model resilience and effectiveness in regional planning and development assessments. Our test results show that prediction accuracy improves by inflating and varying datasets.

The most effort-intensive part of the process lies in data collection. Algorithms capable of classifying orthophotos can automate some analytical processes. Attention must be paid to uniform spatial/temporal resolution of data sources (e.g., orthophotos from similar flight times should be analyzed together to minimize bias). While missing data could be added manually in this article, further research is needed on the applicability of automated algorithms to enrich training data and expand samples.

There are issues related to implementation and scalability: For practical implementation, training data should be collected and compiled at the federal level. Training of the models should be organized jointly for regions with homogeneous spatial and settlement structures. Trained models will then be used by municipalities for prediction, since single municipalities cannot manage this by themselves. Transferring models across Austria will require generalization and homogenization of data, as planning regulations differ between federal states (land use categories, building regulations, etc.). Natural and green areas may also differ between eastern and Alpine regions in Austria but can be generalized based on European standards (e.g., implemented in INSPIRE and SENTINEL data). For urban areas, models are likely more transferable but depend on regional building regulations.

5.2. Outreach and Expected Impact of the ML4Nature Model for Planning

Adaptation to climate change and the development of NBS are strongly linked to the planning decisions and actions of local policymakers because of their responsibilities in land use regulation and land use planning, as is the case in Austria. Transparency on the impacts of soil sealing and the opportunities for the application of NBS could lead to more comprehensive planning and decision-making processes. A variety of studies confirm that both the diversity and structural variety of green spaces significantly influence biodiversity, emphasizing the importance of conservation in both large areas and small green elements along streets or in backyards (Fuller & Gaston, 2009; Matthies et al., 2017)—the availability of space and unsealed soil is a prerequisite for their implementation. The ML approach outlined in this article shows the need for larger training dataset developments to create transparency not only on sealing and availability of open space but also on individual structures such as old trees and hedges, which provide crucial habitats for various species and contribute to biodiversity based on their physical characteristics and the surrounding environment (Gosling et al., 2016). This will also allow reflection on vegetation along traffic structures, which plays a key role for both conservation in settlement areas (Helldin et al., 2015; Thomas et al., 2003) and climate change adaptation (Morakinyo et al., 2020). Only then is the impact of planning regulations more specifically traceable. The model has potential to reflect specific capacities for both biodiversity conservation and climate change adaptation via more detailed recognition of the natural structures. Reducing heat through shading and transpiration, for instance, varies by tree species and interrelationships among environmental conditions (Zölch et al., 2019). Factors such as the width of hedges, an important factor in ecological value, would require additional development of the model. In addition to biological factors, such as tree size or the leaf area index, microclimatic aspects, such as radiation, wind direction, or speed and soil conditions, e.g., soil moisture and temperature, influence the transpiration performance of trees and vary depending on the spatial structure (Offerle et al., 2007). Integrating this more specific information to connect to climate change adaptation more precisely will be part of future studies in cooperation with climatologists and biologists. An actor-centered approach, including methods such as interviews and stakeholder workshops, could further support reflection on the role of data and transparency in planning decisions and the potentials and implications of an ML application.

The proposed approach (including data acquisition, training data, model training, and NBS potentials derived from prediction and status quo), however, serves as a base data layer to support policymakers in their actions. This applies particularly with regard to creating transparency on the most crucial factors for adaptation to climate change, in keeping open spaces (natural hazards/ventilation), avoiding sealing, increasing infiltration capacity, greening and networking green corridors and green structures, promoting blue infrastructure, and a combination of these.

6. Conclusion and Directions for Further Research

Green and open spaces are often neglected in spatial planning and treated as residual areas. The Sustainable Development Goals and their targets are difficult for municipalities to implement in planning practice. This is mainly due to a lack of knowledge about the effects of planning decisions and a lack of action support for planning actors within a planning process. In this study, a regression model was developed that can serve as a supporting tool for strategic analysis of past and future planning impacts. It provides the conceptual fieldwork foundation for the development of learning datasets. These are designed to allow the strategic use of analysis algorithms and can be used in other models and methods where transparent land use classification and nature and climate impact analysis are required.

When trained for different regions, spatial situations, and planning regimes, these models can provide valuable insights and a basis for iterative planning and decision-making processes in local spatial planning. In addition, the models should aid and encourage authorities to monitor and enforce the implementation of planning guidelines. In order to minimize data gaps and increase the power of interpretation, participatory approaches also offer potential for future studies.

To address the concept of virtual NBS elements and their implementation, average tables for different setups based on collected and analyzed data are needed. These could serve as benchmarks or reference points for configuring training datasets to ensure real-world reflections. The average setups allow input variables to be standardized across models for more consistent and comparable results.

Further research should identify current knowledge and technology gaps to better preserve soil and reduce sealing, while also evaluating the effectiveness of specific NBS implementations. This could involve developing advanced data analysis algorithms, exploring innovative materials and designs for NBS, and gaining a deeper understanding of their socio-economic impacts. Implementing pilot projects as part of this research can provide real-world testing and refinement of theories and models, yielding practical insights.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The research data can be provided on request.

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REVIEW

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Past, Present, and Future Perspectives on the Integration of AI Into Walkability Assessment Tools: A Systematic Review

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Abstract

This study employs a systematic literature review (PRISMA methodology) to investigate the integration of Artificial Intelligence (AI) in walkability assessments conducted between 2012 and 2022. Analyzing 34 articles exploring data types, factors, and AI tools, the review emphasizes the value of utilizing diverse datasets, particularly street view images, to train supersized AI models. This approach fosters efficient, unbiased assessments and offers deep insights into pedestrian environment interactions. Furthermore, AI tools empower walkability assessment by facilitating mapping, scoring, designing pedestrian routes, and uncovering previously unconsidered factors. The current shift from large-scale spatial data analysis (allocentric perspective) to a ground-level view (egocentric perspective) and physical and perceptual features of walking introduces a subjective lens into current walkability assessment tools. However, the efficacy of current methods in addressing non-visual aspects of human perception and their applicability across diverse demographics remains debatable. Finally, the lack of integration of emerging technologies like virtual/augmented reality and digital twin leaves a significant gap in research, inviting further study to determine their efficacy in enhancing the current methods and, in general, understanding the interaction of humans and cities.

Keywords

artificial intelligence; digital twin; human perception; urban built environment; walkability; walkability assessment; walkable environment

1. Introduction

Walkability is a central concept within urban design, planning, and transportation disciplines, with each emphasizing its influence on achieving specific goals (Ewing & Handy, 2009). Southworth (2005) defines walkability as the extent to which the built environment supports and encourages pedestrian activity. This includes prioritizing pedestrian comfort and safety, fostering connectivity between destinations within a reasonable timeframe, and offering visual interest throughout walking journeys. Notably, this definition encompasses various active travel modes, such as utilizing strollers or wheelchairs. Enhancing walkability offers a multitude of benefits for both individuals and communities, impacting public health, transportation efficiency, and environmental sustainability (Sallis et al., 2015).

Walkability fundamentally depends on the dynamic interplay between pedestrians and their surrounding built environment. Pedestrian needs vary based on demographic factors such as age, gender, disability status, and other socio-economic characteristics. Understanding the built environment is equally crucial, as it comprises various spatial, physical, and perceived elements that influence walkability. Data pertaining to these elements can be analyzed from two key perspectives: egocentric (ground-level, user-centric, and subjective) and allocentric (aerial and objective; Mou et al., 2004). Some factors, such as sidewalk connectivity, can be assessed from both viewpoints across various scales: micro (property-to-property), neighborhood (block-to-block), and city (neighborhood-to-neighborhood).

Traditional approaches to walkability assessment often rely on manual methods, such as observation-based scoring. These methods, while prevalent, can be resource-intensive and time-consuming, hindering widespread implementation (McGinn et al., 2007). Therefore, there exists a pressing need for the development of novel and time-saving evaluation instruments.

The emergence of Artificial Intelligence (AI) offers significant potential to revolutionize the walkability assessment process. Integrating AI into these assessments holds promise for increased efficiency, accuracy, and scalability (Koo et al., 2022a). AI algorithms can automate manual processes associated with data gathering and analysis, significantly reducing the time and effort required to produce results. This automation allows communities to receive timely feedback on existing walkability issues and potential improvements.

Innovative tools and technologies leveraging AI can seamlessly integrate diverse data sources and perspectives into the walkability assessment process. The inherent capabilities of AI enable the effective merging of egocentric and allocentric data, subjective and objective data, and qualitative and quantitative information. Through the analysis of this comprehensive dataset using AI algorithms, data-driven assessments can be generated to support more informed urban planning decisions (Delavar et al., in press). This approach ensures that crucial factors such as safety, accessibility, aesthetics, community preferences, and urban indices like morphological structures and sustainability are thoroughly evaluated (Boujari et al., 2024; Hassanzadehkermanshahi & Shirowzhan, 2022; Tehrani et al., 2024; Wang et al., 2019).

Motivated by the importance of walkability in urban environments and harnessing the potential of AI, the present study aims to provide a solid basis for advancing future walkability measurement tools. The study identifies and examines recent research in the field of walkability that incorporates AI methodologies and data analysis that could feed into this domain. Our analysis centers around three key research questions:

> RQ1: How do AI models and emerging technologies enhance understanding of specific aspects of human perception related to walkability, such as safety, comfort, and aesthetics?

RQ2: How can spatial, physical, and perceived walkability features (e.g., street connectivity, barriers, and aesthetics) be effectively extracted and integrated into AI models to provide comprehensive walkability assessments?

RQ3: What specific gaps exist in current research, and what potential applications of AI and emerging technologies remain unexplored?

By systematically analyzing these research questions, this study aims to establish a robust foundation for developing and implementing future walkability assessment tools that are not only technologically advanced but also cater to the unique requirements of various populations. This, in turn, will contribute to the improvement of walkability in urban environments for all.

The remainder of the article is structured as follows. Section 2 briefly reviews some of the past walkability measurement methods. Section 3 details the methodology employed for the systematic literature review following the PRISMA guidelines. Section 4 presents a comprehensive analysis and classification of the identified research findings. Finally, Section 5 discusses the future of walkability assessment and outlines promising avenues for future research in this domain.

2. Background on Walkability Assessment

Academics and practitioners utilize various methods to evaluate walkability. Established tools include index systems (McGinn et al., 2007), subjective questionnaires for perceived data, and analysis of big urban data. Publicly accessible assessments include Walkscore (property-level scores) and the US National Walkability Index (census block scores). While these metrics provide walkability scores across the US, they rely solely on allocentric data, neglecting on-the-ground conditions.

The past decade has seen the emergence of street environment platforms like the Systematic Pedestrian and Cycling Environmental Scan (Pikora et al., 2006), and the Scottish Walkability Assessment Tool (Millington et al., 2009). Additionally, US organizations have established guidelines for walkable streetscapes, such as those developed by the National Association of City Transportation Officials (n.d.), the Portland Bureau of Environmental Services (n.d.), and the Austin Transportation Department (n.d.). However, most platforms primarily rely on allocentric data. This disconnection between allocentric and egocentric data highlights the challenge of achieving accurate and relevant assessments. Researchers actively seek solutions to integrate subjective, localized data with automated methods for increased accuracy (Chiang et al., 2017).

Six prior literature reviews related to the topic provide valuable insights into various assessment methods. Three reviews (Blečić et al., 2020; Hasan et al., 2021; Wang et al., 2022) focused on factors influencing walkability evaluation and data collection advancements. The remaining three reviews (Biljecki & Ito, 2021; Cinnamon & Jahiu, 2021; Yongchang Li et al., 2022) specifically addressed the use of street view imagery in walkability research. These prior literature reviews identified two key considerations impacting tool applicability: (a) assessment scale and (b) hierarchical arrangement of related factors.

3. Methodology

The literature review in this article is designed to identify research at the intersection of AI tools and the assessment of the built environment for walkability. The articles are classified based on AI methodologies, more specifically the machine learning processes of teaching (datasets), learning (algorithms), and inference (validation).

We examined studies published from 2012 to 2022 that delve into the specifics of AI methodologies—datasets, algorithms, and validation techniques. As outlined in Table 1, the articles were identified by query keywords in the title, abstract, author keywords, and keywords across Scopus, Web of Science, and ScienceDirect databases. Following PRISMA guidelines (Moher et al., 2009), we excluded research focused solely on pedestrian interaction (pedestrian recognition and pedestrian flow) or active transportation beyond walking (cycling). This rigorous process resulted in 34 articles for in-depth analysis (Figure 1).

The selected articles were analyzed to extract data across five crucial dimensions: general information, objectives, methodology, findings, and limitations. Key study characteristics, study area and population, data types, factors, perspective, physical and perceptual features, and AI tools, are specifically extracted.

3.1. Topic Modeling

A topic modeling analysis investigates the lexical patterns employed in studies to ascertain trends. The technique is a valuable indicator of topics and trends representing the selected literature's corpus by analyzing the abstract content (Ochoa, 2021).

Table 1. Search strings queries within Scopus, Web of Science, and ScienceDirect databases.

Search query strings
("AI") and ("walkability")
("AI," "deep learning," or "machine learning"), ("walkability" or "pedestrian environment"), and ("measurement")
("AI," "deep learning," or "machine learning") and ("walkability" or "pedestrian environment")
("AI," "deep learning," or "machine learning") and ("walkway," "footpath," "pedestrian path," "pedestrian mobility," or "active transportation")
("Automatic information extraction") and ("walkability")
("Automatic information extraction") and ("walkway," "footpath," "pedestrian path," "pedestrian mobility," or "active transportation")
("Image processing," "computer vision," "scene recognition," or "image recognition") and ("walkability")
("Image processing," "computer vision," "scene recognition," or "image recognition") and ("pedestrian" and "walking")
("Measure," "measuring," or "measurement"), ("automated," "automation," "automating," or "automatic"), and ("walkability," "walkway," "pedestrian environment," or "walkable")

Note: These search string queries were conducted within the articles' title, abstract, author keywords, and keywords plus (suggested keywords by the databases).

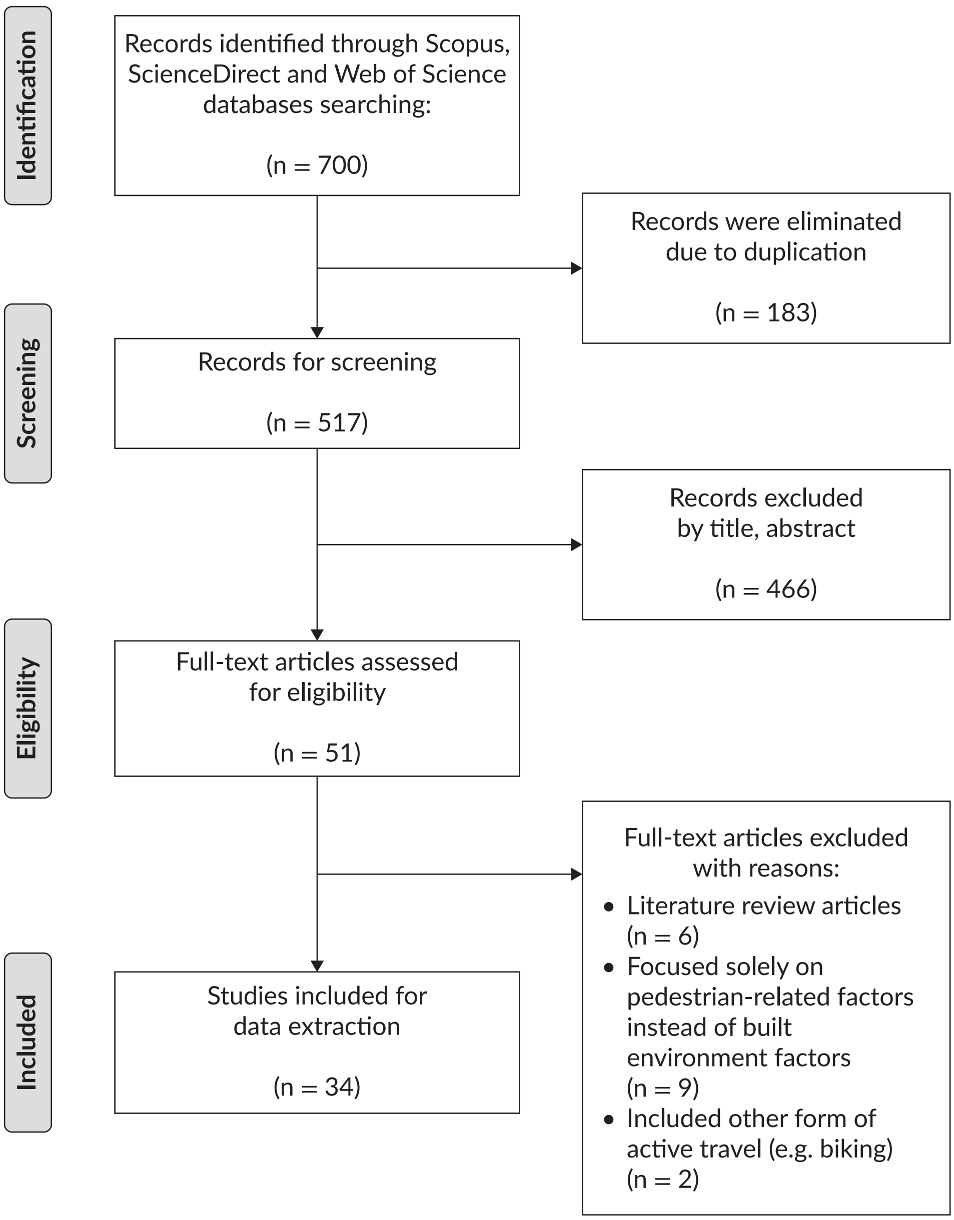

Figure 1. PRISMA flowchart of the systematic review process.

Here, topic modeling reveals the differences and similarities between two sets of studies: one comprising 700 identified articles and the other encompassing a broader selection of 4,967 articles on "walkability" from 2012 to 2022. This additional collection was sourced from the Web of Science using keywords like "walkway," "walkable," "walkability," "pedestrian environment," and "footpath." To compare both searches, topic modeling compiled a list of words from both sets of articles' abstracts and analyzed their frequency (Figures 2 and 3). These words underscore the respective focuses of each topic and provide a quantitative basis for comparison.

