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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

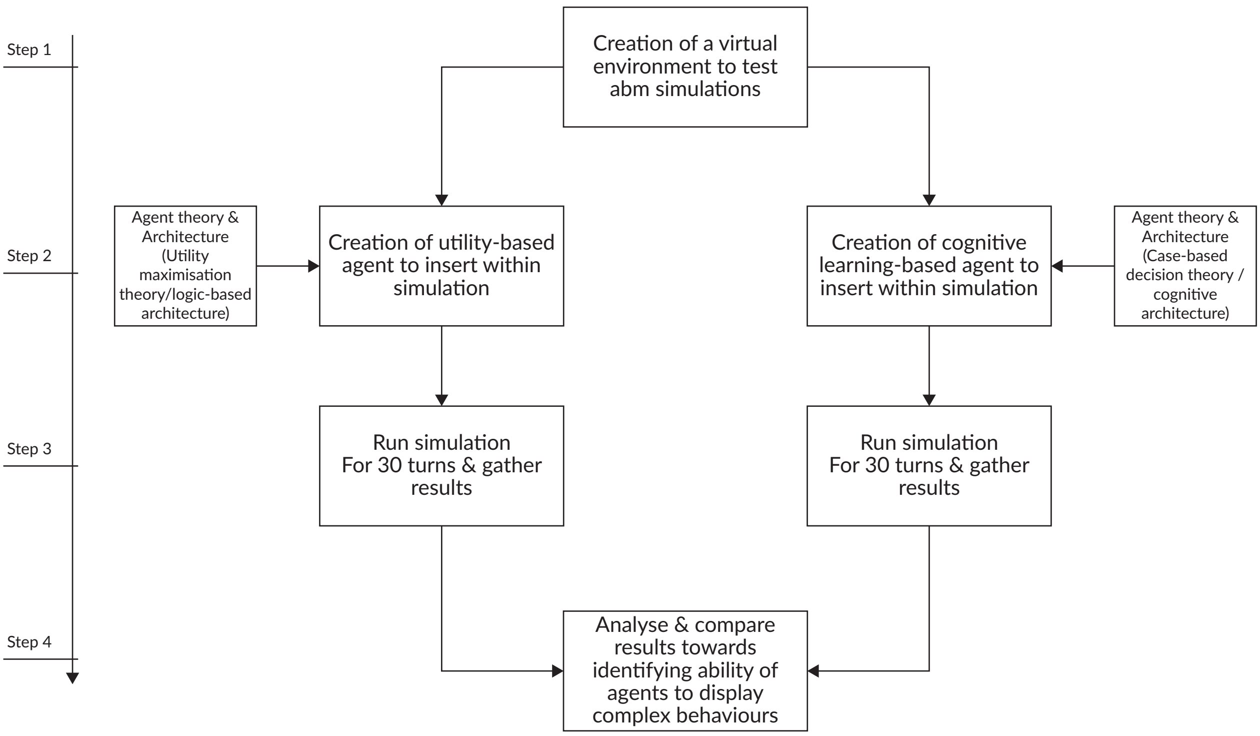

Figure 1. Diagram of methodology steps.

