Incorporating Alternative Rational Behaviour Theories Into Urban Simulative Models

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ABSTRACT

Within urban design and planning, computational models help understand and explore future demand for space in specific locations and situations. In the literature these are a category of urban simulative models classed by this research as real-estate demand models. These models incorporate modules that deal specifically with market forces of demand in an attempt to anticipate human behaviour and response to future intervention and policy change. The current trend of increasingly disaggregated urban scale operational planning support models revolves around microsimulation and agent-based models (ABM) that incorporate individual behaviour. The individual behaviour represented in these real-estate demand models lends heavily on economics theory. The thesis aims to enhance the evaluation and prediction of demand and value associated with specific designs or spaces within the urban environment. It addresses the gap in current urban simulative models, which primarily rely on objective rationality theories to predict individual decision-making regarding land, space, and design choices. The research investigates the potential of new disaggregated behavioural techniques, focusing on improving agent decision-making mechanisms to allow for subjective rationality. This involves exploring innovative theoretical bases and agent architectures to better represent individual behaviours within computational models.

The thesis objectives include a classification of real-estate demand urban simulation models, a systematic review of these models that evaluates current agent architecture usage, the construction of novel computational models for real-estate demand, their validation through human role-playing simulations, and the drawing of conclusions on their capacity to represent

subjective rationality. The findings of the initial review indicate that current real-estate models lack certain agent attributes, such as cognitive abilities, collaboration, belief-desire-intention structures, and pro-activeness traits. The research creates three distinct ABMs incorporating different theoretical foundations and agent architectures: Theory of Planned Behaviour with Belief Desire Intention (BDI) agent architecture, Case-Based Decision theory with cognitive agent architecture, and a classic utility maximization model with logic-based architecture. The suitability, strength and weakness as well as external validity for each type of model is analysed against the results of an active role-playing simulation that substitutes the decision-making of computational agents with those of real people in a virtual environment that mimics the one present in the aforementioned three different computer agent simulations.

The research demonstrates the potential of introducing currently lacking agent attributes in the field through innovative theoretical bases and agent architectures, as evidenced by the performance of the created models when compared to the human role-playing experiment. Key findings include the demonstration of the limitations of traditional neo-classical economic theories in urban modelling, and the potential of alternative decision-making theories. Moreover, it emphasises the potential of cognitive agents to improve decision-making processes and design outcomes in urban planning. Additionally, it comments on the need for future research to overcome limitations, such as the lack of real-world representation and the impact of scale on agent decision-making. Overall, this work underscores the importance of considering subjective factors in urban modelling and design to better reflect real-world complexities.

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CHAPTER ONE: GENERAL INTRODUCTION

1.1 Background to research and opportunities to advance research.

Design has many ambitions and definitions that are often contradicting each other with some placing the emphasis on the end product (Julier, 2000) while others on the activity of design (Liz Sanders, 2008). Frankel & Racine consider both aspects and argue that 'design is an activity for planning and implementing new products, which includes the by-products of the processes involved such as drawings, models, plans, or manufactured objects'(Frankel & Racine, 2010, p. 3).

In the field of Architecture and Urban Planning, design operates between current trajectories of change and desirable future outcomes (Ulysses Sengupta, 2011; Ulysses Sengupta et al., 2016; Ulysses Sengupta, 2017). The focus of this speculative design research is simulation which constitutes a means of researching future possibilities and scenarios. Within Architecture and Urban Planning, simulations are run through urban simulative models that have various forms, but all seek to inform their users of the future performance of different spatial configurations and interventions. These generated future outlooks are intimately related to the design of these spatial futures, often informing planners of viable alternatives not just projections. The outcomes are rooted in existing knowledge informed through data analysis and theories as a means to predict possible behaviours and responses.

This type of research has its roots in Architecture with the Modern movement and Le Corbusier being a fundamental first step to establishing formal design methods as part of scientific research in the 1960s (Frankel & Racine, 2010). The scientific design research methods set out in the 1960s are further separated into different types of design research. Buchanan (2001) noted that depending on the design problem, the research needed may be viewed as clinical, applied or basic. He was not the first to attempt to categorise different types design research with Frayling (1993) notably calling for a differentiation between research for, through and into/about design. Both Buchanan's and Frayling's taxonomies have been interconnected (Frankel & Racine, 2010) with clinical associated to research for design (establishing conditions, processes, specifications and data that designers can use to achieved desired end results (Downton, 2003)), applied associated with research through design (action-reflection approach with an emphasis on creating design knowledge and not the project solution (Findeli, 1995)) and lastly basic associated with research about design (work undertaking a design inquiry to determine experience of designers and users alike (Buchanan, 2007)).