The findings of the analysis indicate that while there are some commonalities in both research areas, such as "pedestrian," "environment," and "system," there are also significant differences. In the "walkability and AI" literature, additional terms appeared more frequently, including "learning," "street audit," "imagery," and

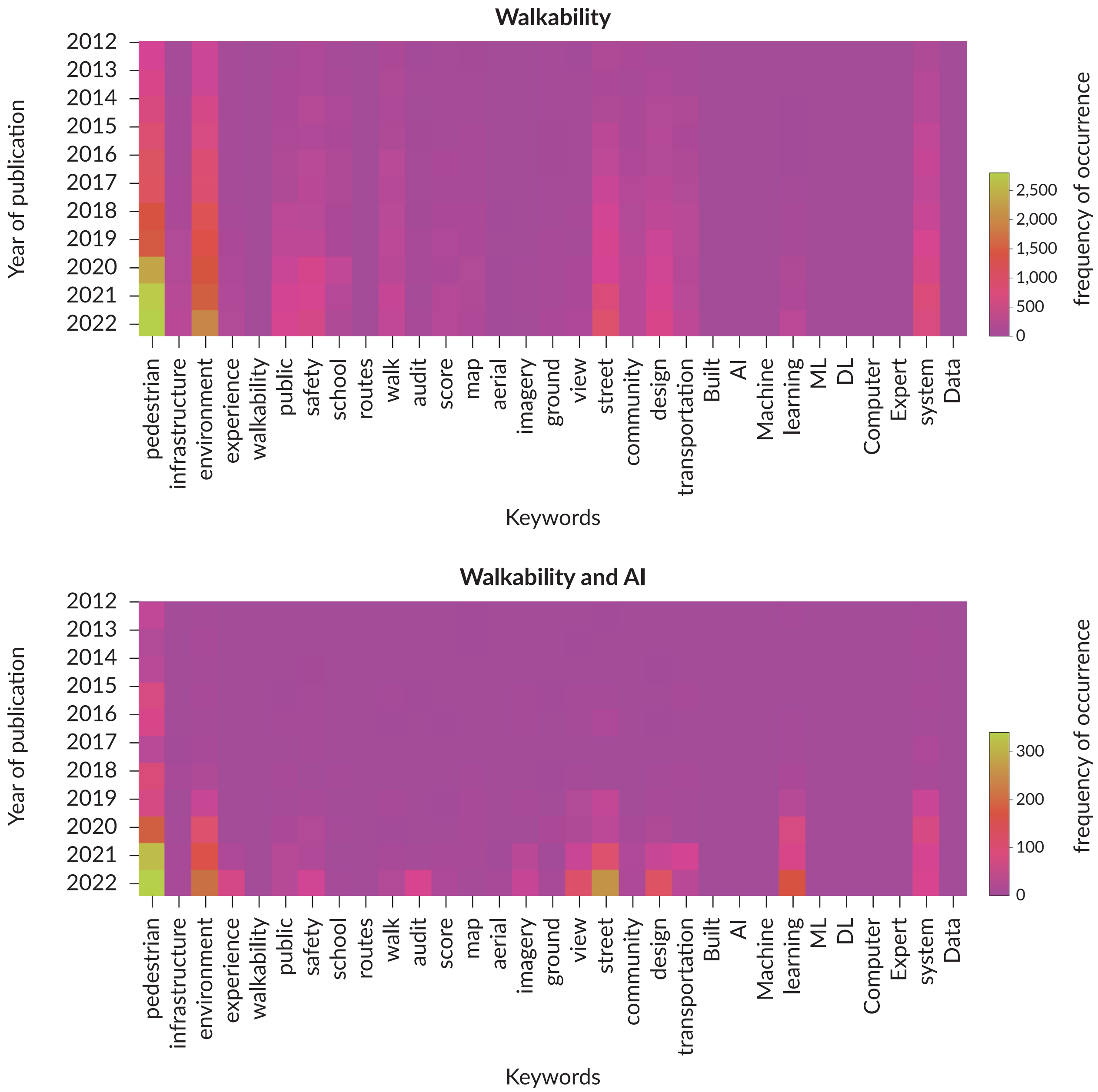

Figure 2. A 10-year analysis of lexical distribution in published literature on "walkability" (top) and "walkability and AI" (bottom).

"view," reflecting the use of AI technologies to improve walkability assessment by analyzing imagery data at the street level. The search for "walkability" alone highlighted terms such as "public," "safety," "walk," and "design," which reflect the focus on urban planning and infrastructure design to improve the quality of the walkability experience.

In the broader "walkability" research articles, the most common words are "environment," "walking," "study," "neighborhood," "area," "city," and "activity." These terms focus on the physical aspects of walkability, such as the built environment, urban design, and promoting walking as a physical activity. On the other hand, the literature on "walkability and AI" highlights different words, including "model," "street," "study," "method,"

Figure 3. Lexical frequency in published literature on “walkability” (top) and “walkability and AI” (bottom), 2012–2022.

“feature,” “image,” and “data.” These terms indicate a focus on using AI technologies to analyze and improve the subjective features of the walkability of urban environments by developing models and methods that can be applied to street-level imagery data.

4. Results

The table in the Supplementary File summarizes the results and the different attributes considered for the analysis, categorized in the following subsections.

4.1. Use and Perspective

Use classification refers to the specific demographic needs and behaviors that impact walkability, such as the requirements for safe routes for children, accessible pavements for the elderly, and gender-specific safety concerns. Perspective classification, on the other hand, pertains to the vantage point from which walkability is assessed. Egocentric perspectives provide a ground-level, user-centric view that captures the subjective pedestrian experience, while allocentric perspectives offer an aerial, objective view using broader spatial analysis tools like GIS data and aerial imagery. By integrating both use and perspective classifications.

Research spans the globe, with studies in Asia, North America, and Europe leading the way, and sufficient studies in Africa are lacking. Researchers primarily focus on understanding how everyday people navigate walking environments. However, some studies delve deeper into the experiences of elderly pedestrians, people with disabilities, and even university students on campus (see Supplementary File).

Our analysis of 34 articles revealed a preference for egocentric perspectives (17 studies) that leverage street view imagery to understand the pedestrian experience at the street level. In contrast, allocentric approaches, using broader spatial analysis (GIS data, Aerial images, etc.), were used in six articles. Interestingly, eight studies combined these perspectives, potentially to validate findings or explore discrepancies between them. One study stands out in this framework, incorporating physiological data from wearable sensors to analyze and evaluate pedestrian behaviors in the built environment (Bandini & Gasparini, 2020).

4.2. AI in Walkability Assessment

Our approach to classification is based on the three stages of AI's methodology involving: teaching, learning, and inference (Ochoa & Comes, 2021).

4.2.1. Teaching: Data Types, Features, and Factors

In the teaching stage, the focus is on the data. 95% of the revised studies used supersized learning. Therefore, the work was on labeling data, which consists of input data (also known as features) and the corresponding output or label. The algorithm uses this data to learn the underlying patterns and relationships between the input and output data and to create a model that can accurately predict outcomes based on new input. The goal of the teaching stage is to create a model that can generalize and predict with high accuracy the label to new, unseen data.

The reviewed articles utilize labeled data that can be broadly categorized into five types: geospatial data, imagery, historical data, sensor data, and survey. Imagery data appears most frequently among these data types, highlighting its significance in scholarly discussions. The imagery data, which encompasses street view images, aerial images, digital video, and panoramic images, is labeled based on the detection and measurement of street furniture, visual enclosure, openness, greenery, breakage, barriers in sidewalks, and so on.

Geospatial data provides a spatial framework, pinpointing locations, and their associated attributes. Key examples include land-use classification (residential, commercial, and park), street network configuration (highway and local road), street design elements (crosswalks and sidewalks), and public transit infrastructure (bus stops and train stations). Additionally, traffic flow data, often represented by volume and speed measurements, contributes to geospatial characterization.

Sensor data encompasses various measurements utilized in urban design and walkability studies. Remote sensing data from satellites and aircraft collects environmental information such as pollution, light levels, and traffic flow data (Yunqin Li et al., 2020). Notably, geospatial data can also play a role in environmental analysis. By examining street connectivity and land-use patterns, researchers can gain insights into walkability or the distribution of green spaces within a city (Giles-Corti et al., 2014).

Beyond these established categories, sensor data can be further categorized based on the source of measurement. Physiological data from wearable sensors provides insights into human experiences (Bandini & Gasparini, 2020). Examples include biosignals (heart rate and skin conductivity) and GPS data for tracking movement patterns (Miranda et al., 2021). This data offers a unique perspective on the interaction between pedestrian perception and the urban built environment.

Historical data can be incorporated into walkability studies to provide valuable insights. Pedestrian data, often labeled based on the number of pedestrians observed at specific locations and times, offers information on pedestrian volumes and patterns. Additionally, historical accident statistics, categorized by accident type and severity, can shed light on potential safety concerns within the built environment (Bustos et al., 2021).

In the training phase, studies typically employ diverse labeled data types, often combining information from different sources or domains to enhance their models' accuracy (Koo et al., 2022b). For instance, Wang et al. (2019) examined China's elderly using street view images (egocentric) and surveys. They trained a model (Fully Convolutional Network) to find links between walkability features (like enclosure) in the images and self-reported depression/anxiety in the surveys. Adams et al. (2022) compared allocentric and egocentric data (street view, GIS, and surveys) in Phoenix, US, to assess general pedestrian walkability. They used machine learning (convolutional neural network) and expert systems (Decision Support System) to analyze features like sidewalks, crosswalks, and lighting. This allowed them to both evaluate walkability and automate sidewalk feature detection. Similarly, in studies on the evaluation of pedestrian accessibility, the researchers used the GIS features from the OpenStreetMap website and surveys as input for their model (Lucchesi et al., 2023).

4.2.2. Learning: AI Tools

In the learning stage, the model is trained with the test data. The model's accuracy is evaluated based on its performance on this test data. If the model performs well on the test data, it can be considered trained and ready to proceed to the inference stage. In this phase, the choice of algorithms and techniques is influenced by the type of labeled data. The reviewed studies encompass various categories of algorithms, including machine learning, expert systems, computer vision, and robotics.

Machine learning appears most frequently among reviewed algorithms, constituting 58% of the labeled data. Most studies leverage supervised learning techniques like decision trees (Kim et al., 2022) to train models on image data. This focus on imagery is reflected in the dominance of the architecture of convolutional neural networks—referenced in 14 articles. Convolutional neural networks excel at recognizing walkability features, including not just physical aspects like sidewalk width and slope (Zhao et al., 2016) but also factors influencing pedestrian experiences, such as the presence of greenery and shade (Wang et al., 2019). This approach goes beyond traditional safety concerns and incorporates elements influencing how enjoyable a walking environment is.

Studies utilize image segmentation for feature categorization (Lee et al., 2022; Ning et al., 2022), and instance segmentation for object detection, particularly in mapping sidewalk features. Robotics research focuses on developing prototype systems for data collection via computing devices (Bandini & Gasparini, 2020; Zhang et al., 2021). The reviewed literature reveals that researchers commonly use a combination of algorithms. For instance, to evaluate walkability indexes, a study employed the expert systems model to train the GIS features. At the same time, street-view images were used as input for the computer vision model (Yunqin Li et al., 2020). Additionally, expert systems and computer vision were combined to define a walkability index (Miranda et al., 2021).

4.2.3. Inference: Validation and Research Findings

In the inference stage, the trained model makes predictions on new, unseen data. The model takes in the input data and uses the relationships learned during the previous stage to predict. The goal of the inference stage is to use the trained model to make accurate predictions on new data.

Researchers employ various methods to evaluate walkability within the built environment. One approach utilizes walkability indices, including safety, comfort, and accessibility (D'Orso & Migliore, 2018; Yunqin Li et al., 2020, 2022; Yuan & Chen, 2022). These indices assess pedestrian routes based on these factors. Other indices, such as those focusing on desirability (Miranda et al., 2021) or elderly pedestrians (Gorrini & Bandini, 2019), have been developed to provide more specific evaluations of walkability. Additionally, certain studies quantify both physical and perceived features of pedestrian routes (Giles-Corti et al., 2014; Kim et al., 2022; Lee et al., 2022; Ma et al., 2021; Nag & Goswami, 2022; Yang et al., 2022; Yunqin Li et al., 2022; Zhou et al., 2019).

Beyond core walkability factors, some models incorporate additional data to improve prediction accuracy. This data can include factors like walking time (Nagata et al., 2020), time of day (Lai & Kontokosta, 2018), and even biosignals from pedestrians (Kim et al., 2022). These additional considerations highlight the multifaceted nature of walkability and the ongoing efforts to develop increasingly comprehensive models. Certain studies have employed various methods, such as defining a walkability score (Alfosool et al., 2022), rating pedestrian access to urban amenities provided by the city (Blečić, Cecchini, Congiu, et al., 2015; Blečić, Cecchini, & Trunfio, 2015), assessing the resilience of pedestrian pathways (Ku et al., 2022), and evaluating the quality of services available on sidewalks, as means of measuring walkability (Zhao et al., 2016). Some models employ different approaches, such as making predictions by identifying optimal pedestrian accessibility routes (Blečić, Cecchini, Congiu, et al., 2015; Blečić, Cecchini, & Trunfio, 2015) or proposing design solutions and evaluating their impact on walkability (Shao et al., 2021).

Detecting microscale streetscape features associated with pedestrian physical activity is one way to measure walkability, as demonstrated by the effects of these features on walkability (Adams et al., 2022; Blečić et al., 2018). Furthermore, advancements in automation are leading to the development of tools that can automatically detect and map these features. Research by Theodosiou et al. (2022) explore the use of automated barrier and obstacle detection for sidewalk feature data mapping.

The reviewed models also demonstrate another form of inference, which involves automating sidewalk features and data mapping. A trained model could significantly reduce the time and cost of collecting sidewalk mapping data by minimizing the need for human surveyors (Zhang et al., 2021). In another study to assist mobility-disabled users, a model could predict sidewalk features in previously unseen data (Ning et al., 2022). In addition, an attempt to map out walkability elements involves an automated audit that could serve as a highly scalable and dependable alternative to virtual audits (Koo et al., 2022a). Mapping can also be achieved by predicting the hazards on pedestrian routes through classified street images based on the likelihood of pedestrian-vehicle and vehicle-vehicle accidents (Bustos et al., 2021).

Finally, leveraging AI in the field of walkability, inquiries about the correlation between certain factors and walkability. Bandini and Gasparini (2020), Yin and Wang (2016), and Yue et al. (2022) investigate the connection between walkability and mental health, using visual enclosure and levels of depression and anxiety as datasets. Wang et al. (2019) also explore this relationship but with a focus on elderly pedestrians. Additionally, Lucchesi et al. (2023) examine the barriers and incentives of walking and find that areas with low walkability are typically car-oriented and unoccupied, with heavy vehicle traffic and significant vegetation. Conversely, denser areas with proximity to public transportation and lighting are more pedestrian-friendly, encouraging residents to walk.

4.3. Limitations and Existing Gaps

Current walkability assessment methodologies face limitations in data, evaluation methods, and accuracy of AI models. Challenges persist in processing complex data like street view images, adequately considering all relevant factors influencing walkability, and seamlessly integrating data from diverse sources (e.g., GIS and human subject surveys). Beyond technical challenges, there exists a notable gap in representing the experiences of diverse demographics and geographic contexts in walkability assessments. Many existing approaches may not adequately capture the subjective aspects of walkability, including non-visual factors like aesthetics, which are crucial for understanding how different communities perceive and interact with their urban environments. Importantly, these challenges are exacerbated by the limitations in scaling findings from localized studies to larger areas, hindering the applicability of walkability assessments on a broader scale.

In addition to these fundamental challenges, the integration of emerging technologies holds immense potential for revolutionizing walkability research. Devices such as eye-tracking devices, biosensors, wearables, and virtual/augmented reality (VR/AR) platforms, along with digital twin technologies, offer new avenues to enhance the precision and scope of walkability assessments. However, the full utilization of these technologies remains largely unexplored in the context of walkability studies.

A limitation of street-view images for walkability assessment is the misalignment between pedestrian and street-view image viewpoints. This misalignment introduces measurement challenges and distorts 360° panoramic images, affecting the accuracy of walkability evaluation (Lee et al., 2022). Furthermore, current models may not effectively predict transient visual elements such as cars, bicyclists, and pedestrians, which are crucial factors influencing walkability (Ma et al., 2021). Temporal and spatial limitations also impact walkability assessments based on street-view images. Images collected at different years or seasons may not accurately represent the current streetscape, compromising the validity of the assessment (Nagata et al., 2020). Additionally, the uneven spatial distribution of imagery introduces bias in evaluating neighborhood walkability, potentially leading to incomplete or skewed findings (Zhou et al., 2019).

The quantity and quality of street-view images pose challenges to comprehensive walkability assessments. Insufficient images and limited instances of less frequent barriers and obstacles on sidewalks limit the effectiveness of the assessment (Theodosiou et al., 2022). Moreover, the color similarity between sidewalks and vehicle roads can impact the accuracy of segmenting sidewalk pixels and predicting walkability attributes (Yang et al., 2022). To mitigate some limitations, researchers suggest collecting images from the sidewalk point of view, providing a more accurate representation of pedestrians' experiences (Lucchesi et al., 2023).

Non-visual aspects of walkability, including auditory and haptic perception (soundscapes and uneven sidewalks) and air quality (pollution affecting health choices), are often overlooked, limiting the holistic understanding of walkability (Yang et al., 2022). Demographic and area considerations also pose limitations to walkability assessment. In addition to technical assessment, walkability is subjective and varies among individuals, necessitating discussions on indicator weighting to account for these variations. Studies focusing on specific areas and age groups may limit the generalizability of their findings, emphasizing the need for testing diverse demographics and locations (Yunqin Li et al., 2020; Nagata et al., 2020). Furthermore, while using surveys and field observations as a means of labeling data is effective for smaller areas, their application to extensive urban street evaluations presents challenges and impracticalities (Yunqin Li et al., 2020).

5. Discussion

The proliferation of street view imagery and advancements in image processing techniques have facilitated the integration of AI into walkability research. The AI models used in the reviewed studies use algorithms with diverse data sources and architectures. The most common architecture was neural networks, and the applications extended to streetscape feature detection, mapping, scoring, and designing walkable routes. This flexibility highlights the potential of AI to analyze walkability from multiple perspectives. While topic modeling analysis confirmed knowledge about walkability factors, processing street view images presents challenges. These include misalignment with pedestrian viewpoints, image quantity and quality inconsistencies, and color similarity issues. The identified limitations and challenges discussed point to the ongoing need to integrate manual and human data sources into walkability assessments where AI tools cannot fully or accurately assess factors and/or such sources are needed to confirm assessments by fully automated AI tools. With currently available technologies, this study has highlighted the inability of AI to assess experiential factors, human perception of space, and micro-barriers that appear minor or are physically small yet create large barriers to walkability and may conflict with Americans with Disabilities Act standards. Future research should address these limitations and consider non-visual and temporal aspects like noise pollution, air quality, and comfort for a more holistic understanding.

Historically, walkability assessments concentrated on objective factors. However, with AI and street view data, the focus has shifted to a subjective, ground-level pedestrian perspective. AI models can learn to measure perceptual features such as safety or pleasurability by analyzing greenery or building abandonment through image processing. This transformative approach can enhance our understanding of the intricate relationship between the built environment and pedestrians. Despite several advantages over traditional methods, including time savings, comprehensive analysis, reduced bias, and scalability, AI tools constantly evolve to better capture human perception. New technologies like digital twins, eye-tracking devices, biosensors, wearables sensors, and VR/AR offer opportunities to move beyond current methods and achieve a more comprehensive understanding. Existing research lacks training models that leverage these emerging technologies.