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

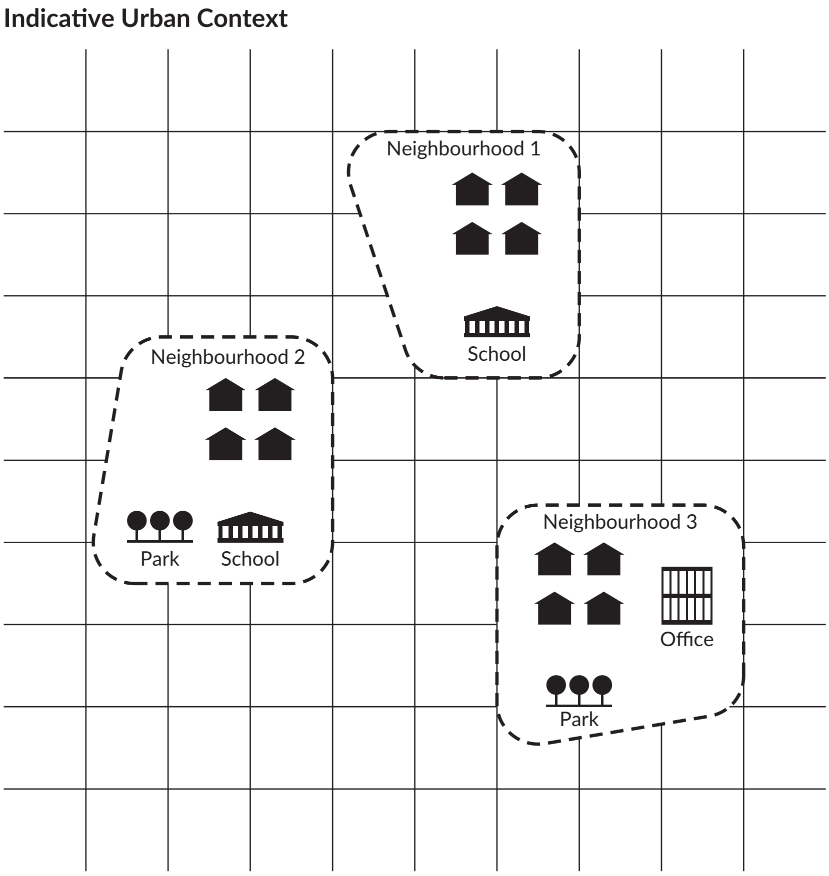

Figure 2. Simulation virtual environment.