This thesis undertakes design research, with a particular focus on futures using unique design processes that are specifically geared towards it. These involve forecasting, speculative design with a look at specific elements in isolation. They are separated from context in an attempt to generate new solutions and knowledge through design experimentation (Sevaldson, 2010). This type of research is both informed and contributing to new and existing theories and practices (Sevaldson, 2010) that transcend disciplinary boundaries. Acknowledging the role of simulation as a useful research tool to develop an understanding of future context and demands, its development and use is associated to research for design. It seeks to speculate about future possibilities, to design potential outcomes, and/or to test multiple different design outcomes.

The history of simulation, in particular urban applications of simulation, include spatial input-output models, mathematical programming models and spatial-interaction models (Cordera et al., 2018). They date as far back as the early 1950s (Iacono et al., 2008a) and have been used in the design of future cities, housing, real estate and supply and demand analysis. These have evolved following the work of McFadden (1973, 1978) on modelling choice behaviour using random utility theory with applications in transportation and the real estate market forming the basis for a new generation of urban simulative models. These models began to surface in the 1980s and 1990s (Cordera et al., 2018) with an equilibrium modelling approach. During the 1990s, as a response to the increased availability of fast computers and general advancement in computer science (An, 2012) urban simulations evolved to follow a complex systems theoretical approach with the use of Cellular Automata (CA) and ABM to achieve a highly disaggregated model with a series of heterogeneous agents interacting with each other, achieving complex behaviours from seemingly simple rules/actions (Wolfram, 1994).

Designing futures through simulated systems requires more than just a robust computational coding framework generated within the computer science discipline. Any spatial adaptation of simulation in an urban environment requires the best possible integration of human behaviour within the agent-based simulation. If this is not considered, then the simulations remain disconnected from desirable outcomes unable to showcase a genuine understanding of future possibilities. Within urban simulative models, human behaviour and choice is modelled by incorporating a wide range of interacting heterogeneous agents with the ability of more aspects influencing decision-making such as consumer behaviour and the concept of rational choice / bounded rationality (H. Simon, 1972) from the spectrum of microeconomic theory. This disaggregated ABM approach of current urban simulations enables some understanding of complex urban interactions and the plurality of views and preferences that exist within an urban environment. It potentially offers the means to unlock an understanding of consumer and urban citizen values in a way that informs design of space beyond quantitative measures but with the inclusion of qualitative aspects. This makes the actual elements replicating human decision-making, including the theoretical basis of those decisions, a primary concern.

Considering the durability and anticipated longevity of the design product itself, be it a single building or an urban plan, the designer must contemplate both the current and future needs of users as well as other stakeholders such as government and developers. It is, however, impossible to understand future demands without analysing and understanding the context first. As such, the context, its state and morphology shaped through decades of conflict and past political, professional and institutional ideologies can only be understood as the consequence of the sum of past planning decisions depicted on the urban fabric (Ward, 2004). There have been a series of notable theoretical approaches linked to the practice. The initial theory, rational comprehensive planning, is a theory that views communities as a collection of constantly interacting and changing patterns that form the shifting nature of society with the role of the planner meant to guide/control change in these relationships in a rational and objective manner, considering all alternatives and selecting the one whose consequences best fit the desired end result. Lately, the prevalent theory is Collaborative planning, challenging formal rationality and instead emphasizing substantive rationality, taking into account individual values and perspectives to reach agreement. The planner's role is to facilitate this discourse and accept a pluralistic orientation with multiple futures.

These theories, amongst others explored in chapter 2, have formed the basis for the process by which cities form strategic plans and evolve over time. Throughout the last century, they have informed planners on how to tackle the urban issues that disrupt and threaten cities and enabled the design of planning solutions that consist of strategic plans, urban designs and architectural interventions. They inform and create new design practices for use in urban and architectural design. Therefore, the process of design within this field is in itself a research undertaking.

Urban planning aims to increase the efficiency of a city and maintain its constant development rate to optimal levels, avoiding periods of stagnation (Bettencourt et al., 2007), while balancing social, environmental, and economic aspects in dynamic relation. However, according to Michael Batty (2008), the concept of achieving and maintaining equilibrium in an urban system is flawed, stating that there is only a constant movement towards different equilibriums. Therefore, urban systems are far from equilibrium, existing in a state of tension as different opposing forces build up and break down on a range of spatial and temporal scales resulting in an array of urban forms and functions (Michael Batty, 2017). The complexity of future scenarios cannot be fully understood as linear and predictable. Urban dynamics are driven by collective behaviour, where many urban actors' decisions build on previous decisions made by other urban actors (Portugali, 2006, 2018; Portugali & Haken, 2018). Historic, personal, and collective influences are important to the explorations enabled through the specification of bottom-up, agent-based, simulated urban models. Simulation of different scenarios in these disaggregated models can lead to exploration of alternative strategies towards influencing and understanding future demand and urban patterns with respect to self-organisation, and path dependencies. Therefore, the improvement of both the agent-based simulated models' theory and coding, with respects to better incorporating complex, bottom-up behaviours, forms an important pursue towards better understanding future demand.