6. Conclusion: Further Research and Outlook

With the help of digital twins and VR/AR technologies, it is possible to create a controlled environment for different scenarios of streetscapes. These virtual models can integrate various data sources, including street view imagery, GIS data, and real-time sensor readings. Researchers can manipulate variables like traffic density, building heights, and green space to simulate real-world conditions. The immersive nature allows participants to provide nuanced insights into their perception of safety, comfort, and ease of movement. Additionally, researchers can better understand pedestrian attention patterns by integrating eye-tracking technology. Furthermore, virtual pedestrian agents can be programmed to navigate the environment, providing insights into safety, comfort, and route surface evenness. Participants could virtually walk through simulated environments, providing feedback on their perceived walkability.

Pedestrians can wear AR glasses that overlay digital information, highlighting incentives and barriers in their walking experiences. This time, participants or surveyors could physically walk through physical environments, providing feedback on their perceived walkability. Afterward, AI can analyze video data captured through AR wearables, feedback, and labeled data to automatically identify behavioral walking patterns and environmental interactions. This approach could be particularly beneficial for studying the needs of specific populations, such as children or individuals with disabilities. While acknowledging challenges regarding accessibility, inclusivity, and data privacy, the possibilities offered by digital twins, VR/AR, and AI are undeniable. This approach signifies a shift in walkability assessment, moving beyond current methods to understand the subjective and cognitive experience of walking.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The data that support the findings of this study are available from the corresponding author, Yasin Delavar, upon reasonable request.

Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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REVIEW

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The Potential of AI in Information Provision in Energy-Efficient Renovations: A Narrative Review of Literature

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Abstract

Energy-efficient renovation (EER) is a complex process essential for reducing emissions in the built environment. This research identifies homeowners as the main decision-makers, whereas intermediaries and social interactions between peers are highly influential in home renovations. It investigates information and communication barriers encountered during the initial phases of EERs. The study reviews AI tools developed within the EERs domain to assess their capabilities in overcoming these barriers and identifies areas needing improvement. This research examines stakeholders, barriers, and the AI tools in the literature for EERs. The discussion compares the functionalities of these tools against stakeholder needs and the challenges they face. Findings show that tools often overlook methodologies in human–computer interaction and the potential of textual and visual AI methods. Digital tool development also lacks insights from social science and user feedback, potentially limiting the practical impact of these innovations. This article contributes to the EERs literature by proposing an AI-supported framework and outlining potential research areas for future exploration, particularly improving tool effectiveness and stakeholder engagement to scale up the EER practice.

Keywords

AI; energy-efficient renovations; information and communication barriers; stakeholders

1. Introduction

Energy transition triggered by climate change is taking place in every carbon-emitting industry worldwide, following the UN Framework Convention on Climate Change pledges in the last decade (UN Framework Convention on Climate Change, 2015). As one of the most essential parts of anthropogenic climate change, the built environment is a key ecosystem that needs to go through an energy transition due to its impact on emissions. There are many pathways for decarbonizing the built environment, and one of the most prominent ones for Europe is renovating the existing built environment to create a more energy-efficient stock (European Commission, 2020). However, sustainable transitions are challenging and not linear pathways (Loorbach, 2010). Although several methodologies and tools are available in the construction sector to respond to the renovation challenge, collaboration between stakeholders is crucial for these to succeed (European Commission, 2024). As renovating the existing building stock requires the collective effort of various stakeholders, it is important to understand the stakeholders' needs and the barriers they face during Energy-efficient renovations (EERs). Much of the scientific research into EER tool development has addressed the technical challenges, and much less attention has been given to the challenges resulting from the collaborative nature of EERs.

It is important to investigate EERs holistically due to their multi-actor and multi-phase nature. EERs require many stakeholders to interact at various stages of renovation measures. The challenge is not only technical, relating to renewable energy sources and their integration into domestic energy systems, but also social, relating to the willingness and ability to adopt innovations and change behavior. Therefore, addressing socio-technical challenges through scientific research demands more than merely enhancing metrics, such as accuracy and speed, of existing methods; it requires a comprehensive approach considering the broader societal context. Scientific research may consider that individuals are not merely users but also actuators in practices, such as EERs (Reckwitz, 2002; Shove et al., 2012). Thus, the impact of the research for a support tool might be less effective without a deeper understanding of the design requirements for the developed tools (Brazier et al., 2018). The benefits of these approaches are that existing problems are investigated from many perspectives, from individual to societal.

Furthermore, EER processes also need policies and supply-side support to facilitate decision-making by providing information, financial subsidies, required technologies, and labor. The information type and how it must be communicated differs at each phase of the EERs (Prieto et al., 2023). However, the initial phase, where the decision-makers, such as homeowners, gather information and decide to proceed, is vital. This information-gathering stage (Arning et al., 2020) requires proper information provision and communication from trusted actors. This phase is followed by an acceptance phase where stakeholders try to gather information on existing solutions. The information discrepancy between the initial phase and the subsequent decisions in later phases can impact how occupants interact with their buildings (European Commission, 2024). On the other hand, research on AI gained momentum in energy studies where vast amounts of information can now be processed to organize, analyze, predict, and generate knowledge crucial for energy transition. This research focuses on AI tools to overcome information provision and communication barriers for EERs, emphasizing the early phases, key stakeholders, and the potential of AI tools developed, and aims to investigate these by asking: "What are the communication gaps in information provision and the potential of AI tools in ERR for key stakeholders?" We aim to find the gaps in current technological developments in AI, addressing the various stakeholders in the early phases of EERs. The recent developments in computing technologies and methods have also increased the amount of academic research on "machine learning" (ML) and AI to scale up energy renovations by developing decision support tools for stakeholders in energy renovations. Research into developing AI tools for energy renovations is diverse, and various barriers and stakeholders are investigated. However, the needs of every stakeholder at each phase are different. Therefore, this research aims to reveal the gap in the development of the EERs literature tool by mapping the key decision-maker and influential actor at the initial stage of the renovation with the developed tool in the literature by reviewing AI tools in energy renovations (Figure 1).

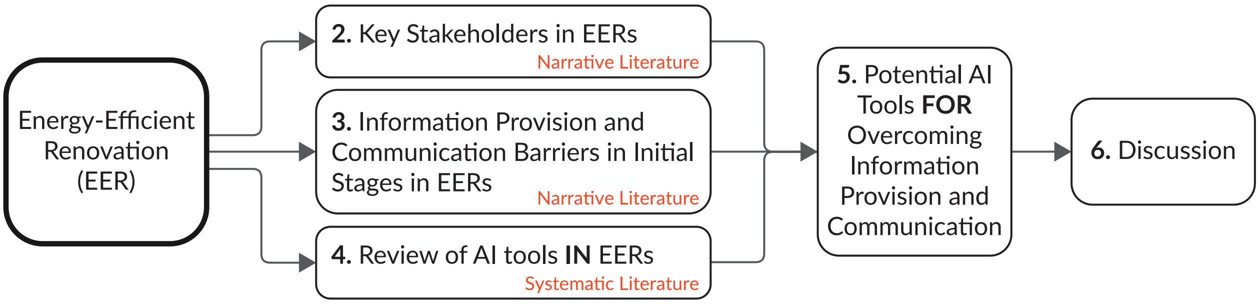

Figure 1. The flow of the article.

The article is divided into three sections to answer four linked research questions, mapping the findings to each other:

> RQ1: Who are the key stakeholders in the decision-making of EERs?
>
> RQ2: What are the information provision and communication barriers in the initial phases of EERs?
>
> RQ3: What AI tools in EERs literature address users, features, and methods to overcome these barriers for stakeholders?
>
> RQ4: What are the potential AI applications and methods from other fields to overcome information provision and communication barriers in EERs?

New developments in AI are also considered in the research scope due to the technical advances and the increasing number of research studies incorporating these methods in tool development for energy renovations. Furthermore, an expanding amount of AI-supported digital infrastructure is being implemented in many parts of digital environments and social platforms (see Section 5).

In Section 4, the existing reviews focused on energy prediction and benchmarking but often overlooked the social contexts of renovations. Seyedzadeh et al. (2018) compared ML methods for energy prediction and provided valuable benchmarks. Arjunan et al. (2020) did not specifically review the literature but compared ML models in energy benchmarking, which is one of the main decision-making factors of energy renovations, both from homeowners' and policy-makers' points of view. Gan et al. (2020) did not focus specifically on renovation challenges while reviewing the studies for energy consumption and carbon emissions. Wei et al. (2018) reviewed the data-driven energy analysis methods in the literature. Lygerakis et al. (2022) focused on ontologies used in buildings and various frameworks developed using knowledge graphs, and the part on occupants and the information exchange between stakeholders, pointing out the need for interactivity for end-users in decision-making. Roman et al. (2020), on the other hand, reviewed the artificial neural networks in metamodels on energy performance simulations. Shariq and Hughes (2020) review the state-of-the-art methods in building inspection for energy demands and their review reveals the importance of vision-oriented AI models to audit buildings. Lately, Yussuf and Asfour (2024) reviewed the literature on energy efficiency and AI, where they also focused on the applications of AI in many energy-related phases of the building lifecycles.

Other reviews, like those by Guyot et al. (2019), who reviewed artificial neural network applications in the building energy sector, and Grillone et al. (2020), who provided insights into energy prediction techniques and showed relevant themes but did not fully focus on stakeholders in renovations. The studies by Abdelrahman et al. (2021) on bibliographic natural language processing (NLP) analyzed the literature, and Deb et al. (2021) offered methodological insights, which are not fully aligned with EERs. Alrobaie and Krarti (2022) focused on model verification methods, reviewing only a randomized selection of the literature. Anastasiadou et al. (2022) conducted a bibliometric analysis that revealed findings but did not focus on renovations. This review highlights a need for research that bridges the gap between technological EER-related research and specific renovation practices, emphasizing the need for stakeholder-oriented analysis.

While the primary focus of reviews in this field has largely been on ML and AI methods for energy prediction and benchmarking, there is a need for more literature on energy renovations and how this research connects with stakeholders. Our research expanded to include reviews on renovations and their early stages, intelligent systems, and building interactions to enhance energy efficiency. Seddiki et al. (2021) identified significant gaps in tools developed in grey literature, especially the lack of user preferences in the web-based tool literature, which is vital (Seddiki et al., 2021). This review also highlighted the lack of financial information and step-by-step guidance in existing tools. Nielsen et al. (2016) explored early-stage renovation tools primarily utilized by professional building owners but noted difficulties due to the predominance of offline tools. Ferreira et al. (2013) analyzed decision-making tools for refurbishment, pointing out that although their study was slightly outdated, the fundamental gaps in stakeholder focus remain relevant. Day et al. (2020) examined building-human interfaces and their impact on energy efficiency, stressing the importance of interface design for better communication.

The reviews suggest that the linkage between stakeholders and AI-powered tools in the context of building renovations is insufficiently explored, particularly concerning user definitions and information interfaces. This shows the need for research that not only investigates these tools but also integrates stakeholder feedback and requirements to create an impact on renovation strategies.

The article is divided into six sections. Section 2 investigates the stakeholders in energy renovations, their power in decision-making, and the influencers. Section 3 delves into the barriers in the early stages of energy renovations. Section 4 reviews the AI tools in energy renovation literature. In Section 5, we cross-discuss the gaps in the literature and the AI tools that have the potential to be implemented in EERs literature. Lastly, Section 6 proposes a framework to steer future research trajectories in AI, EERs, and sustainability transitions for information provision and communication.

2. The Key Stakeholders in Energy Renovation

Energy renovations are multi-stakeholder processes involving property owners, designers, contractors, energy companies, urban planners, policy-makers, and others with niche roles. The research on these stakeholders, their roles, and their impact has been getting more attention in the last decade. The research to define key stakeholders matters due to the slow renovation rates all around the globe, especially in the Netherlands, where the goals are set higher than those of other European nations (Ministrie van Economische Zaken en Klimaat, 2019). Sebi et al. (2019) also mention the goals set by other developed countries and the policies to drive homeowners to renovate their properties, these even include mandatory actions such as requiring an Energy Performance Certificate in France or using renewable energy sources in Germany. However, the financial incentives and the fiscal policies to support these renovation actions require delicate adjustments due to the growing inequalities in homeownership and renovations (Fernández et al., 2024).

For example, there are three types of housing in the Netherlands: social housing, rental market, and homeowners. According to Klimaatakkoord, the number of houses to be renovated by 2030 is around 1.4 million, and almost half comprises homeowners (Broers et al., 2022). Homeowners are among the main decision-makers concerning home renovation (Laguna Salvadó et al., 2022). This shows that addressing homeowners as the key stakeholders has a potentially high impact on the practice. However, homeowners do not decide on the renovations by themselves. Their peers or other actors influence them in the renovation ecosystem (de Wilde & Spaargaren, 2019; Mogensen & Gram-Hanssen, 2023). Addressing the most influencing factors is also important to understand the links between the stakeholders.

Intermediary actors are important stakeholders in the EER process due to their ability to curate knowledge, tailor complex information for homeowners, and influence their decisions (Bertoldi et al., 2021; de Wilde & Spaargaren, 2019). Therefore, decision-making in EER is affected by influencing actors; in this sense, it is vital to understand their roles. Intermediaries are key influencers in the early phases of renovation and ensure trust with decision-makers. However, the social environment also plays a role in EER decision-making (Ebrahimigharehbaghi et al., 2022). The social interactions and the individuals who went through the EER process affect homeowners' decisions or their awareness (Mogensen & Gram-Hanssen, 2023). This interaction also points out the importance of social influence in energy renovation, where the information spreads with trust from peers and intermediaries.

Social influence is one of the key elements in energy transition. Social norms and individual interactions greatly influence the decisions made by homeowners (de Vries, 2020). Therefore, one of the barriers in the literature on information is the reliability of the sources and the actor who brings it (Ebrahimigharehbaghi et al., 2022). Social influence also plays a role in digital platforms as well, where respected people from the community have the potential to influence a local community by sharing their experiences online (Kwon & Mlecnik, 2021). It is essential to bring awareness to homeowners, yet it is also beneficial to apply energy renovations at scale, such as in condominiums, neighborhoods, or even districts.

Scaling up the renovation project is the most efficient route to energy transition in the built environment and is needed to speed up the transition. Scale is vital for many factors, including financial, administrative, and carbon mitigation. As the scale goes up, the prices for construction and administration go down, and the support from the local governments increases as well (Mlecnik & Hidalgo-Betanzos, 2022). However, the participatory processes and their facilitation hinder scaling up the energy renovations due to personal conflicts, various motivations, and lack of coordination (Cirman et al., 2013; Mlecnik & Hidalgo-Betanzos, 2022). The intermediaries in energy renovation also focus on this challenge (Elgendy & Mlecnik, 2024). Despite the features and functions intermediaries provide, they have recently become one of the main topics in energy transition. This is due to the possibility of the actors' influence on policy-making (Janda & Parag, 2013) and the business potential they possess (Elgendy & Mlecnik, 2024).

Intermediaries are also the link between the supply-side and the demand-side. Intermediary actors connect homeowners, contractors, and other experts with the financial information needed (Boza-Kiss & Bertoldi, 2018). Therefore, their knowledge is not limited to expertise in energy renovation procurement but also extends to demand and bureaucratic aspects, where they have in-depth insights into what homeowners want, value, or dislike, and which financial tools to use. For example, the existing financial schemes from the Dutch government are various and they change based on the province, city, and neighborhood, thus they can be too complicated for many to apply (Uitvoeringsoverleg Klimaatbeleid Gebouwde Omgeving, 2023). Alongside the efforts from academia and the government, the energy renovation policy can benefit from the experience of intermediaries (Janda & Parag, 2013).

Our research pointed out that even though home and building owners are the main decision-makers, intermediaries and social interactions are the key influencing factors. However, the decision-making phase is important when addressing these stakeholders. In residential EERs, the main decision-makers are the homeowners (Laguna Salvadó et al., 2022); however, in the initial phase, homeowners are open to influence from actors such as intermediaries or peers in EER decisions. Section 3 investigates the barriers in the early stages of information and communication, focusing on the actors mentioned in this section.

3. Information Provision and Communication Barriers in Initial Stages in Energy Renovation

The research defined various phases in EERs, such as an awareness phase (Arning et al., 2020), an information search (or orientation) phase, a design and planning phase, and an implementation and monitoring phase (Konstantinou et al., 2021; Prieto et al., 2023; Sequeira & Gouveia, 2022). The early stages of decision-making for EERs are also mapped, and the stakeholders differ there in their influence (Laguna Salvadó et al., 2022), yet in homeowners' case, the intermediary actors play an essential role due to their ability to craft information and communicate it well (Decuypere et al., 2022).

There is research about the barriers in EERs, and some of them even have specific focuses on the scale of the renovation, ownership of the buildings, and government policies (de Vries et al., 2020; Johansson et al., 2023; Klöckner & Nayum, 2016; Prieto et al., 2023). Furthermore, context-specific research is vital in the renovation practice due to the difference in enablers and cultural norms (Ebrahimigharehbaghi et al., 2019; Jia et al., 2021; Mogensen & Gram-Hanssen, 2023). There are various categorizations of barriers in the literature from individual to institutional levels. At the individual level, some significant barriers arise due to the financial burden of EERs, such as investment costs (Bertone et al., 2016; Jensen et al., 2013; Yang et al., 2021) or transaction costs (Ebrahimigharehbaghi et al., 2019). For example, in Germany, individually planned and subsidized renovation plan policies can support citizens with subsidies to encourage them to apply deep renovation measures to their homes based on the individual application plans (Directorate-General for Energy et al., 2020). However, the financial tools to apply these strategies were found to be biased (Fernández et al., 2022), and the information to use these subsidies is too complex to navigate for citizens (de Vries, 2020). A simplification of the bureaucratic process would ease the access to financial funds of the homeowners (Pérez-Navarro et al., 2023).

Moreover, information complexity is not just limited to financial tools but also includes building information, renovation technologies, and the renovation process itself (Jia et al., 2021). The information on the EERs can be complicated for people without expertise in the field (Arning et al., 2020; de Wilde, 2019, p. 19). Information about the existing building can also determine the EERs, where the physical properties of the building can be hard to renovate (Cirman et al., 2013; Long et al., 2015). Furthermore, the amount of information can be overwhelming and result in procrastination of the action, which hinders the renovation rates (de Vries, 2020). Tools such as the Energy Performance Certificates can enhance the understandability of the building's energy measurements and consumption by providing homeowners and tenants with simple energy labels, thereby influencing their decisions to renovate their properties (Charalambides et al., 2019). Furthermore, Building Retrofit Passports aim to enhance interoperability and facilitate long-term renovation planning for homeowners, policy-makers, and intermediaries, such as architects, by organizing the building information into a digital logbook (Gómez-Gil et al., 2022). Despite their benefits and the mandatory practices in the EU, even Energy Performance Certificates are still found to be too technical and need improvement to be more user-friendly (Zuhaib et al., 2022), and Building Retrofit Passport is still a new tool to implement in the built environment and requires further practice.