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,

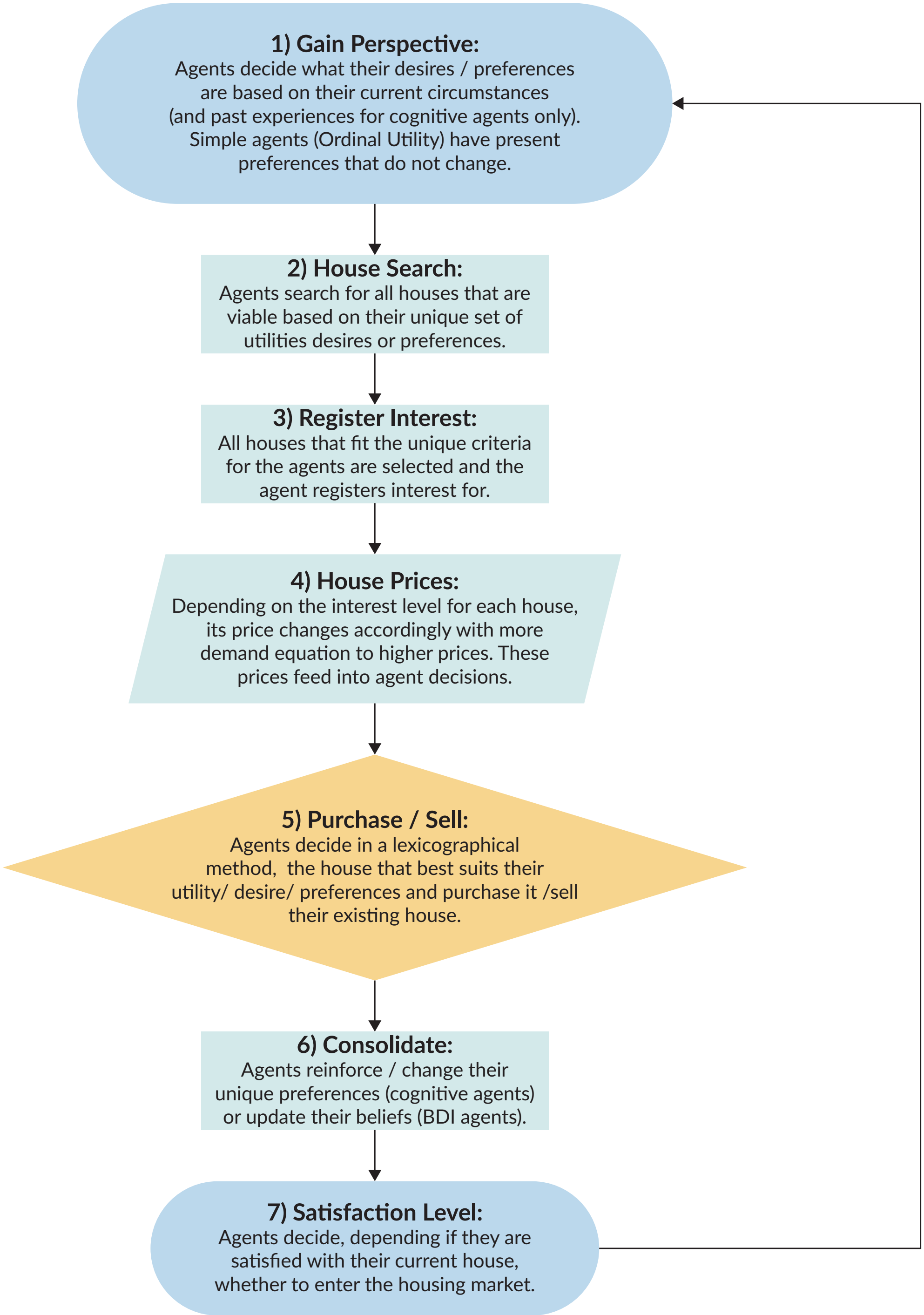

Figure 3. Overview of the seven-stage process run at each turn of the simulation.

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.

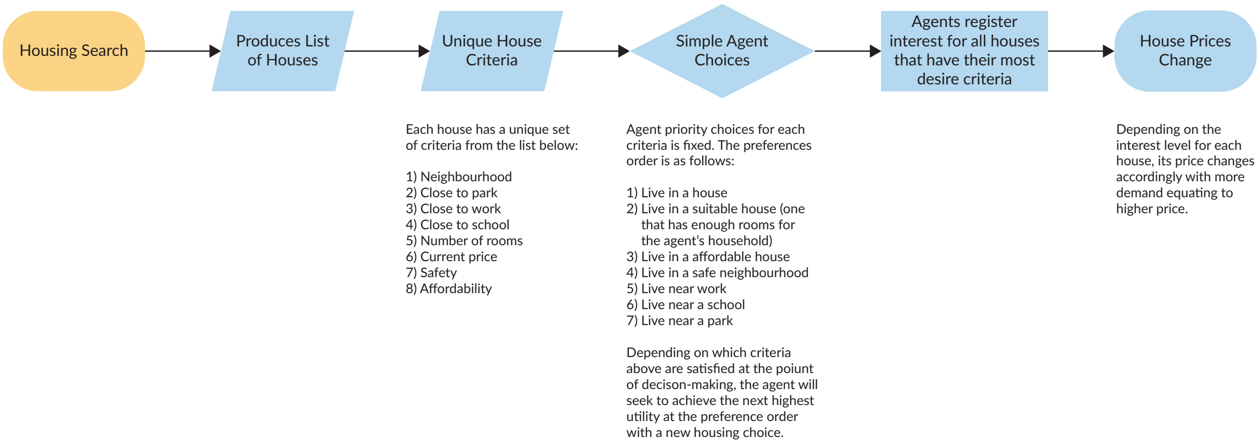

Figure 4. Diagram outlining the decision-making process for simple agents (logic-based architecture).