Generally, agent decision-making is heavily based on economic decision theories to lend validity to the urban simulative models. Reliability in the empirical generalizations is what allows for an intended result based on estimated actions by individuals to have validity (Gerth & Mills, 1946). The fundamental issue with judging and predicting an individual's decision in any situation heavily relies on whether the empirical generalization by which the prediction scenario's rules are based on, were constructed under a "subjective" rationality or "objective" rationality. The distinction here is important because an objective rationality choice is scientifically, factually correct, or right. The decision maker himself on the other hand, directly influences the correctness or justification for a subjective rationality choice. In essence, the subjective choice for the individual has little to no empirical grounding in facts but relies on the perceived notion of the individual's own perception of right and wrong.

Such subjective rationalities are what account for choices of taste or for choices under uncertainty. Here lies the gap in measuring value and demand for land/space/design in urban simulative models. In many previous cases, the demand for land is justified from survey data of homeowners and their activities in a particular period in time. This enables the empirical generalization for space choice of individual heterogenous agents that are representing real-world homeowners in urban simulative models. The issue here is the subjectivity in this decision. Though empirically assessed, the validity only stands for that moment in time for that particular population making decisions on those particular spaces within that particular context.

The evolution of economic theory predominantly in the area of consumer behaviour established how a range of internal determinants, relating to one's own motivations, and external determinants, relating to outside factors have the possibility to influence decision-making on an individual level (Gibler & Nelson, 1998). The subjective rationality behind consumer behaviours relating to land / building / space / design choices creates the issue with the current theoretical applications of expected utility, random utility, and utility maximisation in urban simulative models. It is primarily trying to create objectivity in an otherwise subjective rational choice by relying on people acting in the most effective way to objectively realise their goals. One can argue of the method's necessity in order to create a scientific method by which to predict future states, but the limitations of this approach have been heavily criticised as it lacks any transferability and offers no way of accounting for disruptions that can cause changes in the empirical patterns observed. Disruptions caused by the Covid19 pandemic have rendered urban theories of agglomeration unable to explain new patterns of housing choice.

The new wave of urban simulative models since the 1990s, builds on the notion of disaggregated modelling with more intricate behavioural aspects for agents and decision-mechanisms / variables. A number of identified shortcomings 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 (P. H. 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 the need for more advanced behavioural agents. Furthermore, Ettema et. al. (2005) mentions 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. The literature clearly indicates that 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 author's knowledge, currently there are no geographical spatial applications of advanced cognitive behaviours and agent architectures (A. Heppenstall et al., 2016).

In light of this limitation / gap, the thesis applies a design science research methodology with an objective-centred solution focus towards the advancement of disaggregated modelling within urban simulative models. First, the thesis explores a range of social science-based theories and a range of social science-based disciplines such as psychology and behavioural economics in an attempt to identify potential concepts for agent behaviour in space demand models. These concepts include notions of cognition, judgment and decision-making processes, consumer behaviour and the role of experience in decision-making. These are then applied to novel simulative models of housing demand using a range of previously unexplored agent architectures for the area such as cognitive agents and BDI (belief, desire, intention) agents. Agent architecture is the move from specification to implementation, how all these agent behaviours get build in a computer system. It is intended to support decision-making process by being the foundation of agent reasoning mechanisms (Chin et al., 2014). Three distinct computer models are created using BDI agent architecture, cognitive agent architecture and logic-based agent architecture. The latter acts as the control experiment with both the theoretical basis and agent architecture mirroring that of a typical module of its nature as used in the wider literature. All three models run a computer simulation in a virtual environment featuring 3 neighbourhoods, 12 houses and 24 agents seeking to choose a house that best satisfies their needs. The aim is primarily to test the potential of the new theories and agent architectures used within the three models.