The barriers in EERs are different at every stage of the process. Early stages are the awareness and information collection stages (Arning et al., 2020; Klöckner & Nayum, 2016; Konstantinou et al., 2021), followed by the stages of audits, planning, and concept designs, which require homeowners, designers, and constructors to communicate. In these stages, communication and coordination issues in EERs are among the most mentioned barriers in the literature (Prieto et al., 2023). The complexity of the implementation of EERs (Ebrahimigharehbaghi et al., 2022), the administration of the process (G. Liu et al., 2020), or not being able to participate in the decision-making process in multi-stakeholder settings due to a lack of knowledge (Xue et al., 2022).

The research about the information provision barriers, how it is communicated, and the communication between the actors at different stages of the renovation process becomes prominent. The various stages and scales in energy renovations require different information to be communicated based on the stakeholders involved in the process, yet information communication is essential (Johansson et al., 2023; Prieto et al., 2023). From the homeowners' perspective, even being aware of the need for renovation is a step where the initial ideas start (Arning et al., 2020). Furthermore, awareness of energy renovations plays an important role in initiating audits (Palmer et al., 2013). The role of information provision and communication in the initial step, where understanding the needs of stakeholders, raising awareness, and then focusing on the understandability of the information, are essential.

The previous section, and this one, have provided the contextual background on energy renovation, including barriers, key stakeholders, and potential points to focus on to increase the speed of energy transition; these two sections also tried to answer the first and second RQs. However, in Section 4, this context will help link state-of-the-art methods with barriers, stakeholders, and potentials in the literature by reviewing the existing tools using AI for energy renovations.

4. Review of AI Tools in EERs

In this section, we explain the methodology of the review and the findings. This review section aimed to investigate the AI tools developed to support energy renovations or similar topics in the built environment, such as energy renovation-related policy support or energy performance certificates, to understand their relation with the stakeholders, and the barriers in EERs research in the literature. Therefore, the keywords in the review were scoping four sets of words, including the action(renovations), the context (building or housing), the technique (AI), and the purpose (energy efficiency). Since the word "buildings" may not represent all the types of buildings, we also added "housing" and included other residential studies such as social housing and housing policies. The technical keywords were limited to AI and ML since any other method is a sub-research field of these two. Our primary scoping keywords included "built, building, housing," "energy," "renovation, retrofit, refurbishing," and "AI, ML." These terms were used to search through Scopus, Web of Science, and ScienceDirect databases and search engines to ensure comprehensive coverage of the existing research in these areas on 9 February 2024 (see Figure 2). The review included all the indexed publications except the review articles because their research methods were on analyzing the literature rather than developing a tool.

In the first phase, we applied specific inclusion criteria to identify studies that explicitly mention using tools, platforms, or applications within the research outcomes to titles and abstracts. This includes any article that discusses developing or utilizing web-based services, interactive technologies, or those offering tailored or targeted information. Furthermore, the inclusion criteria required that the studies address the communication or involvement of specific actors or stakeholders within the field, excluding those that focus solely on processes, institutions, or non-interactive actions.

For the second phase, we applied exclusion criteria to refine the scope of our review further by reading the introductions and conclusions. A study was excluded if it did not discuss a specific tool or technological application designed for user interaction in the context of building and energy. This two-pass review process helped us focus on studies related to AI tools in energy renovations involving stakeholders. This approach also allowed us to analyze how AI methods are employed to enhance energy efficiency and user engagement in the building sector, reveal an overview of the current landscape, and identify gaps for future research.

This section aimed to understand the relationship between the main stakeholders in the literature, the main barriers in the early stage of EERs, and the AI tools. Furthermore, how the features, methods, and addressed users of AI tools help overcome the barriers in EERs literature. We discussed that homeowners are found to be the main stakeholders in decision-making, yet intermediaries and social relations are the most influential actors in Section 2. Furthermore, we mentioned in Section 3 that information and communication barriers are among the most prominent barriers in the early stage of the EERs. Therefore, we mapped the number of features and users addressed together in the studies reviewed and discussed them regarding the stakeholders and the barriers in previous sections (see Figure 3).

The findings from the review showed that there is a focus on speed or efficiency in computing, a graphical user interface, data provision for renovation, and user data input in features (see Figure 3). Only a quarter of the studies inherit features that can support the information in visual formats, such as graphical user interfaces and visualization. The visual interface elements help represent complex information, yet there are only 11 studies

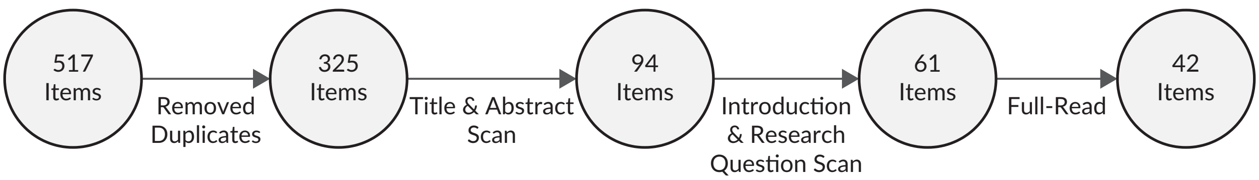

Figure 2. Review process chart.

Row Labels	Architects / Designers	Home / Building Owners	Stakeholder	Non-Technical	Facility Managers	Public/Local Authorities	Policymakers	Industry	Urban Planners	Contractors	Experts	Decision-Makers	Builders	Citizens	Researchers	Consultants	Auditors	Residents	Developers	not Specified	Buyers	Tenants	Spesific Software Users	Engineers	Energy-Saving Institutio	Remodeler	End-user	Portfolio Managers	Energy Decision-Makers	Real-estate Enterprises	Investors	Asset Holders	Technicians	Wall designers	Planners	Households
Interface Design	6	3	3	1	3	2		1	1	2	2		1	1		1	1	1	1	1				1			1	1			1	1	1			
User Inputs	9	4		2	1	2		1	1	2	2	1	1	1		1								1		1							1			
GUI	5	3	3	2	1	1		1		2	2		1										1			1	1							1		
Fast	3	1	2	2			3	1				2		1	1					1	1	1	1	1	1					1						1
Data for Renovation	2	3	2	1	3	1			1	1	1	1	1			1	1	1	1	1							1									
Scalable	2	2	1	1	1	2	3	1	3			1			1	1																				
Automation	4	2	1	2		1	1	1	1		1				1					1					1					1						
Visualization	2	1	2	1	1	2	1	1	1					1	1																					
User Interaction	2	1	1	1	1					2	1		1	1			1	1	1																	
LCC / LCA	2		1	1	1							1																1	1		1	1			1	
More Accurate			1		1		2	1	2											1	1	1							1							
User-Friendly	1	1		1	1					1	1		1				1	1	1																	
Immersive	1	1			1					1			1				1	1	1																	
Real-time Data Analysis	1	1	1		2	1			1							1																				
Real-time Feedback	2	2	1			1		1				1																								
Prediction		1	1	1			1					1									1	1		1												
Robust Learning Model for Prediction					1		2	2	1						1														1							
Building Monitoring	1	1	1		2	1			1							1																				
Online Connection	1	1			1					1			1				1	1	1																	
Digitalization	1	1			1	1			1			1				1																				
Easy	1		1	2																	1	1	1													
Information Provision		1		1		1		1			1	1		1																						
Tailored Information		1		1		1		1													1	1														
More accessible tool	1		1	2							1												1													
Time Effort	1					1		1	1						1																					
Understandable	2	1										1		1																						
Understanding Moisture Durability	1									1			1													1								1		
Summarization			1				1																		1					1						
Interoperability	1			1						1	1																									
Transferable			1	1								1																								
Historical Buildings																												1			1	1				
Bottom-up			1				1		1																											
Privacy		1				1		1																												
Social Influence		1				1		1																												
Exergy Analysis							1	1							1																					
Spatial			1				1		1																											
Mobile Ready				1								1																								
Step-by-Step										1	1																									
Material Database	1																																			
Optimizing EPC														1																						
Supply Integrated	1																																			
Interactive			1																																	
Explainable	1																																			

Figure 3. Features (right column) and users (top row) are addressed in the literature. Note: The coding is based on the definitions by the authors of the reviewed articles.

that applied a method to define design requirements or validate the tool by gathering feedback based on the design prototype. This shows a lack of focus on user-centric tool development research.

Moreover, only 19 of 42 studies provide features critical for user-friendliness and effectiveness, such as explainability, interactivity, step-by-step guidance, summarization, understandability, and ease of use. Only a few studies have combined these features with an interface design and visualization, pointing out a significant area for improvement. Although 10 out of the 42 studies mentioned collecting feedback through workshops, interviews, and surveys, only two did so before the tool's development. The remaining studies conducted validation exercises in post-development, pointing to a potential gap between tool design and end-user needs.

Although there were parameters included as "social," these parameters were more focused on the users' comfort and preferences. However, we should note that only 15 out of 42 studies allowed user input;

despite allowing this interaction, the tools in the literature were not open enough to engage with the users. This finding also matches previous reviews (Seddiki et al., 2021), though the number of tools that allowed user inputs or preferences was more than the previous review on grey literature.

Demographically, the studies mention various user groups, with homeowners being the focus at 31%, design professionals at 38%, and policy and planning stakeholders at 21%. However, 36% of the studies vaguely reference general decision-makers or stakeholders, suggesting a lack of specificity in targeting user needs.

Of the 42 studies, only two utilized computer vision as a medium for AI. The reviewed literature has no research focusing on NLP to develop energy renovation tools. An additional literature search using the terms "NLP" and "LLM" rather than "AI" and "ML" further confirmed this gap, indicating an underutilization of these methods in scientific indices. Although studies use NLP to analyze the literature (Abdelrahman et al., 2021), the technique has not been implemented in the tool development.

Regarding decision-making support methods in the review, nearly a quarter of the studies investigated utilize multi-attribute optimization, multi-criteria analysis, multi-criteria decision analysis, multi-criteria decision-making, multi-objective optimization, analytical hierarchy process, and preference ranking organization method for enrichment evaluation. These methods facilitate cognitive decision-making processes by quantifying key decision factors, showcasing a robust approach to complex decision environments. However, visualizations can help ease decision-makers cognitive load (Padilla et al., 2018), yet these have not been considered in many studies. The studies in the review discuss different models, such as black-box (data-driven), white-box (physics-based), and hybrid models, which integrate both models and their advantages for use cases.

Despite existing tools for renovation practices, expertise, and policy, there is a lack of tools to inform policymakers using input from the stakeholders. The tools in the review do not mention connecting the stakeholders and policymakers in a scalable manner. Users' input through their interaction with EERs and policy-making is connected, yet the studies do not mention any form of connection between this practice and informing policy-making, especially in a scalable and explainable way for EERs.

Lastly, this review reveals a significant deficiency in tools designed for social influence. Tools focusing on homeowners, designers, and planners are common, yet those facilitating knowledge exchange among intermediaries for social impact are missing. Some studies mention the social influence aspect of the EER decisions; however, only one of the studies targets homeowners as the tool's users and implements UI and user feedback (B. Liu et al., 2023). This lack of integrated tools suggests that while many tools address several aspects of energy renovations, comprehensive solutions that integrate multiple perspectives, such as social influence and user-centricity, are still needed. The findings from the reviewed literature reveal the need for more interactive, user-focused, and integrated tool development in energy renovations.

5. Potential AI Tools for Overcoming Information Provision and Communication Barriers in EERs

In this section, we will discuss the stakeholders, barriers, and AI tools reviewed in the previous sections to reveal the gaps in the literature and the potential research trajectories to cope with the barriers in the literature for better tool-oriented research. We will discuss how to improve information provision and communication barriers to the main stakeholders using the methods mentioned in the reviewed literature and potential methods used in other fields to overcome similar barriers.

The tools in the literature are mostly being developed to improve the previous studies' accuracy, robustness, and scalability. While technical improvements are necessary for research, the literature on human–computer interaction, such as research-through-design (Zimmerman & Forlizzi, 2014), to improve the usability and application of these tools is missing. The tools developed in the reviewed literature also have complex systems, including societal, financial, political, and environmental aspects. However, there is no mention of methodologies such as complex systems engineering (Brazier et al., 2018). Even though the prototypes of the tools have been developed, the methods, such as design prototyping (Gero, 1990) or similar, are not mentioned. This gap also shows that tool development in EERs has not embraced methodologies for tool development for specific users despite the addressed users or stakeholders in the literature.

As Day et al. (2020) also suggest, the users' behavior greatly affects the usability and the impact of energy efficiency. The research on tool development for energy renovations must consider that user behaviors and lifestyle are important factors in the interaction design of the tools. The users' values can play an essential role in transitions and, therefore, the development of user-oriented tools. The research on social values and how they can motivate sustainable transitions is vital (Mouter et al., 2019). Furthermore, the methods to scale these value interpretations by computational methods have great potential as they can link the policy-makers with citizens (Mouter et al., 2021; Siebert et al., 2022).

Despite many studies mentioned in the literature on the acceptance of AI, and related trust issues such as black-box models (Kelly et al., 2023), meaningful human control is not mentioned in the reviewed literature. Concepts such as "explainable AI" or "hybrid intelligence" that help the stakeholders understand and control the models in a meaningful way were missing (Guszcza et al., 2022). This gap is important because AI systems are becoming more dominant in all fields, and their controllable scalability without biases is a vital problem.

The review showed that the tools are mostly not developed considering the social aspects of EERs. The influencing actors and the dynamics between these actors play an important role, and these dynamics can shape the renovation practice based on the local cultures (Camarasa et al., 2020). The research points out the importance of intermediaries in EERs and their influence on homeowners' decision-making for EERs (de Wilde & Spaargaren, 2019; Sequeira & Gouveia, 2022), as well as the influence of social interactions within homeowners' social circle (Ebrahimigharehbaghi et al., 2022). Kwon and Mlecnik (2021) suggest that online platforms sharing the experiences of locals through local authorities might influence the residents to consider EERs.

Moreover, in this perspective, NLP methods are not considered in the reviewed literature. The complexity of the information that might influence the decision-makers can be simplified and delivered to the users. There are studies used to gather information using NLP-based models in similar contexts (Zhang et al., 2023), or to simplify complicated large climate reports (Bingler et al., 2022). These developments also show us that AI methods in other mediums (text, sound, image, and video) can help increase the scale of interactions and information provision, thus facilitating communication in EERs.

One of the features of intermediary actors in EERs is tailoring information based on the needs of the stakeholders (Yang et al., 2021). This shows the impact of tailored information provision. Yet, the scalability of intermediary actors is limited due to their physical reach, such as information meetings or in-person conversations with stakeholders. However, the tools in the review do not account for this kind of scalability at all. The digital platforms developed by reliable actors such as local authorities and the information provision with input from the stakeholders using textual or visual AI models have great potential in scaling and keeping reliability together. This does not mean overriding the intermediary actors in the ecosystem, yet it is quite possible to augment their reach to more stakeholders by using EER-specific tools that have multi-modal information provision. These tools are embedded subtly in our lives as instant messaging apps or send emails using popular email service providers, and they can potentially improve our communication skills (Hancock et al., 2020). That includes the multi-stakeholder deliberations for multi-stakeholders (ACM Collective Intelligence Conference, 2022; Siebert et al., 2022), such as multi-owner buildings or district-scale energy renovation projects. The help of AI using visual models also applies to architectural design processes (Castro Pena et al., 2021) and deliberations over multi-stakeholder project designs or visuals (UrbanistAI, n.d.)

Our analysis has shown that the tools discussed in the literature have various features to address the challenges of EERs; however, the main stakeholders, such as homeowners and other intermediaries, still do not receive the required attention. This review has shown that AI tools insufficiently challenge the information and communication barriers at the early stages of energy renovations. Furthermore, there is a lack of focus on user input in the early development phase and, therefore, user-centric tool development. Lastly, the potentials of various AI models were not considered most of the time in the literature.

6. Discussion

In this section, we discussed the future trajectories in EERs research and the potential of AI to create an integrated and scalable ecosystem. This study aims to define the gaps in the EERs literature, focusing on AI tools, and tries to compare three perspectives (stakeholders, information barriers, and AI tool literature) in EER studies to find the potential AI methods that can be applied in EERs context to overcome the information provision barriers.

The EERs ecosystem is a complex system, and to tackle information barriers, we have to think about the problem in an interactive framework (see Figure 4). The framework is an experimental way to connect all individuals and institutions via an adaptive AI-supported interface. The results of the review and the potential AI methods to implement in the EERs context mention that the literature lacks social influence aspects, unscalable information tailoring, lack of human-in-the-loop perspective, and, lastly, the missing link between the stakeholders and policy-makers.

In the framework (Figure 4), we wanted to point out that all these aspects should be considered together in an integrated architecture. Here, five nodes are interconnected to each other via a central node. The "social influence" node is connected to the center to achieve a scalable information provision based on the needs of the "individuals" and gather the experiences from their EER experiences; moreover, this interaction aims to also deliver the information from other individuals to influence socially. "Integrated data platform" aims to collect, organize, and provide knowledge, such as policy, expert opinion, and successful projects in the

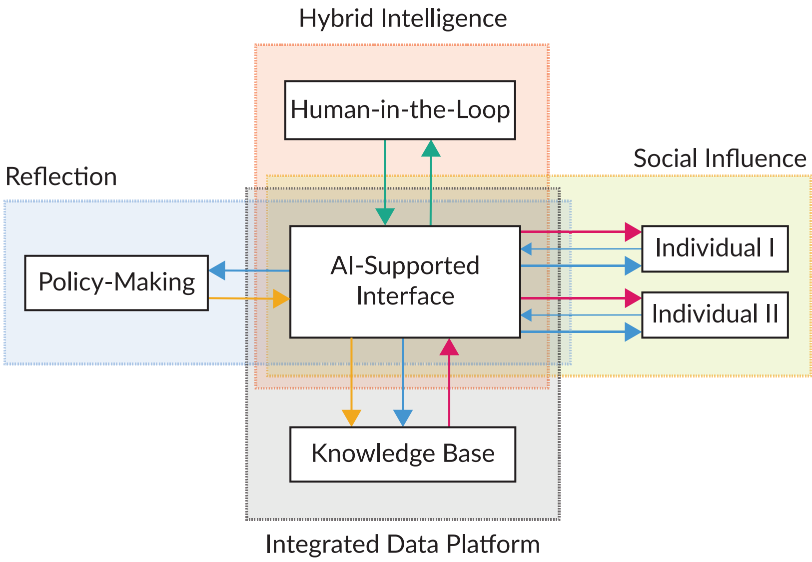

Figure 4. AI-supported interface framework.