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

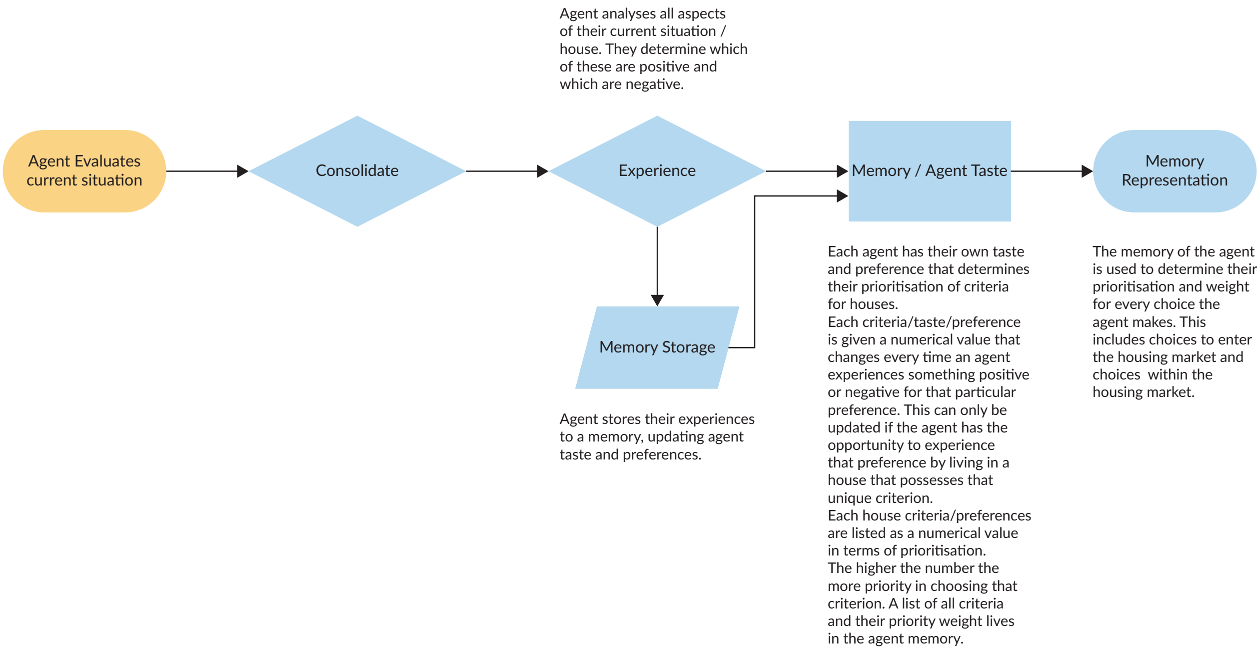

Figure 5. Cognitive agents' overview of inputs to and from memory through experience.

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.