The capabilities of the new agents created gets tested through a laboratory experiment featuring an active role-playing simulation where people replace the very agents in the computer simulation and make decisions on their behalf. The participants of the experiment are given the same attributes and roles as their counterparts in the computer simulations while being placed in the same virtual environment with the same choices and objectives. The aim of the experiment is to validate the potential of the new theoretical basis and agent architectures created as part of this research. Though laboratory experiments are limited to testing the effects of set parameters and variables within a controlled environment, it provides external validity to the research. Furthermore, it provides an avenue for the novel computational models created to be explored further towards application to real world scenarios.

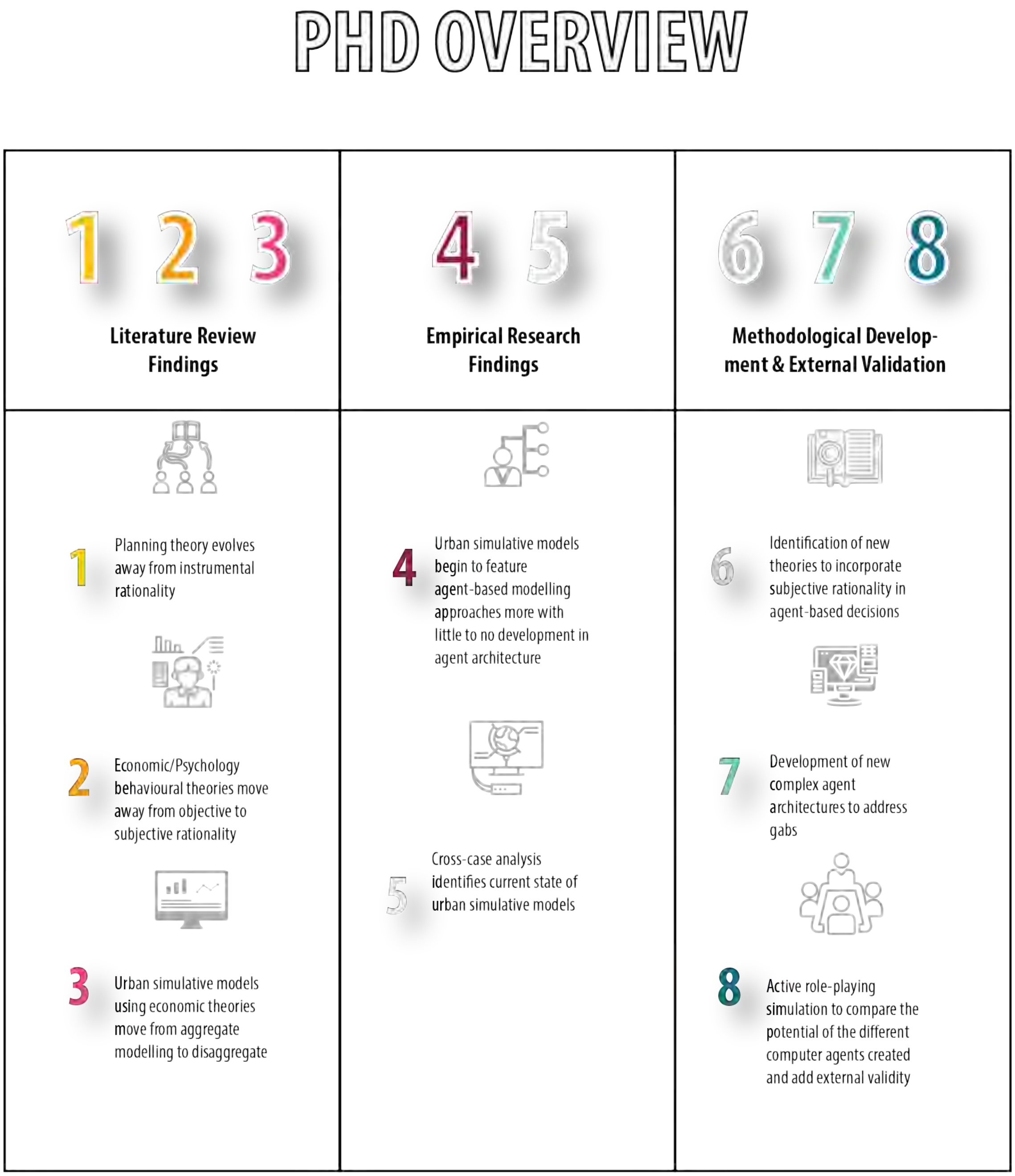


Figure 1: Overview of PhD thesis broken down into eight parts that include the literature review, empirical research, and methodological development & external validation.

1.2 Research objectives and questions

The identification and classification of subjective decision-making theories will be developed as part of a methodology to help create a subjective and evolving decision-making process for agents in space demand urban simulation models. This leads to the research question for this PhD:

What effect does the incorporation of alternative rational theories and architectures have on the ability of agents to display more complex behaviours in urban simulative models?