"knowledge base," for the central node. "Reflection" is the node where insights from individuals, expert opinions, and policies are compared and reflected on for better "policy-making."

"Hybrid intelligence" is the audit part of the AI-supported interface framework where experts in the ecosystems intervene in the AI system as "human-in-the-loop" to improve the reliability of the central node. Lastly, the "AI-supported interface" aims to receive the information coming from all sides and deliver it to each node based on their queries.

Sustainability transition requires information delivery between different levels of management (Loorbach, 2010); from strategic to operational levels and back. The framework (see Figure 4) also considers the knowledge that affects the social influence with the practices that evolve and are disseminated by the mediums of communication (Shove et al., 2012). Studies that try to frame sustainability transitions help researchers understand the values, motivations, and meanings behind EER decisions, therefore helping them find the most impactful tool to develop.

For future research, it is crucial to understand that EERs are not solely technical processes but rather socio-technical transitions. This requires understanding the stakeholders, social challenges, and pathways to create impact at their intersection. This involves enhancing AI tools' technical specifications and ensuring they are designed with a thorough understanding of the socio-technical systems they aim to support. By addressing the current gaps in tool functionality and stakeholder engagement, the adoption of EERs can be accelerated. Further research on AI-powered tools can contribute to the broader sustainability goals and reduce environmental impact in the built environment.

7. Conclusion

This article investigated EERs in the built environment, focusing on the main stakeholders in decision-making and influencing, as well as the information and communication barriers at the initial stages the stakeholders encounter in renovation projects. In our review of AI tools supporting EERs, we identified gaps in methodologies and tool functionalities that align with the requirements of key stakeholders, particularly homeowners and intermediaries. While AI technologies offer promise for improving the decision-making process in EERs, there remains a strong need for tools that address information and communication barriers stakeholders face during the early stages of EERs.

The literature review highlights the lack of user-friendly, interactive tools that allow user input, step-by-step guidance, and stakeholder communication. The reviewed literature showed that the user-centric human–computer interaction methods to develop tools for targeted users were mostly not used. This gap points to the necessity for a multidisciplinary approach in tool development, integrating insights from social sciences to ensure digital solutions are grounded in the practices of stakeholder interactions and community dynamics in addition to the need for "stakeholder-oriented analysis." We proposed a framework to cover the literature gaps and explain the links and nodes that respond to these specific problems.

Furthermore, the research suggests the potential for other AI techniques, such as NLP and computer vision, to develop more tools to improve how information is communicated within the EERs ecosystem. Such tools could help stakeholders by simplifying complex textual and visual knowledge and making decision-making more comprehensive. Moreover, when needed, they can facilitate more interaction and information provision to different stakeholders at different phases of efficient renovation (European Commission, 2024; Prieto et al., 2023).

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Conflict of Interests

In this article, editorial decisions were undertaken by Neil Yorke-Smith (TU Delft, the Netherlands).

Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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ARTICLE

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Speculative Criminality at Home: Bypassing Tenant Rights Through Police Surveillance in Detroit's Rental Housing

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Abstract

In 2016, Detroit, Michigan's police department piloted a city-wide public-private-community video surveillance program called Project Green Light (PGL). Businesses that host the service, typically gas stations and convenience stores, receive priority response times for emergency dispatch calls, artificially decreasing 911 response times in a city with historically low emergency response capacity. This has led to many senior care homes with medically vulnerable residents to subscribe to PGL, as well as landlords of residential apartment buildings. While the program has been identified as a marker of gentrification by housing and anti-surveillance activists and residents, it has also raised concern about perpetuating the criminalization of Black Detroiters, specifically those living in rental housing that hosts the technology. In a city that is rapidly evolving through private, institutional, and public partnership developments while elected officials espouse to maintain racial and economic equity as core values of Detroit's upcoming master planning process, the lack of foresight of the impact of surveillance tech is striking. The article's focus is on surveillance technology as a defining element of contemporary urban development which enacts both a forbearance and expansion of rights through the application of technology to property relations. Relying on the automation of policing and racially biased artificial intelligence perpetuates criminality based on race, class, and perceived gender while additionally tying those experiences to the bundle of rights associated with the ownership of property.

Keywords

criminalization; forbearance of rights; policing; surveillance; tenant–landlord relations

1. Introduction

The year 2024 marked 10 years since Judge Steven W. Rhodes confirmed the plan of financial adjustment that led to Detroit "exiting" municipal bankruptcy, the largest filing of its kind in US history (Barnes et al., 2021). A foundational feature of the city's bankruptcy proceedings was the state appointment of emergency financial manager, Kevyn Orr from 2013–2014. Orr's oversight removed legislative authority from the majority Black elected representatives of Detroit's City Council, and effectively ceased democratic decision-making power in the nation's largest majority Black city (Breznau & Kirkpatrick, 2018). Hours before Orr's time as emergency manager ended in December 2014, Chief of Police James Craig, hired under the authority of Orr, requested approval for access to $7.5 million, which was granted. These funds established the city's Real Time Crime Center (RTCC) and procured $6.1 million worth of police surveillance equipment (Baker et al., 2022). The infrastructure of what would become an expansive network of interconnected surveillance apparatus was procured and installation began. This marked a new era of policing, governance, and financial transition under the eye of the nation to demonstrate that Detroit—a city that had been racistly characterized for decades as ungovernable, vacant, and dangerous (Boyle, 2001; Chanan & Steinmetz, 2005)—could be responsibly governed.

Detroit has continued to be expected to prove itself as a city of law and order, rule and effective governance over its citizens since its establishment as a colonial outpost on Anishnaabe land in 1701, and contemporarily during the neighborhood uprisings of 1967. Detroit's July 1967 uprisings, catalyzed by police brutality and the criminalization of Black life and culture, has been deservedly archived and analyzed, and recently revisited by cultural workers and activists to commemorate the 50-year anniversary of the '67 rebellion and its lasting influence on Detroiters' history of resisting and persisting through ongoing state violence, economic crisis, and ongoing police brutality. The civil rights era of resisting police oppression amid the continuous rollout of urban disinvestment and growing white suburbanization and its impacts on policy and urban development initiatives has been thoughtfully detailed in Thomas Sugrue's *The Origins of the Urban Crisis*, William Bunge's *Fitzgerald*, and Amy Maria Kenyon's *Dreaming Suburbia*, to name a few. The influence of Detroit's summer of 1967 on the collective memory of residence and the city's landscape is lasting, and the events hold their rightful place within US urban and civil rights histories. However, the rebellion is often selectively remembered by public-facing elected officials in the city today.

2. Policing in Detroit

On the precipice of political change in Detroit following the July 1967 uprisings, residents elected Roman Gribbs who served as Detroit's last Caucasian mayor for over four decades, from 1970 to 1974. Gribbs vowed to take decisive action to decrease crime during his time in office. He served as an architect, alongside police chief John Nicols of Stop the Robberies, Enjoy Safe Streets (STRESS), a neighborhood policing unit that functioned between 1971 to 1973 and was known by community members as the "killer squad" of police (Farley, 2015). STRESS officers murdered 22 Detroiters in the unit's short period of operation (Boyd et al., 1981; Sugrue, 1996). The unit was understood to be a response to tensions that remained between police and community members as a consequence of the police murder of 38 civilians during the '67 rebellion, as well as the arrest of more than 7,000 Detroiters over the course the four days in July '67. The unit willfully relied on racial profiling as well as decoy and diversion tactics to coax Black bystanders into illegal situations that led to arrests (McCoy, 2021). Though anti-STRESS organizing and coalitions were able to pressure elected officials into dismantling the unit, violent police–community relations have remained a fixture in the city's landscape more than half a century later.

Mayor Mike Dugan was elected into office in 2013, and like Gribbs, the last Caucasian mayor before him, his mayoral administration has invested heavily in the armament of police, increased police hiring, and procured the largest expansion of the city's police surveillance infrastructure. In July of 2024, in response to gun violence fatalities at a Detroit block party following multiple unresponsive calls to the Detroit Police Department (DPD) from residents (Barrett, 2024), the Duggan administration and the Detroit chief of police announced the immediate creation of a new STRESS-like unit that would specifically patrol neighborhoods for "illegal" parties. The creation of this new unit is illustrative of how lessons that could have been learned from such violent police–community relations that catalyzed the 1967 uprisings have gone unacknowledged, brutally and fatally by the DPD. On July 12 2024, Detroit resident Sherman Lee Butler was tasered, shot, and killed by a court bailiff and Detroit Police while being evicted from his apartment unit in a building undergoing mass renovictions. Weeks later, on the 57th anniversary of the 1967 uprisings, Detroit's mayor unveiled a plaque at the Algiers Motel, commemorating the lives of three Black teenagers who were murdered by police at the motel during the uprising in 1967.

From excessively high unresolved civilian complaints against police officers in 2024 (Herberg, 2024) to growing unaffordability and gentrification across the city's neighborhoods, and increasing oversight of once normal activities like barbeques and block parties, Detroiters remain under heavy police watch alongside growing unaffordability and deeply uneven development that are increasingly untenable. Residents have labeled the new STRESS-like police unit as part of the "New Detroit," an era marked by the professionalization of labor, financialization of municipal assets and housing, and the municipally facilitated open season investment opportunities for billionaire and small business owners alike and the ensuing gentrification that has followed (Marotta, 2021; Peck & Whiteside, 2016). The business-focused, entrepreneurial, and exclusionary culture of New Detroit has been decreed by residents as causing deeper racial and economic disparities, and the erasure of a city that lifelong Detroiters have called home (Cummins, 2016).

3. Surveilling "New Detroit"

In 2015, the Detroit Police partnered with General Motors, the business ventures of the Gilbert and Illitch Families (of Little Caesar's Pizza and Quicken Loans wealth, respectively), and a Southeast Michigan utilities provider to expand surveillance technologies throughout Detroit's downtown business district to fill in the holes left by capacity issues within the police department (Bernd, 2015). Among Gilbert's metastasizing 100 plus heavily tax abated investment properties that have solidified a gentrified consumer and entertainment focused stronghold throughout downtown and the recently rebranded Midtown in Detroit's Cass Corridor neighborhood, more than 500 surveillance cameras and a private 24/7 security force monitor the areas surrounding Gilbert's properties (Anderson, 2016; Biles & Rose, 2021). In addition to the influence of the "Gilbertville" surveillance network, Detroit's post-bankruptcy planning regime has included the expansion of surveillance technologies, marking a speculative harbinger of business investments yet to come. Where there is potential for a business district to grow, existing business owners are solicited to host Project Green Light (PGL) to attract further business development. PGL corridors, where multiple lights and cameras are installed to serve adjacent and neighboring businesses within a multi-block radius continue to be established throughout the city. As of January of 2024, Detroit's collection of surveillance infrastructure includes gunshot detection technology, cellular phone readers, automated license plate readers, mobile fingerprint readers, and an expansive closed-circuit camera network. The DPD is one of several public agencies that utilize surveillance technology, in addition to the Detroit Fire Department, the departments of Public Works, Parks and Recreation, and Housing and Revitalization. These technologies, some of which utilize artificial intelligence (AI) and facial recognition technology, have been approved through procurement requests made to the city's Public Health and Safety Committee and City Council. Although the protocol for preparing and submitting a procurement request is clearly outlined in the city's Community Input Over Government Surveillance Ordinance, which became active legislation in 2021, DPD and other government agencies regularly ignore procurement requirements that the ordinance defines as transparency measures for surveillance related spending, resulting in at least one procurement focused lawsuit against the city (Rahal, 2022).

In Detroit and in many US cities, surveillance data is processed at centralized police data hubs that are a byproduct of the 2001 PATRIOT Act (Vasi & Strang, 2009). Surveillance data in Detroit is funneled directly to Detroit's RTCC, modeled after the post-9/11 Department of Homeland Security Fusion Centers that were designed to gather, analyze, and share information related to threats to homeland security (Przeszlowski et al., 2023). Due to Detroit's proximity to the US–Canada border, memorandums of understanding across enforcement agencies require data collected for law enforcement purposes by DPD to be shared with Michigan State Police, county police, and US Customs and Border Protection.

PGL was the first of the post-bankruptcy technology procurements to draw oppositional public attention. The private-public-community surveillance program was piloted in 2016 when eight gas stations installed CCTV video cameras monitored by the DPD. Cameras and the live video streams they captured were accompanied by flashing green signal lights to indicate to passersby the location was under police surveillance. These lights freckle the city's landscape, particularly in commercial corridors. Since 2016, more than 1,000 additional locations have joined the program, each with a minimum of three cameras ("Detroit Police Department celebrates 1K Project Green Light partners," 2024). In the program's brief operation, three Black Detroiters have been wrongfully identified and arrested by DPD (Hill, 2024). These misidentifications are the result of PGL utilizing AI facial recognition software that routinely misidentifies the faces of Black people upwards of 96% of the time (Benedict, 2022). The assumed objectivity of surveillance technology ignores that automated anti-Blackness is a form of racism perpetuated by biases that are engineered directly into technology through machine learning processes (Nkonde, 2019). In 2022, PGL was graded by the National Institute of Justice as a program with "no effect," meaning "implementing the program is unlikely to result in the intended outcome(s) and may result in a negative outcome(s)" (National Institute of Justice, 2022).

Recent uprisings opposing police brutality, from localized responses in Ferguson, Missouri following the police murder of Michael Brown, and the global responses following the murders of Breonna Taylor and George Floyd by police make clear that ongoing police antagonism against Black communities through acts of state sanctioned brutality do not go unopposed. However, mechanisms of "proactive" policing such as surveillance technologies that become embedded within urban infrastructure are constant and passive, and receive much less attention and public concern despite their pervasive nature of "the gaze without eyes" (Koskela, 2000) that is deployed into neighborhoods as regular features of rising business districts and housing developments. Detroiters on the other hand have been collectively opposing the pervasive expansion of surveillance technology through city-wide coalitions, not dissimilar from those that formed against the aggressive expansion of policing in Detroit during the operation of STRESS in the 1970s. Recent Detroit-based coalitions have opposed police surveillance by giving presentations during meetings of City Council and the Board of Police Commissioners, holding educational discussions among community members, art activism, street level protests, and pressuring city government to pass the 2021 Community Input Over Government Surveillance Ordinance which was deeply supported by the American Civil Liberties Union (ACLU). In 2016, the ACLU launched the national Community Control Over Police Surveillance initiative with the intention to support the development of legislation mandating that local communities be provided a meaningful opportunity to review, comment on, and participate in all decisions concerning the procurement and use of surveillance technologies used by public agencies in their cities (Southerland, 2023). This community opportunity for oversite is a mode of resistance against the normalization of technologies that speculatively criminalize all residents—particularly residents of color—through constant monitoring of their everyday activities.

There is too often an unexamined acceptance within the academic disciplines of planning, geography, criminology, and among professional urban planners about how surveillance has always been part of urban life (Fussey & Coaffee, 2012). The current era of surveillance urbanism, in which surveillance technology connecting apparatus on the ground, in the air, and perched upon points of elevation across the urban landscape to endlessly collect data for law enforcement agencies from nonconsenting passersby are relatively normal if not unconscious components of urban life. Surveillance urbanism manifests in the socio-economic logic of governmental and judicial entitlement to personal information collected through architectures of mediated computational inputs, and networked data sharing of the top-down technocratic digitization of urban life (Bibri et al., 2022). Fussey and Coaffee (2012, p. 201) describe surveillance in cities as a constant and defining component of urbanism:

> Surveillance has always been a part of urban life. Yet despite such antecedents, stretching back to antiquity, a number of changes in both city life and the means of observing it have animated significant changes in the scope and techniques of urban surveillance.

In no insignificant way have the professions of urban planning and policing contributed to cultures of surveillance, often through authoritative powers of regulating spaces, hostile anti-homeless architecture and criminalization of homelessness, and encouraging self-disciplining and stigmatization of behavior through bylaws and fines (Harris, 2011). In this acceptance of cities as normalized spaces of surveillance, surveillance culture continues to grow, often without clear focus from urban planners about how surveillance further entrenches racial inequality into the urban landscape, creates disproportionate outcomes for resident wellbeing, and literally seeks to embody criminalization through (mis)identification of specifically Black and brown residents. In this way, planners demonstrate ambivalence and benevolence toward some measures of "safety" within cities while claiming responsibility for others, justified through claims of professional jurisdiction.

Though the 1980s was the last decade when the occurrence of crime in US cities was actually on the rise, CCTV systems use among city policing agencies grew throughout the 1990s into the 2010s, often thought of as a response to reports about increasing crime (Barker, 2010; Tcherni-Buzzeo, 2019). What has drawn public support and municipal buy-in of CCTV technology is the misinformation that crime rates continue to rise, fear of crime, and "the coalescence of video surveillance into existing dominant administrative discourses of crime control" that influenced the popularity of CCTV within policy circles (Fussey & Coaffee, 2012, p. 202). CCTV technology has evolved since the 1990s and now often utilizes AI to analyze data, such as facial recognition technology. Its use in public space may afford passersby with a sense of security, though these systems were initially thought of as anti-terrorist technologies rather than tools for local crime reduction in the post 9/11 era (Graham, 2009). The continuous growth of smart city AI technologies employed by municipal agencies via corporate third-party vendors has rightfully raised questions concerning privacy and data ownership and retention from immigrant rights organizations, legal practitioners, activists, and community members (Goodman & Powles, 2019). Though the effects of AI continue to prove to be antithetical to the goals of urban planning, to increase quality of life and equity of urban living indiscriminately for city residents, urban planning practitioners seem absent or at best passive in conversations about the impact of the increasing use of surveillance across cities (Batty, 2018). If anything, projects like Sidewalk Toronto indicate that planners are willing to uncritically hurl the profession and practice of urban planning into the AI unknown (Lorinc, 2019).

The increasing use of AI technologies, from public works and planning departments to police services, requires mass amounts of data to train "intelligence" models, and even more data for analysis and "intelligence" decision making to train predictive functions. Elected officials and civil servants' willingness and acceptance to utilize AI software, often despite uniformed decision making about product function, facilitates the expansion and reliance on AI as an increasingly normative suite of apparati that confuses surveillance with intelligence through governmental-corporate and judicial-corporate partnerships that are central to the function of civic and social institutions. Whereas property has been a primary category for scholars concerned with race-making (Blomley, 2016; Bonds, 2019), the effects and impact of surveillance and AI present an additional category of race-making that forefronts criminality and property relations, just as the lantern laws that regulated the nighttime movement of Black and indigenous slaves in New York state in the 18th century (Browne, 2015), so too do the green lights marking the landscape in Detroit. PGL's use of facial recognition technology that compares collected imagery to the state of Michigan's mugshot database indicates that speculative criminality that perpetuates the criminalization of Black residents by design is a core organizing principal in the city's current era of redevelopment.