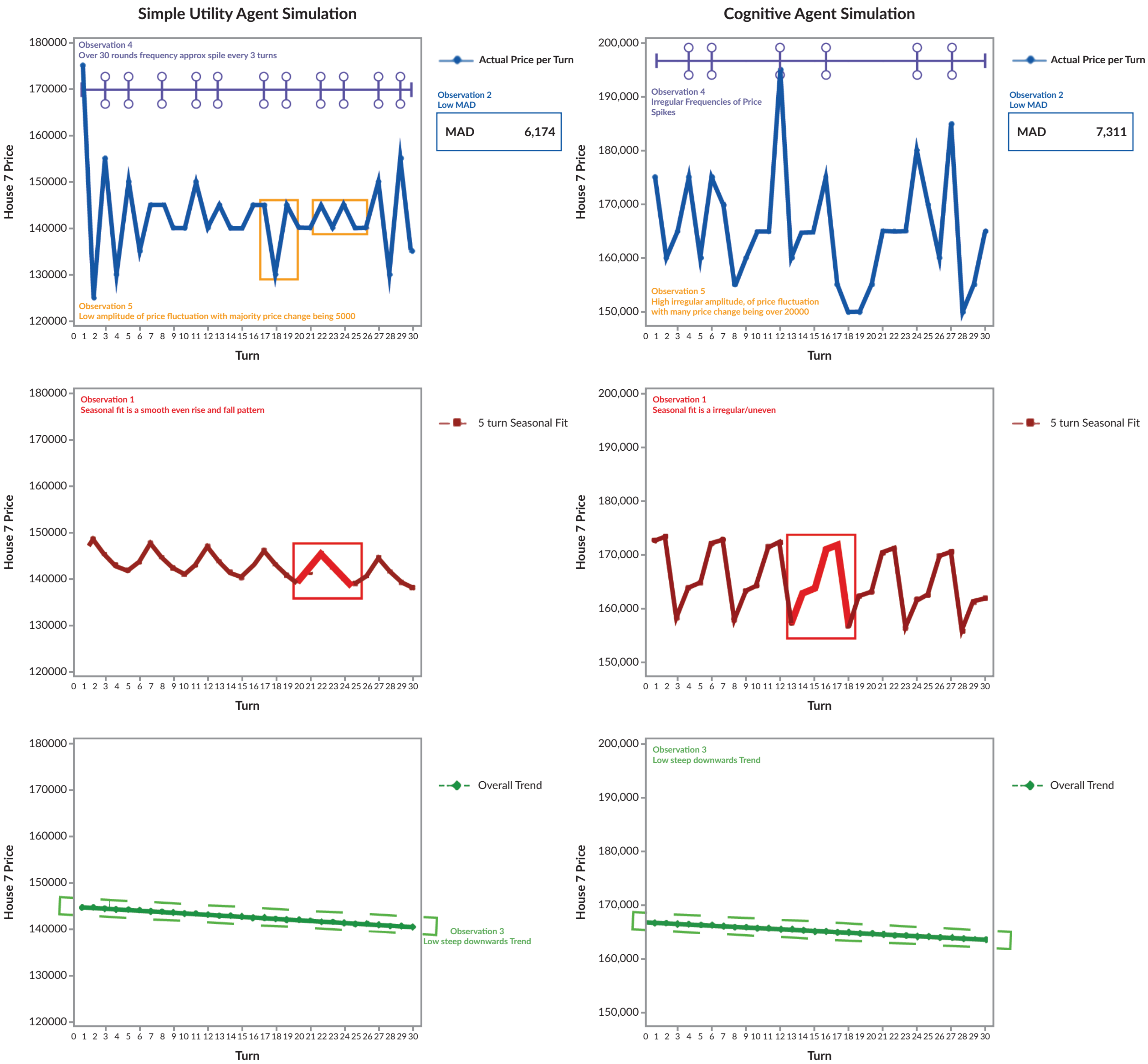

Figure 6. High-value house decomposition analysis results with five turn seasonal fit for utility-based agents vs cognitive agents.

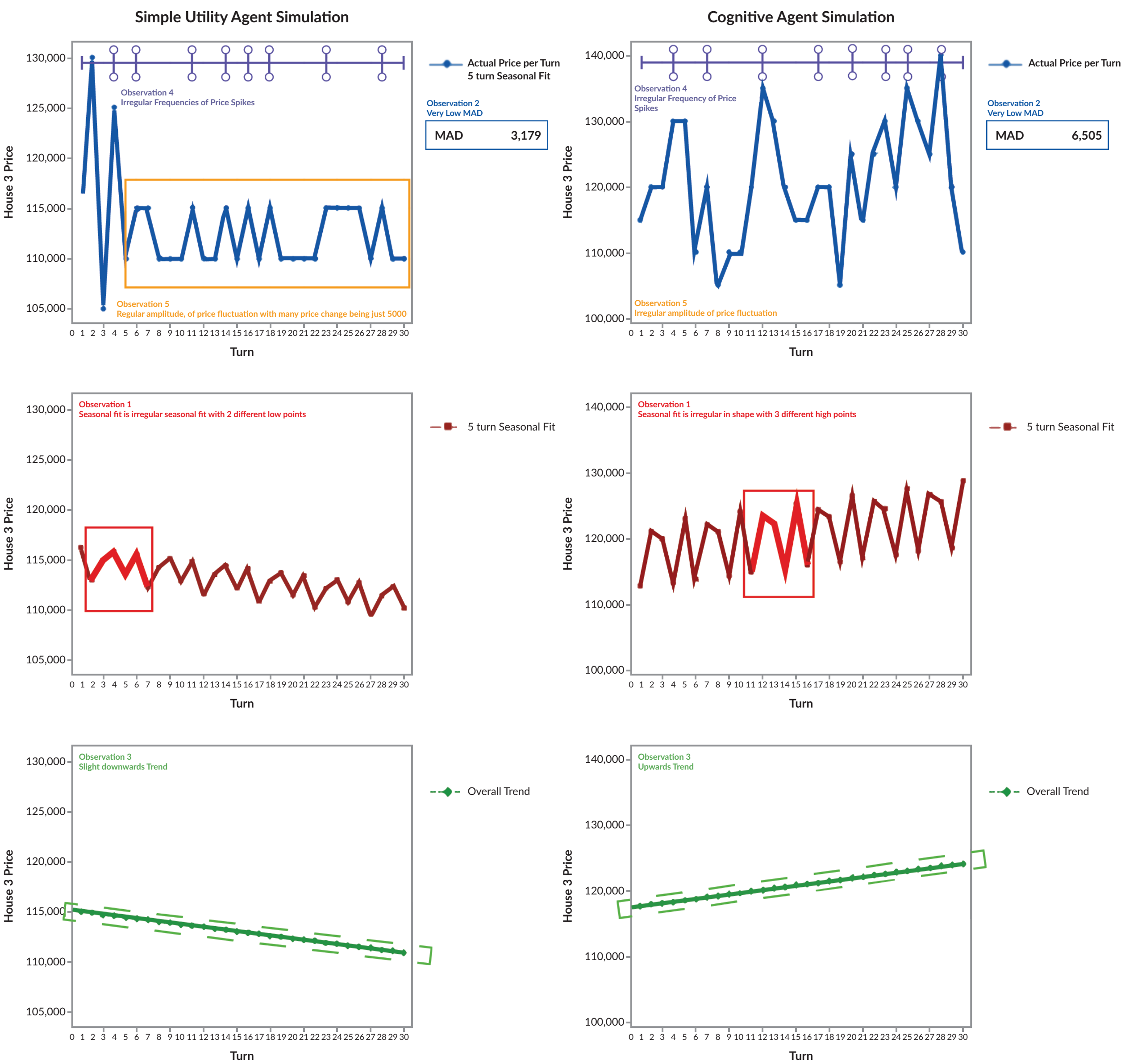

Figure 7. Low-value house decomposition analysis results with five turn seasonal fit for utility-based agents vs cognitive agents.