Surveillance technologies that collect biometric data create particularly uneven experiences of criminalization and punishment for women of color and the trans community. While urban space in essence is always gendered (Koskela, 2000), and always designed with dominant binary genders in mind, the uneven gendered experience of urban living is reaffirmed through such practices as members of the trans community being targeted by police for *existing* in public spaces and being more likely to live in areas where police surveillance and specifically facial recognition technology is in use (Daum, 2015). While richly melanated skin tones are frequently misidentified by AI-modeled facial recognition software (Lohr, 2022), the people responsible for engineering binary and bias gendered analysis into FRT trained such software utilizing the images of white cis gender men (Buolamwini & Gebru, 2018), engineering even greater risk of criminalization and arrest onto the lives of cis women, the trans community, and people of color at large. While many criticisms of the use of AI in policing are focused specifically on the failings and inequalities perpetuated by the technologies themselves, such as race and gender bias being engineered into their analysis models (Herruzo, 2021; Khan et al., 2022), the use of AI technologies in policing also changes the behavior of police and policing as an institution (Joh, 2022), which requires critical thinking on the part of planners as to how the evolution of policing necessitates a re-evaluation of planner's conceptualization of building safe and liveable cities.

Importantly, as Lois Wacquant (2009) describes in *Punishing the Poor*, there have been countless efforts by the primary targets of policing and penalization to resist, divest, and divert the effect of the penal state on their communities. Including movements of resistance from the streets and the grassroots in theoretical analysis of urban change is critical in understanding the broad perspectives, direct actions, and coalitions that shape the urban sphere, as is understanding the role of policing, police powers over property, and the effects of the expanding militarization of the cities we live in. Green Light Black Futures(GLBF, 2019–2021) was a coalition of local and national partners who opposed the expansion of surveillance technology in Detroit, in which the author of this article was a member of the coalition's research team. The coalition hosted political education workshops, conflict mediation trainings and community safety events to build capacity across Detroit for conflict mediation and harm reduction strategies without relying on policing or carceral forms of punishment. The coalition designed and distributed a city-wide community safety survey that asked Detroiters their thoughts, perceptions, and experiences of safety in their neighborhoods, and sought opinions about DPD's recent implementation of a variety of surveillance technologies. The coalition's research team's analysis of survey responses found that Detroiters identify safety as the result of investments in their neighborly relationships, pro-social amenities and resources such as parks, health care, and access to affordable housing and food (Baker et al., 2022). Analysis also found Detroiters hold a general distrust in the police. If a city is an ecosystem of governing agencies, interpersonal and spatial relations, and economic and ecological flows, how safety is conceptualized necessitates addressing the totality of that ecosystem. Safety is cultivated through public health initiatives, city building departments, the affordability and habitability standards of rental housing, road infrastructure, food accessibility (Calise et al., 2019), the quality and accessibility of public transit, and access to free recreational spaces (Wood et al., 2017). By understanding and accepting that safety is made and cultivated beyond policing, which social movements against police brutality have relentlessly demonstrated time and again, the monopoly policing agencies are granted to serve and protect becomes easier to look beyond, to build community safety that does not have the capacity to shoot and kill residents.

The timing of the GLBF survey's distribution enabled some multi-scope organizing to take place that served the interests of the coalition and met urgent community needs during the initial twenty-four months of the COVID-19 pandemic. One such need was to address looming housing insecurity among tenants who had lost their employment because of pandemic "shelter in place" orders. Through coordinated outreach among tenant organizers, tenants were engaged with the safety survey as well as know-your-rights educational materials through door knocking and community outreach. Through additional landlord research, it was found that less than 5% of all apartment buildings that host PGL, of which there were 40 in 2021, followed the city's rental ordinance and were illegally operating as residential units, while simultaneously providing surveillance data 24/7 to the city's RTCC. The City of Detroit rental ordinance states that landlords must register their rental property in the city's rental registry, and obtain a certificate of compliance from the Building, Safety, Environmental and Engineering Department that indicates their property meets required structural and habitability standards. If both requirements are not met, the ordinance states that the collection of rents is prohibited. The illegality of landlord operations at PGL host residential buildings was brought to the attention of the city's building department as well as the Housing and Revitalization Department by the GLBF research team and tenant organizers. However, city agencies took no issue with this lack of compliance and landlords continued to be allowed to surveille tenants and passers-by while collecting rents.

Though fourth amendment rights have been a focal point of critical inquiry among surveillance scholars (Gray, 2017), PGL presents a set of circumstances in which tenants' rights to privacy are undercut by landlords' rights to the security of their property, despite the extra-legal operations of nearly all apartment buildings hosting PGL. Rather than approach this circumstance with the legal method of balancing costs and benefits for all parties (Aleinikoff, 1986), the prioritization of property ownership and landlord retention supersedes fourth amendment rights, demonstrating that property ownership endows greater rights to one's privacy, security from unreasonable searches, and the requirement of probable cause. While the right to privacy is superficially universal according to the US constitution, the collusion of landlords and police to allow for the surveillance of illegally operated rental units indicates an extension of the right to privacy afforded to those who hold claim to the bundle of rights property owners are entitled to, to criminalize and wield authority over people who rent their housing.

A tendency among urban planners in the US and Canada is their willingness to bend toward pro-growth and smart growth interest groups (Hawkins, 2014), and to welcome the influence of real estate developers into policy development and decisions of local governments, while simultaneously approaching genuine community concerns about equity and displacement as a balancing act against market possibilities, developer interests, and private–public partnerships. The common troupe among planning practitioners is that residents lack understanding of the complex relationships between developers and financers in planning projects, which results in planners deeply managing public engagement by presenting community members with pre-determined outcomes of proposed planning initiatives that undercut the democratic potential of engagement to begin with (Coleman & Firmstone, 2014). Rather than holding a holistic perspective of the impacts and possibilities of planning, governing authorities within a city government are taxonomized through the division of departments and mandating of responsibilities that create deficit gaps in how the work of planning, to create livable and functional cities, is carried out. This departmentalization of responsibilities artificially limits the capacity of planners to engage in a broader scope of thinking and influence about wellbeing, safety, and how to reconcile the quality of life of the residents impacted by their work and that of fellow city agencies, including the police.

The last tumultuous decade and a half of increasing financialization of housing following the Great Recession has produced cascading crises, including record breaking years of tax foreclosures in the US, the threat of evictions during a pandemic, and now a growing affordability crisis in its wake (Coquelin et al., 2022). Landlord–tenant relations have deteriorated toward the emboldening of landlord authority through increasing use of tenant screening practices, the adoption of landlord technologies that build surveillance practices into tenants' rental terms, conditions, and surroundings (Fields, 2022) employing dispossessive tech-based practices (McElroy & Vergerio, 2022), restrictions on household pets and number of allowable tenants, and denying tenant applications from people perceived to have high water bills, to name a few (Grief, 2018). Though urban planners have little input over landlord–tenant relations, rental housing ordinances and building departments can provide standardization and some oversight over the conditions tenants are legally or illegally subject to when renting or defending their right to stay housed. What limits the impact of these tools is enforcement. Tenant activists are responding accordingly through self-organization, political education, and direct action against these forms of landlord pressure and property negligence (Baker & Ferrer, in press) though existing legislation that could prohibit landlord negligence often continued to be unenforced.

4. Motor City Surveillance

In response to the uprisings that followed the police murders of Breonna Taylor and George Floyd in 2020, the US Department of Justice expanded Operation Legend to Cleveland, Detroit, and Milwaukee on June 29th, to coordinate federal law enforcement with local state and municipal agencies to “fight violent crime” (US Department of Justice, 2020). Operation Legend triggered the deployment of 42 agents from the Federal Bureau of Investigation (FBI), the Drug Enforcement Administration, and the Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) to Detroit. Eleven new permanent ATF and FBI agents assigned to Detroit were tasked with addressing gun violence, violent crime, and gang activity. The city had not experienced such a rapid influx of federal and state law enforcement agents since the summer of 1967. Not coincidentally, by June 29th, 2020, activists opposing anti-Black police brutality in Detroit were on their 34th consecutive day of widely attended organized street demonstrations that included democratically and collaboratively authored demands issued to the City of Detroit and the DPD to disciplinarily address police misconduct and acts of brutality against Detroiters. Activists became targets of further police violence throughout the summer of 2020 while demonstrating against police brutality, and eventually filed and won a suite that found the city and the police department had violated the constitutional rights of protestors (National Lawyers Guild, 2022).

The highly racialized relations of policing in the US became even more amplified during this time, as were social and radical representations of space commanded through street protest, congregating to discuss political values and ideas, and creating moments of powerful self-representation of people united to build Black liberation in the face of state-sanctioned political violence perpetrated by police. Eugene McCann (1999) notes the important task of proper theoretical translation of Lefebvre’s understanding of representation and space within US urban contexts, and urges that spatial thinkers and practitioners adequately contextualize the sociospatial processes of race relations to develop fulsome understandings of contemporary urban processes. In increasingly militarized urban centers where racial injustice is opposed through collective direct action via street protests and demonstrations, and disciplined through state sanctioned violence and pervasive surveillance, what is represented is a confluence of resistance and defense; defense of the racial project of American cities by state agencies, and disruptive resistance against that project continuing by people who believe in urban futures free from myriad manifestations of white supremacy.

As of 2021, PGL was installed at 40 residential apartment buildings throughout the city; though far more residential units host this technology when long term care homes are accounted for. To support tenant organizing efforts in the city as renters faced COVID-era evictions, each of the PGL residential host sites was searched in the Building, Safety, Environment and Engineering Department’s (BSEED) violations case history database for outstanding building code violations. This data reflecting landlord fines for non-compliance with the city’s rental ordinance and BSEED habitability requirements exceeded $100,000 at PGL apartments in 2021. Cross referencing BSEED data with court records indicated that failure to attend landlord property negligence hearings by BSEED inspectors repeatedly resulted in fines being waived, and landlords or their representative property managers or attorneys leaving court hearings without financial penalty. Of the 40 apartments hosting PGL in 2020, all but one were in violation of the city’s residential rental property ordinance. Through tenant organizing efforts and advocacy, this information was brought to the attention of the BSEED, the Board of Police Commissioners, and members of city council. When presented with the information that PGL was overwhelmingly deployed at residential apartment buildings that were actively in violation of a city ordinance in additional to building code violations, the agencies responded by taking no action. When the issue was brought to the attention of a member of city council and a state senator who represented a large number of tenants in their shared district being effected by an extralegal eviction during the federal COVID-19 eviction moratorium, in addition to being subject to surveillance at a non-code compliant PGL apartment building, the landlord of the building was contacted and the extralegal eviction was temporarily stalled. However, these representatives took no initiative to proactively prevent future similar emergencies. In response, a policy revision to the city rental ordinance was written by tenant organizers including the author of this article, introducing a provision that no landlord who was non-compliant with the rental ordinance would be eligible to evict tenants. Met with the inopportune barrier of delayed response times by the city's legislative and policy division to expedite the revision for discussion among City Council, tenant organizers submitted the amendment directly to the 36th district court judge. Though the judge was amenable to instituting the order, the State Supreme Court's administrative office determined the order would likely produce an equal protection filing at the circuit court level, given that the compliance scheduling for the city's rental ordinance did not equally apply to all zip codes across the city, with some zip codes having been required to comply by 2018 and others not yet required to comply at the time these events took place in 2020.

PGL does not fit neatly within the definition of being a "landlord technology" because landlords do not have access to the data collected or control over the technology. Tenants have and continue to resist being subject to PGL, just as tenants elsewhere organize against landlord technologies that are not necessarily connected to law enforcement but do require tenants to be subject to forms of surveillance and data collection that involve their finances, freedom of movement, and the collection of biometric data (McElroy & Vergerio, 2022). Buildings where PGL is installed gain priority response times when 911 is called, which is of particular benefit to landlords in cases of fire and arson to protect their property. This is a feature of PGL that business owners highlight when rationalizing their decision to subscribe to the service. In 2013, Detroit EMS response times ranged from 39.8 to 58 minutes (Bialik, 2013; Eisinger, 2014), with an improvement to 30 minutes in 2019 (Jones, 2019). Through conversations with property managers of PGL apartments in 2021, it was found that PGL is used both as a deterrent for some tenants and a magnet for others, highly determined by the neighborhood and income of the target tenant population and landlord intentions. Landlords of buildings with mostly low waged renters discussed PGL as a security measure to ensure tenants are not conducting illegal activity, whereas landlords attempting to attract tenants in market rate buildings near the Detroit Medical Center and Wayne State University tout PGL as a luxury feature that protects the safety of tenants and their possessions through priority 911 response.

Perpetuating the perceived criminality of low-income and majority Black tenants is not unique to Detroit and does not require AI-based technologies. In 1988, the Chicago Police Department carried out "Operation Clean Sweep" in which police officers barricaded the entrances and exits of a Chicago Public Housing apartment building, staging an unannounced and warrantless search of each apartment unit, searching for weapons and drugs and illegal residents (Yarosh, 1993). Through Clean Sweep, the Chicago Public Housing Authority (CPHA) became the first in the county to utilize warrantless and non-consenting home searches (Yarosh, 1993). Immediately following the sweeps, the ACLU filed a class action suit that outlined how the searches constituted a violation of the fourth amendment rights of public housing tenants (Hellman, 1995). In 1995, the Department of Housing and Urban Development (HUD) and the Department of Justice (DOJ) attempted to address perceived high rates of criminal activity within public housing units in Chicago by attempting to incorporate a lease consent plan. This plan would have required tenants to sign leases allowing blanket consent for police searches throughout Chicago public housing units. This program was proposed in response to a federal judge invalidating police sweeps that took place without warrants in Chicago, citing violation of tenants' fourth amendment rights. The CPHA sweeps and searches as well as the HUD and DOJ proposal to incorporate mandatory consent agreements for police sweeps into the leases of public housing tenants is another example of the racialized and classed expansion of the bundle of rights of property owners over those of people who rent their housing, even when the property owner is a state agency providing the public good of affordable housing. Such an agency may have the capacity to recognize that public housing will increase the wellbeing and livability of a place, but lack the foresight and interest to ensure long-term wellness of tenants, or to be proactive in preventing the criminalization of those tenants. Similar to respondents of the GLBF safety survey, CPHA tenants who were interviewed about the sweeps overwhelmingly reported that police tactics would not be necessary if tenants had access to higher wages, places for children to play, adequate transportation, and jobs. This particular case as well as that of PGL apartments suggests that the bundle of rights property owners assume includes criminalizing majority Black, brown, and low-waged populations as proactive protection of that bundle of rights, as though the violation of fourth amendment rights and the dehumanizing act of racialized and classed unconstitutional searches is an unwritten component of that bundle of rights. Building a culture of community safety beyond reliance on surveillance technology and violent policing requires expanding the scope of resources and services that affect community health and wellbeing that planners interface with, and a willingness of planners to take a bold position against police violence and technologies that criminalize and surveille residents.

5. Closing Thoughts

The use of PGL CCTV surveillance data collection at rental apartment buildings in Detroit, where landlords have failed to uphold their responsibility to maintain habitable, safe, and legally registered rental units, presents an important question about what kinds of safety holds value, and that not all forms of safety are valued equally. As of July of 2024, 10% of residential rental units in Detroit comply with the rental property ordinance (Rahman, 2024). When a majority Black population is subject to potentially hazardous structural and faulty infrastructural living conditions and surveillance that claims to increase safety, a lesson is presented about property relations that is shaped by the contemporary moment of policing, rentiership, and race-capital relations that is made possible through urban planning and governance. The forbearance of enforcement of structural safety standards granted to landlords can be thought of as an exchange of rights and responsibilities that further embeds the property relations emblematic of white supremacy into a majority Black cityscape in which the physical safety of Black people who do not own their housing is less important that the ability for landlords to surveille these tenants under the guise of the right to protect one's property and fight crime. What emerges through the forbearance of rights to privacy for Black renters and the privileging of the right for landlords to protect one's property is not a set of competing values but sets of rights whose value is clearly demonstrated through enforcement, both through permissible non-compliance of life saving habitability standards of rental properties, and the anticipated criminality of majority Black renters whose physical safety holds no value in comparison. What is needed is a multi-agency approach to addressing safety and wellbeing that is unafraid to criticize, and transform the function of city agencies to broaden planning practice to holistically address livability and resident wellbeing that values Black lives by decreasing exposure to policing.

While professional planners have tended to uphold departmental silos of urban governance, each seen as responsible for their own contribution to the operations of a city, this mode of operating has willfully distanced planners from a confluent approach to urban form, function, and outcomes for residents. While this may serve the interests of de jure urban development that so often deepens racial and economic disparities despite community engagement and best intentions, such an approach unquestionably leaves matters of safety in the hands of police, or at best as a consideration among transportation planners concerned with pedestrian and vehicular safety. Access to structurally sound and legally habitable housing is a matter of quality of life and life itself, particularly among populations who are systematically criminalized by police and AI technologies. Bundling the right to criminalize with property rights through AI surveillance reinforces deeply uneven relations to property along race and class lines that hold the potential to lead to death. Planners have an opportunity and responsibility to be transformative in their work and take up the mission of "livability" in serious terms.

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Conflict of Interests

The author declares no conflict of interests.

Data Availability

Property negligence fines issued to landlords analyzed for this research can be found on the City of Detroit Department of Administrative Hearings Violation Case History website.

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From Vision to Reality: The Use of Artificial Intelligence in Different Urban Planning Phases

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Abstract

In an urban context, the use of artificial intelligence (AI) can help to categorise and analyse large amounts of data quickly and efficiently. The AI approach can make municipal administration and planning processes more efficient, improve environmental and living conditions (e.g., air quality, inventory of road damages, etc.), or strengthen the participation of residents in decision-making processes. The key to this is "machine learning" that has the ability to recognise patterns, capture models, and learn on the basis of big data via the application of automated statistical methods. However, what does this mean for urban planning and the future development of cities? Will AI take over the planning and design of our cities and actively intervene in and influence planning activities? This article applies a systematic literature review supplemented by case study analyses and expert interviews to categorise various types of AI and relate their potential applications to the different phases of the planning process. The findings emphasize that AI systems are highly specialised applications for solving and processing specific challenges and tasks within a planning process. This can improve planning processes and results, but ultimately AI only suggests alternatives and possible solutions. Thus, AI has to be regarded as a planning tool rather than the planning solution. Ultimately, it is the planners who have to make decisions about the future development of cities, taking into account the possibilities and limitations of the AI applications that have been used in the planning process.

Keywords

artificial intelligence; decision-making; digital participation; planning phases; smart city; urban planning

1. Introduction: Artificial Intelligence and Its Utilisation for Urban Planning Practice

Artificial intelligence (AI) is changing cities and urban development processes comprehensively and at breakneck speed (Cugurullo et al., 2024a; Pellegrin et al., 2021; Wu et al., 2024). The fundamental potential of AI as a methodological tool for urban planning was already considered 15–20 years ago, but the implication of AI tools could only have been observed in recent years with the increasing availability of ever more powerful information and communication technology systems and more complex data volumes (Lazaroiu & Harrison, 2021; Sanchez et al., 2022).

Even if there is no standardised definition of AI (Cugurullo, 2021; Son et al., 2023), there is consensus that AI systems can perform tasks that typically require human intelligence (Pellegrin et al., 2021, p. 7). AI systems can learn and develop knowledge directly by capturing and analysing a specific environment with sensors such as cameras and microphones, or indirectly by evaluating large data sets in real-time (Cugurullo et al., 2024b, p. 2; see also Batty, 2023, p. 1046). AI systems then make sense of the information that they acquire by extracting concepts from it or by developing new content in the form of texts, images, or videos. In this context, the systems can automate, repeat, learn, discover, and adapt large amounts of data. These capacities are characteristics of their intelligence as they show the ability of the systems to act autonomously in real-life environments without human supervision, finding meaning, recognising ideas, or generating predictions about what is being observed (Cugurullo et al., 2024b, p. 4).

The possibility of AI systems to collect and analyse large data sets, the capacity to solve problems logically, the ability to learn from historical data, and the intelligent search for better solutions are also triggering urban planning practices (Popelka et al., 2023; Son et al., 2023). Digital platforms such as machines and robots are increasingly used to offer and control urban services or infrastructure systems, monitor public spaces, or draw spatial renderings and master plans (Caprotti et al., 2022; Marvin et al., 2022; Park et al., 2023; Zheng et al., 2023). The key to this is "machine learning," which is able to recognise patterns, capture models and learn on the basis of big data, and synthesize data with automated statistical methods. However, there is little research to date regarding the potential benefits and possible effects of AI on urban development. Does the use of AI mean, for example, that our cities will be planned by machines in the future and that everyday planning activities will be replaced? Will AI take over the planning and design of our cities? Or is AI only used in certain cases and planning phases to supplement existing planning tools? Up to now, AI systems in urban planning are mainly used in more technologically oriented fields, offering a wide range of possible applications (see Table 1):

- *Mobility and Transport Optimisation*: AI, for example, can help to observe traffic volumes and monitor traffic flows and reroute them if necessary (Cugurullo et al., 2024a, p. 366). The condition of road surfaces, such as potholes or manhole covers, can also be analysed using image capture with AI (Matouq et al., 2024).
- *Energy and Infrastructure*: AI can contribute to the development of smart grids that increase the security of supply (Kreutzer, 2023, pp. 375–376). Furthermore, AI tools can analyse aerial photographs to determine the potential for solar panels on roof surfaces (Assouline et al., 2017).
- *Public Management, Public Health, and Safety*: AI, for example, can measure, map, and make predictions about air quality (Barcelona Supercomputing Center, 2023). Additionally, AI can analyse aerial images to mitigate the impact of extreme heat waves and to indicate where trees and vegetation should be planted (Ghisleni, 2024).
- *Real Estate, Urban Planning, and Land Use Policies*: AI can be used to develop renderings of buildings, streets, and public spaces on the basis of large datasets and neural models. AI can furthermore be used to develop land use plans (Park et al., 2023; Zheng et al., 2023) or to monitor the rental of residential space to detect illegal rentals (Pellegrin et al., 2021, p. 20).

Table 1. Fields of AI application, examples, and functions in urban development.

Fields of AI-Application	Examples	References
Mobility and Transport Optimisation	Implementation of intelligent traffic light control (depending on traffic volume)	Alkhatib et al. (2022) Fraunhofer IOSB (2022) Sepehr (2024)
	Monitoring and forecasting traffic flows (on the basis of sensors)	Cugurullo et al. (2024a)
	Monitoring of road conditions (identification and classification of road damage and subsequent reporting to the municipal building department or the civil engineering department)	Jagatheesaperumal et al. (2023) Matouq et al. (2024)
	Implementing the infrastructure conditions for autonomous vehicles and autonomous driving	Dowling et al. (2024) Hopkins (2023)
Energy and Infrastructure	Development of smart grids that increase the security of supply and help to reduce costs for the end consumer	Alsaigh et al. (2022) Kreutzer (2023)
	Identifying and analysing the potential of solar panels on roof surfaces (via aerial image analysis)	Assouline et al. (2017) Ortiz et al. (2022)
Public Management, Public Health, and Safety	Surveillance of public spaces (use of neural networks for real-time threat detection)	Bissarinova et al. (2024) Narayanan et al. (2021)
	Identification of deficiencies in public spaces by analysing camera recordings	Amsterdam Intelligence (2024)
	Monitoring air quality in city centres	Barcelona Supercomputing Center (2023)
	Mitigating the impact of extreme heat waves via aerial image analysis (indication suggestions for the planning of trees and vegetation) and predicting the potential of green roofs to improve the thermal performance of buildings and reduce urban heat islands	Ghisleni (2024) Mazzeo et al. (2023)
	Calculating the water requirements of individual trees depending on the weather (by using sensors) and determining water requirements up to 14 days in advance	Rigal (2022)
Real Estate, Urban Planning, and Land Use Policies	Classifying land use patterns with neural networks that can process satellite and aerial imagery	Kumar et al. (2022) Wu et al. (2024)
	Identification of potential building areas by analysing aerial photographs	Rahnemoonfar et al. (2021)
	Automated detection and mapping of informal settlements in various locations	Moreno González et al. (2022)
	Generating spatial plans (on the basis of graph neural networks)	Park et al. (2023) Zheng et al. (2023)
	Rendering buildings, streets, and public spaces on the basis of large datasets and neural models	Lin et al. (2023) Pisu and Carta (2024) Sanchez et al. (2022)
	Control of illegal letting of housing by scanning the real estate platforms	Pellegrin et al. (2021)
	Predicting neighbourhood change and gentrification (or racial discrimination on the housing market) through machine learning	Naik et al. (2017) Reages et al. (2018) Rosen and Garboden (2024)

AI is also already being used in participatory planning processes, e.g., to provide up-to-date information in chatbots (Senadheera et al., 2024), to analyse comments in urban land-use planning procedures, or to create visualisations in participatory processes (Sanchez et al., 2022), often using digital twins, AR and VR applications, climate models, and other digital applications (Batty & Yang, 2022; Brüggemann et al., 2023; Pisu & Carta, 2024). However, the focus of most of the AI studies or research articles is often on specific AI systems or technologies and the functionality of these systems for solving concrete problems in an urban context. In contrast, the effects of AI systems on planning processes have been less considered or researched to date. This particularly applies to the consideration of different AI systems and applications in the course of a planning process and the extent to which AI influences decision-making processes, opportunities for participation, and the results of planning across the various planning phases and specific technical AI applications (Du et al., 2024; Liang & Kang, 2021). This is the starting point for this article, which considers the following research questions: How can AI systems and applications in the field of urban planning and development be classified? What tasks can AI solve in planning processes and projects? Which AI systems and applications are used in which planning phases? How does AI change our understanding of planning?

2. Research Design and Methodology

In a first step, we classify AI systems and applications in the field of urban planning and development following the knowledge map of Corea (2019), which was further developed by Son et al. (2023). As shown above, "AI-enabled technologies are employed to address specific problem-solving activities" (Son et al., 2023, p. 3). Utilising large data collections, either obtained directly via IoT-enabled infrastructures or indirectly via access to data sets (Batty, 2023; Cugurullo et al., 2024b), various AI paradigms can be formulated for different problems and solution capabilities (Corea, 2019, p. 26):

- *Logic-based tools*: Tools that are used for knowledge representation and problem-solving;
- *Knowledge-based tools*: Tools that are based on ontologies and huge databases of notions, information, and rules;
- *Probabilistic methods*: Tools that allow agents to act with incomplete information and data;
- *Machine learning*: Tools allowing agents and systems to learn from historical data and to use the gained knowledge to interpret new data;
- *Embodied intelligence*: An engineering toolbox having the ability to affect the physical environment;
- *Search and optimisation*: Tools that allow intelligent search with many possible solutions.

It is from these approaches that different AI-enabled "technologies" are developed and utilised (Corea, 2019; Sarker, 2022; Son et al., 2023), leading to the categorization of different types of AI, including analytical, functional, textual, visual, and interactive systems (see Figure 1). *Analytical AI* embraces practices of identifying, interpreting, and communicating meaningful patterns of data (Sarker, 2022, p. 157). In this regard, analytical AI aims to discover new insights, patterns, and relationships or dependencies in data and to assist data-driven decision-making. Subsequently, logic-based and knowledge-based tools as well as analytical processing capabilities are of central importance here. The same applies to reasoning, i.e., the capability to solve problems, as underlying the problem-solving classification of AI systems (Corea, 2019). *Functional AI* is similar to analytical AI but executes actions rather than making recommendations (Sarker, 2022, pp. 157–158). Here, perception as underlying the problem-solving classification of AI systems plays a

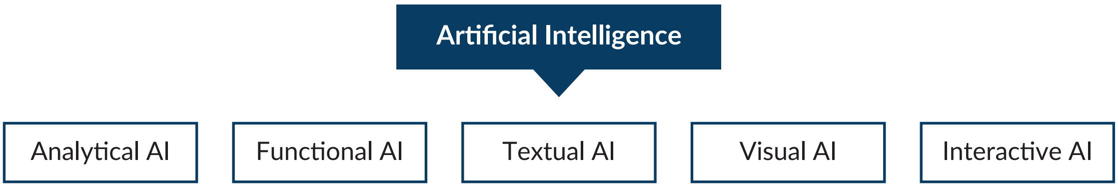

Figure 1. Various types of AI.

key role, referring to the ability of AI to transform raw sensorial inputs (e.g., images, sounds, etc.) into usable information and action (Corea, 2019). At the same time, the embodied intelligence of AI systems is addressed here.

Textual AI covers textual analytics or natural language processing for text recognition, speech-to-text conversion, machine translation, as well as content generation (Sarker, 2022, p. 158). Subsequently, logic-based and knowledge-based tools as well as analytical processing capabilities are of central importance here. The same applies to the ability of the AI system to act with incomplete information. *Visual AI* is able to recognize, classify, and sort items, as well as convert images and videos into insights. This sort of AI is often used in fields such as computer vision and augmented reality (Sarker, 2022, p. 158). Here, the ability to transform raw sensory inputs into usable information and the ability to understand, interpret, and communicate the images and videos accordingly are key conditions for practical use. *Interactive AI* enables efficient and interactive communication models, for example in chatbots and smart personal assistants (Sarker, 2022, p. 158). Here, a variety of techniques such as machine learning, frequent pattern mining, or reasoning are relevant. This also includes the use of various AI problem-solving domains (Corea, 2019), such as the ability to understand language and communicate or the capability to solve problems.

However, our research questions focus not only on the classification of AI, but on different AI systems and applications in the course of a planning process, i.e., the extent to which AI influences decision-making processes, opportunities for participation, and the results of planning. This is of central importance insofar as decision-making processes in urban planning can be defined as a transformation of information that takes place in phases, which are characterised by the search for and selection of information to reduce the degree of uncertainty regarding the decisions to be made. At the same time, different actors are involved during the various planning phases where divergent approaches to information procurement, processing, communication, and knowledge transfer can be observed. This raises key questions particularly with regard to the use of AI in planning decision-making processes, including the availability of data (training data); the accuracy of a problem representation; data protection (protection of personal data); and the acceptance and transparency of planning processes.

In a second step, we thus divide the planning process into distinctive planning phases (see Figure 2). In the *Preparatory or Exploration Phase*, the initial planning situation is analysed. During this phase, informal participation processes and preliminary political consultations take place, resulting in visions and scenarios as well as a joint definition of planning objectives (Diller et al., 2017; Schönwandt, 2008; Yigitcanlar & Teriman, 2015). In the *Feasibility and Master Planning Phase*, feasibility studies are conducted and a (strategic) master plan is developed, which is discussed with relevant stakeholders and builds the basis for the next steps. The *Formal Planning Phase* refers to the development and approval of the formal planning documents (e.g., land use plans, zoning plans, building regulation plans) in accordance with the master plan and the

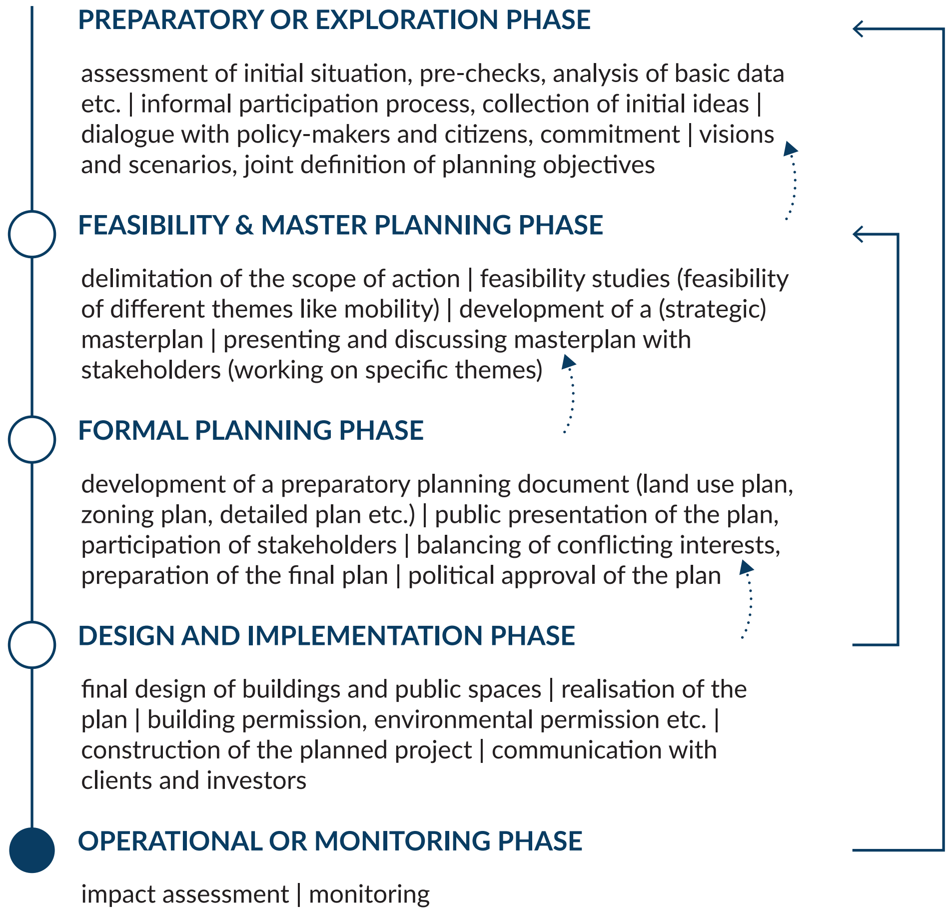

Figure 2. Principal phases of a simplified urban planning process. Source: Own illustration based on Diller et al. (2017) and Urban Learning (2024).

relevant national regulations. This phase includes the participation of stakeholders in public presentations and the balancing of conflicting interests. After the formal plan is approved, the plan will be realized. In the *Design and Implementation Phase*, the final design of buildings and public spaces will be discussed and determined in accordance with the provisions of the formal plan (Baltic Urban Lab, n.d.-b; Urban Learning, 2024). Then the building permit is issued and the planned project can be implemented or constructed. Continuous and transparent communication is important here to inform the public at regular intervals about milestones in the realisation and progress of a project. Feedback in the *Operational or Monitoring Phase* can also optimise subsequent planning processes and contribute to more efficient planning. The illustration depicts the phases of a planning process in an idealised and simplified manner. In line with Diller et al. (2017, p. 8), we have chosen a linear model with circular feedback between individual phases, which is often found in practice (see also Baltic Urban Lab, n.d.-a; Urban Learning, 2024).

In a third and final step, we merge the two classifications or models into a conceptual framework (see Figure 3). The planning phases can be found on the horizontal axis and the various types of AI systems including the AI problem-solving domains on the vertical axis. The framework then allows us to analyse and evaluate different AI systems and applications in terms of their functions, the fit accuracy of the problem-solving approaches, and their impact on decision-making processes in different planning phases considering the role of urban planners (see Section 3).

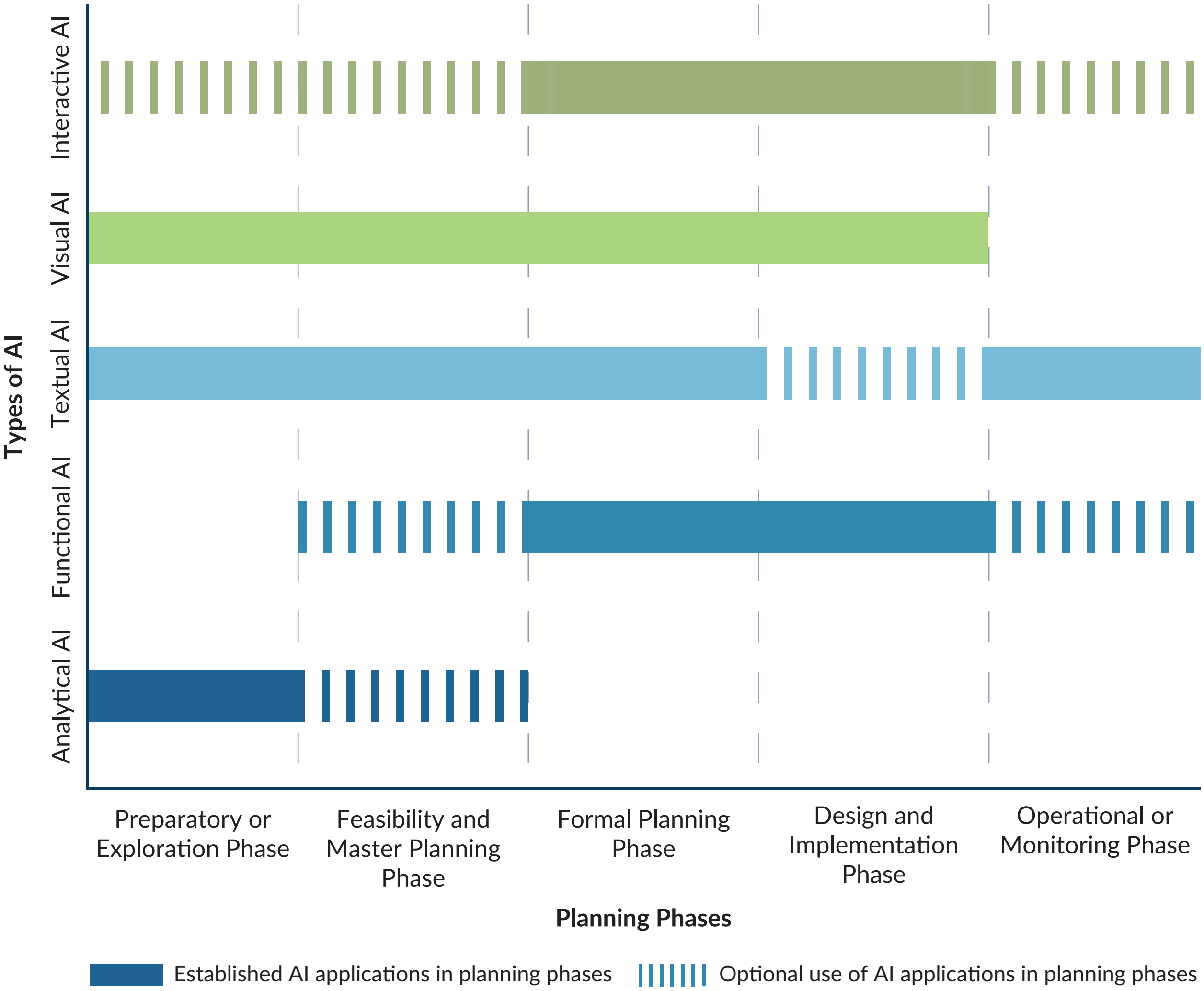

Figure 3. Use of AI tools in different planning phases. A proposal for the use of AI tools related to urban planning in different planning phases.