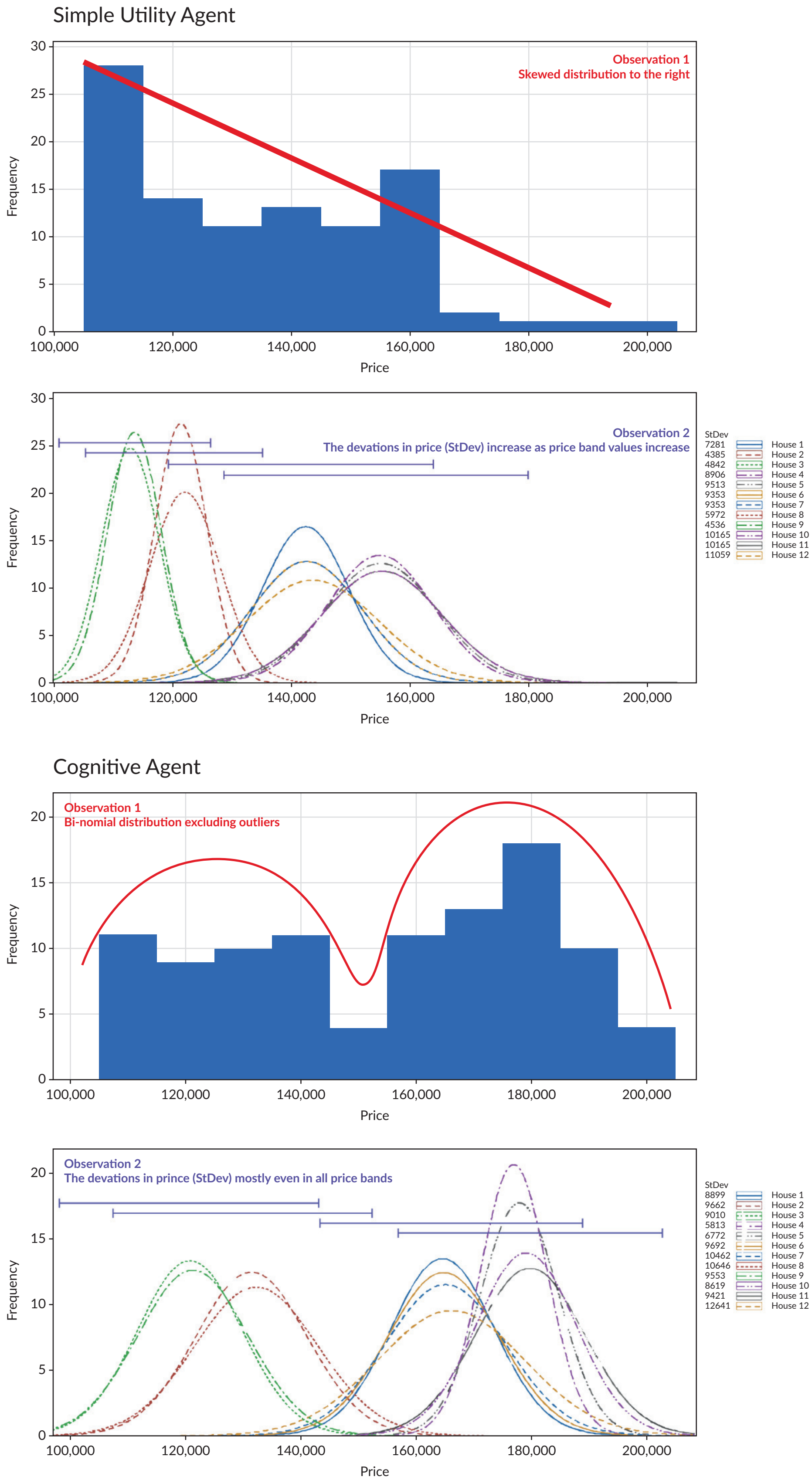

Figure 8. Histogram analysis with normal-distribution for simple utility-based agents vs cognitive agents.

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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