To analyse the impact of AI on planning practices, particularly with regard to the design of planning processes and decision-making, we conducted a systematic literature review based on published articles in the Web of Science, ScienceDirect, and Scopus databases. First, relevant articles were identified using the specific keywords "artificial intelligence," "machine learning," "artificial intelligence and planning processes," "artificial intelligence and urban planning," and "artificial intelligence and decision-making." Second, we read the abstracts of articles from step one to narrow the selection of papers to those in which the terms and concepts in the abstract strongly overlap with the subject of our study. Finally, we identified and analysed 32 articles with the aim of deriving criteria for classifying AI applications and assessing the potentials and weaknesses of AI in urban development processes.

We then transferred and applied these criteria to an internet-based desktop research for practical examples. The identification of relevant examples of AI applications in urban planning for the in-depth analysis followed a rather pragmatic research approach. We combined (a) local practice examples where AI applications have been recently developed and tested, and (b) AI technologies and applications that are typical of current use in urban planning and that in turn represent the different types of AI. Our internet-based desktop research has shown that various metropolitan regions, such as Helsinki, Vienna, and Amsterdam, are among the pioneers in the application of AI systems in urban planning and development, and that different approaches are being pursued to integrate AI into planning processes. Here, we conducted interviews with representatives of the respective municipal planning authorities and with representatives who are responsible for the implementation of AI strategies. Additionally, we identified companies or research institutions that deal with the development and use of AI systems and applications—thus representing specific AI systems and tools without a specific local context—and conducted corresponding interviews with leading experts there. In total, we conducted eight interviews with regard to different AI technologies or AI problem-solving areas to identify the opportunities and challenges of AI in urban planning processes. The interviews were analysed using qualitative content analysis according to Mayring (2015). The results were then grouped and analysed using the conceptual framework (see Figure 3) and compared with the findings from the literature review.

3. The Use of AI in Various Planning Phases

The aim of our study is to classify the use of various current AI systems in the field of urban planning. At this point, relevant practical examples of AI in urban planning are considered on the basis of the literature analysis, the internet-based desktop research, and the expert interviews. These AI systems or tools are first assigned to the basic types of AI before discussing them in individual planning phases and specific fields of application. The results are interpreted qualitatively with regard to the formulated research questions.

3.1. Analytical AI in Urban Planning: AI for Generating Data-Based Analysis and Scenarios

Analytical AI applications are used for creating data-based scenarios and clustering ideas. Park et al. (2023), for example, describe a pilot project to map urban density scenarios for a neighbourhood area in Seoul, South Korea, using AI-based construction of image datasets coded with urban data (Park et al., 2023, p. 1). The aim was to develop an AI advisor that can support laypersons in urban planning participation processes by generating land use plans for selected locations and possible density scenarios (Park et al., 2023, p. 1). In a study on the development patterns of Delhi in India, Kumar et al. (2022) similarly describe the development of an AI model for pixel-based classification of land use data to map the land cover of developed and undeveloped areas with the Google Earth Engine and to describe the changes in urban sprawl with the help of machine learning and powerful computational platforms. Using crowdsourced data and generative adversarial networks, a generational model was trained to create coloured renderings of master plans within seconds that resemble those of experienced urban planners and can be used in participatory processes (Ye et al., 2021). Digital city twins can also use AI to simulate, for example, the microclimate in a neighbourhood. To do this, the AI generates climate models and wind flows and transforms them into the city model. Wind flows can be generated in real-time in every planning phase and analysed in the model in the design variants. The aim is to analyse the microclimatic conditions of a neighbourhood and thus discuss and make adjustments to the draft plans for possible extreme weather events ("AIT CoDeC-Symposium," 2023). For the simulation of wind in drafts, the first planning drafts must be available. According to some of the respondents, participation with the help of an AI-supported simulation takes place in the middle of the participation process. However, it should be noted that, due to the specific orientation of various AI applications, some Analytical AI applications also contain elements of Functional AI if certain knowledge is produced through their use in the planning process, which is why they could also be assigned to this type.

We can conclude here that Analytical AI tools in urban planning are particularly suitable for use at an early planning stage in order to carry out data-based analyses, explore possible scenarios, and prepare decision-making processes. Their use is therefore particularly conceivable in the Preparatory or Exploration Phase as well as the Feasibility and Master Planning Phase, in which specific spatial analysis studies are carried out, for example to prepare design concepts for planning (see Figure 3). The use of AI enables the automated analysis and evaluation of data. This primarily relates to standardised data and evaluation processes, which enable planners to make a comprehensive assessment of development opportunities at an early stage of the planning process and thus support and accelerate the decision-making process.

3.2. Functional AI in Urban Planning: AI-Based Planning Processes

For the use of Functional AI in urban planning, digital tools can be identified that are used for the digital participation of citizens in spatial planning procedures (Geertman, 2002). Such applications are already being used in some municipalities, for example in Hamburg and Rostock in Germany. Here, AI-supported tools are used to organise the entire urban planning process, including the formal participation of authorities, organisations, and citizens online (Lührs, 2017, p. 45). Planning documents can be imported digitally here, plan drawings integrated into maps, users of the application authorised, and relevant organisations and authorities informed of the participation by email. According to one of our interviewees, this makes it possible in the formal participation process to carry out balancing processes in planning and approval procedures in an efficient and transparent way and to facilitate cooperation with sectoral planning authorities (e.g., transport, water, etc.) by supporting the evaluation of the received comments by using AI information models. The AI tool identifies certain topics in the planning process, carries out AI-based keywording, groups similar comments, anonymises personal data, and sends an evaluation result to the groups involved by email at the end of the process.

Accordingly, functional approaches often have elements of a Textual AI, although these can also be integrated into Functional AI. In addition to the example of AI tools in formal urban land-use planning procedures, the use of AI in the granting of planning permission can also be categorised as Functional AI. AI is used here when applying for and granting approval for building permits, meaning that AI is used late in the planning process. During a research project in Vienna, building owners were able to submit their documents for their building project online. Once the documents were submitted, an AI analysed the documents and checked whether everything was complete and whether the client filled out the application correctly. The AI scanned text elements, put them into their basic linguistic form, connotated them, set them in relation to each other, and balanced them. In the final step, the AI then analysed the intention of the content (Urban et al., 2021, p. 7). As one of our respondents confirmed, the AI also checked whether the information in the application complies with the specifications of the city’s applicable planning documents and legal texts. In addition, a model of the construction project was created as BIM (Building Information Modelling). These generated models were intended to make the construction projects clearer and more transparent for citizens (Stadt Wien, 2024). After extracting the relevant data, the AI summarised it into meaningful categories.

Analysing different Functional AI applications in the context of urban planning, we can conclude that these tools are mainly used in the Formal Planning Phase. As the examples indicate, the intention is to structure the planning and approval process and to carry out steps that convert information into concrete actions to improve the planning processes as a whole. However, the AI applications could also be used in the directly subsequent phases of formal processes, e.g., to organise participation processes at an early stage or to structure the Design and Implementation Phase in order to speed things up.

3.3. Textual AI in Urban Planning: AI-Based Evaluation of Text Elements

From a technical perspective, Pellegrin et al. (2021) describe the use of AI in the urban context of urban planning and administration as collecting, interpreting, and analysing data for political decision-making and improving public services. Various forms of data analysis can be carried out and evaluated, having close links to the possible applications of Textual AI that can be used, for example, to analyse documents and thus improve participation opportunities or implement dynamic policies. For example: historical analyses of documents are conceivable to predict future developments and trends on this basis; near real-time analytics enable analyses of indexed data to increase the transparency and monitoring of certain processes; real-time analytics enable the analysis of data directly in an ongoing process to enable immediate evaluation; and predictive analytics encompass statistical models that classify data for the near future and predict events (Pellegrin et al., 2021, p. 19). In this context, Textual AI can be used to analyse the opinions of parts of the urban population by using AI in conjunction with social media. Here, public tweets can be collected and analysed to gain an overview of current issues and needs that affect a large proportion of the population and fall within the remit of local government (Pellegrin et al., 2021, p. 20).

Textual AI is also used in other systems and tools, for example in AI-supported digital participatory platforms that can be used by municipalities to organise participation processes. Here, citizens can find out about planning concepts in their city and contribute with their ideas and opinions. Here, the AI first analyses the citizens' comments and then clusters the comments, for example, according to specific subject areas, demographic data, or the mood conveyed by the comments. According to one of our interviewees, a comparative evaluation of ideas and comments received from planners and a Textual AI shows that the AI analysis process is very similar to the human analysis process and produces similar results. However, the AI only needs a fraction of the time of the planners involved, so that planners gain capacity for the conceptual development and planning realisation of the ideas.

To conclude, we see the use of text-based AI applications particularly in those planning phases in which text-based analyses, for example of participation processes, appear to make sense. Accordingly, this type of AI application is particularly suitable at the beginning of a planning process, e.g., in the Preparatory or Exploration Phase, in order to obtain a basic assessment of the planning proposals from citizens and to systematically analyse the assessments. Using text-based AI applications in the Formal Planning Phase can also accelerate the planning process and support decision-making if citizens' comments are analysed more quickly. Textual AI could also be used in the Monitoring Phase to evaluate the implementation of the plan concept, ensure ongoing citizen participation, and obtain relevant information.

3.4. Visual AI in Urban Planning: AI for Image-Based Generation of Spatial Scenarios

The use of AI tools further enables the image-based generation of various spatial scenarios and alternatives; this is often based on web applications using self-made photographs or images stored in Google Streetview. This makes it possible to present and discuss, for example, different variants for the design of street spaces or public squares, the reutilisation of an old industrial hall, or the design of new residential buildings in participatory planning and co-design processes. The aim is to actively involve citizens and stakeholders in the design of planning processes by allowing their ideas to be directly mapped by the AI. The tools are therefore particularly suitable as a basis for discussion in planning workshops to interactively discuss ideas for urban projects and give users the opportunity to visualise them without specialist and technical expertise.

In addition, AI is already being used to create urban planning designs and concepts (As et al., 2022; Pisu & Carta, 2024). Here, generative design engines built on rule-based systems, parametric design, and neural networks enable the development and visualisation of development structures, building blocks, open spaces, building heights, etc. (Landes, 2022; Sari et al., 2022). As a rule, the Visual AI first determines latent patterns, i.e., identifying building blocks and building hierarchy, before designing and composing new city layouts (3D representations of the corresponding area and buildings). According to various studies (Landes, 2022; Pisu & Carta, 2024; Sari et al., 2022), generative Visual AI allows planners and designers to develop a large number of possible design variants in the shortest possible time and to produce accurate urban models with greater precision than ever before.

According to our research, we can summarise that image-based AI tools are mainly used in informal processes at earlier stages of a planning process. It is therefore conceivable that they could be used in the Preparatory and Exploration Phase as well as in the Feasibility and Master Planning Phase (see Figure 3). The aim of planners in such phases is to have an innovative planning tool in a co-design process to make participation interesting for different target groups and to collect ideas from citizens for the planned area. The AI-generated images and variants contribute here to provide the same level of information for all participants; at the same time, AI can ensure that participants can visualise their comments and suggestions on a project in an ongoing planning process. Image-generative AI approaches also offer the possibility of being used in later planning phases, e.g., in the Formal Planning Phase, although it should be critically noted that planning processes are often already well advanced at a later stage and generated images and ideas may no longer be taken into account in the planning process and the development of design concepts. However, Visual AI offers the opportunity to visualise and discuss specific changes in local land use plans (e.g., changes in building height) and regulations on the ratio of developed and undeveloped areas, meaning that Visual AI can improve the information base of all stakeholders involved in the planning process, as well as the transparency of planning decisions in the Design Phase.

3.5. Interactive AI in Urban Planning: AI-Based Chatbots for Communication and Information

AI language models as chatbots offer an efficient approach to relieve the burden on municipal administrations, which can simultaneously break down access barriers to the administration (Hein & Volkenandt, 2020, pp. 28, 44). The aim of using chatbots is to provide precise answers to citizens' questions in a timely manner and to offer the opportunity to address concerns to the city administration at any time (Senadheera et al., 2024, p. 2). Bots can be embedded in natural language processing and work as a large language model. The applications are trained in such a way that the AI captures the texts as part of a semantic analysis, recognises keywords, and reacts to them. The AI system analyses which questions are asked most frequently and whether its own answers were helpful and can thus continuously improve itself. Chatbots can facilitate the allocation of appointments for registration and vehicle matters for the population, for example, by being set up as a defect reporting and information system or be used as part of the dialogue process in planning procedures to collect and evaluate opinions (Hein & Volkenandt, 2020, pp. 44–45). This means that defects can be reported, the current status of planning procedures can be requested, or information on specific measures can be obtained. In the city of Berlin, for example, an AI-based assistant can be asked questions on administrative matters (e.g., "What measures are planned in Burgfrauenstraße in 13467 Berlin to change the traffic?"). The tool then searches, for example, documents from the main committee meetings of the administration as well as written enquiries and generates short answers—based on the content (as far as possible)—that match the question. Some cities, for example Vienna or Heidelberg, now use AI-based chatbots as citizen service that address urban planning processes. However, it is obvious here that chatbots only have a supporting function for the administration and urban planning. They can provide information on current planning procedures, administrative processes, etc.; however, they cannot develop new plans or make further-reaching decisions.

In the projects we are aware of, Interactive AI systems and particularly chatbots are currently being used for rather limited procedures and phases. This includes tasks that are well suited to the programming of AI systems due to their frequency, delimitation, and structure. Against this background, Interactive AI systems are primarily found in the Formal Planning Phase, the Design Phase, and the Operational Phase. At the same time, it is also conceivable that chatbots and other interactive applications will also be used in earlier planning phases in the future (e.g., to support participatory processes) as there are no limits on the use of chatbots in these phases.

4. Conclusion

AI has found its way into urban planning in recent years. The literature analysis and the analysis of various practical examples show that the areas of AI applications in urban planning processes are as diverse as the timing of its use in the individual planning phases. Wherever AI is currently used in the planning process, innovative applications support the work of planners. For example, complex data-based planning analyses can be carried out with the help of AI in early planning phases to support decision-making (Analytical AI) or formal procedures of the planning process can be simplified and structured (Functional AI). AI can also be used to effectively support the complex evaluation of comments in the participation process, making time-consuming activities easier (Textual AI). AI can take on routine tasks (for example, summarising and evaluating statements, formulating pre-draft documents or designs, creating textual justifications of formal plans, etc.) and provide planners with scope for more strategic and conceptual considerations or participation processes. Additionally, Analytical, Functional, and Textual AI in particular can support internal administrative procedures and planning processes, e.g., checking procedural steps or checking whether the documents required for the planning application are complete. This could—at least based on views expressed by several of our interviewees—possibly lead to a kind of roadmap for administrations on how administrative processes and therefore planning procedures could be systematically supported with AI.

AI can also help to generate planning and design variants quickly and easily (Visual AI), either to increase the visualisation of planning content and planning intentions or to develop planning variants together with citizens as an interactive tool in co-design processes. Here, AI applications as digital tools can help planners make decision-making and planning processes more effective. By involving different stakeholders and using visualization tools, AI applications can help to reduce power asymmetries, discrimination, and social inequalities (Wilson et al., 2019, p. 287). AI-based systems, for example, can carry out automated text analyses in participation processes by using algorithms to analyse and visually process citizens' objections and comments on plan concepts. In addition, AI can reduce the (unconscious) subjectivity and bias of planners towards certain people or planning topics, for example, by automating anonymised evaluation of comments in the participation process to increase the objectivity of planning decisions. However, this does not mean that discrimination can be completely eliminated by AI, but the likelihood of discriminatory decision-making processes could be reduced by training which is a central prerequisite for AI in public planning and participation processes (Pellegrin et al., 2021).

The growth of AI systems might also trigger further innovations and changes for planning (see Figure 3). By linking, for example, Textual AI, Functional AI, and Visual AI it would be possible for planners to analyse comments and documents and to create urban land use plans or concepts on this basis. This future is seen by some interviewees as very realistic, especially with regard to the development of local land use plans. In this vision, the AI first translates the written or verbatim objectives and (legal) framework conditions for a plan into corresponding graphic specifications. The AI then uses the drawings to generate initial proposals for formulating the textual explanations of the plan. Another possibility for the further and increased use of AI could be digital twins that display temperature and wind systems (Analytical AI), communicate interactively with users (Interactive AI), and record and analyse their discussions and comments (Textual AI) into urban designs (Visual AI), considering all the relevant information and data from the other phases.

But what does this mean for the future of urban planners? Will they become redundant, similar to the drivers that become redundant by the introduction of self-driving cars? Does this not mean that urban planners, designers, or architects will disappear eventually, just as the human driver will disappear (Leach, 2022, p. 175)? In our understanding, this question does not really arise. We are convinced that planning processes will not be fully automated by AI. Planning is still dependent on the decisions and valuations of planners, which is confirmed by all of our interviewees. AI-based applications are used here as supplementary tools for the work process: They can contribute to the collection and analysis of relevant information and data, they can support decision-making processes, and they can do this very efficiently, freeing up planners for other tasks or decisions. However, results of AI systems have to be embedded or interpreted against the background of political decision-making processes, the way a society wants to organize coexistence, participatory procedures, or questions of planning and building culture. This is where purely technical systems reach their limits, despite their ability to think. This is one reason why planners can use AI for the future development of cities in different phases, but AI will not replace planners. At the same time, this also raises the question of how ethical concerns of AI, especially as urban planning activities involve human-centred approaches, could be mitigated (Son et al., 2023, p. 9). AI systems are set to act with increasing autonomy and will probably be widely used in the future; consequently, responsible practices are needed to ensure that the technological progress is in line with social values and norms (Pellegrin et al., 2021; Wu et al., 2024). This requires planners to consider the ethical implications of using AI in participatory planning carefully. Ensuring transparency, accountability, and inclusivity in AI decision-making processes is critical to achieving more equitable outcomes (Du et al., 2024, p. 193).

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Conflict of Interests

The authors declare no conflict of interests.

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