This research question, the inquiry into the limitations of current urban simulative models which extends to their agent architecture, is a direct response to both the current planning practice needs and the ambitions of urban modelers.

1.2.1 Research objective and questions

One of the aims of the PhD is to answer the question of what the current limitations of urban simulative models are. More specifically, what are the limitations surrounding the modelling of human behaviour in choosing dwellings, space, and land? This is an important aspect of a simulative model due to the complexity and unpredictability of individuals and the accuracy of translating that to a digital platform being the source of criticism for the wider urban simulative modelling world.

In order to answer this, a design science research methodology utilised with methods that compare and rate current approaches of modelling human behaviour in urban simulative models against the ones created as part of this research.

This leads to the aims and objectives of this thesis:

1) Classify real-estate demand urban simulation models.

2) Undertake a systematic review of real-estate demand models analysing their theoretical basis, model scale, decision factors and spatial interaction modules.

3) Evaluate current agent architectures in use for real-estate demand models and assess any limitations that may exist.

4) Build simplified computational urban simulation models for real-estate demand with a range of theoretical basis for agent decision-making processes.

5) Run a human role-playing simulation/game laboratory experiment with 24 participants playing assigned imaginary roles to externally validate the models.

6) Draw conclusions on the capacity of new computational agent simulation models to display patterns of behaviour befitting subjective rationality through statistical analysis of results and their comparison with role-playing simulation.

The first part of the methodology focuses on the analysis of existing agent-based urban simulative models with respects to their agent architecture. The results of this analysis lead to the identification of gaps and current limitations in modelling human decision-making. These are then addressed by the second part of the methodology that focuses on the creation and testing of alternative rational agent theories and architectures. The role-playing simulation laboratory experiment provides a direct method of comparing real-world agent behaviour against different computational agent simulation observed behaviours.

1.2.2 Simulation model development objective and questions

Through the analysis of existing agent architectures and theoretical basis for decision-making agents in urban simulative models, the thesis will reveal a gap in agent capabilities. Furthermore, following the current state of art analysis using the ESU-AF1 framework, the work will seek to address the gaps identified with the creation of novel simulation models featuring new agent architectures and theoretical basis. These will be focusing on the subjective rationality spectrum with capacity for the continuous evolution of reasoning for the agents.

The first step is to design three computational models with separate agent architecture and theoretical basis, and then analyse the differences in observed results from each one. The aim of the work focuses on the application of new behavioural economics/psychology theories with a new range of computer science agent architectures. The thesis will focus solely on urban computational simulation and contribute to knowledge in both the field of urban simulations and disciplines surrounding it such as urban planning, architecture, computer science and economics. By doing this, it is possible to identify areas of future development of urban simulative models through alternative agent architectures. This approach could lead to the development of more intelligent agents that can adjust their behaviour, and ultimately better simulate the real-world agents' changing and reinforcing patterns of demand brought on by subjective rational thinking. Overall, developing alternative agent architectures and comparing them through computational models could greatly benefit the field of urban simulative models and help improve our understanding of urban systems.

1.3 Overview of the research approach and methodology

1.3.1 The area of research and application to planning.

Behavioural decision theory can be broken down to two parts, normative and descriptive. The normative part deals with prescribing actions based on the beliefs and values of the individual. Descriptive seeks to describe these beliefs and values and understand how they infer in the observable response (Slovic & Lichtenstein, 1977). Since the decisions in the development market happen as a sequence of tasks, it is important to study how the task specification changes over time and how information, available for later choices, depends on the outcomes of previous decisions (Slovic & Lichtenstein, 1977). This will enable the creation of complex agents for urban simulative models and unlock the potential of these models to answer question of greater uncertainty and complexity for their end-users, the spatial planners. The need for such complex agents is evident in the shift of planning theory and practice from a rational comprehensive approach, where the planner's view is perceived as the objective truth in all situations, to a collaborative communicative rationality approach, where the planner understands there is a plurality of perspectives and theirs is not the objectively correct. In that situation the only way to proceed is for an acceptable way to move forward to present itself through the discourse of multiple stakeholders. This is where some of the critic for collaborative planning comes from as perfect speech, required to achieve a meaningful discourse for the generation of a perfect plan, is only achievable when there is a lack of repression, ideology and domination (Allmendinger, 2009). Therefore, in the real world, human nature renders undistorted communication impossible. The ambition is for this discourse to exist in the digital world as complex agents act as participants of collaborative planning in a real-time enactment of the consequences of different plans on a multitude of different stakeholders represented here by a range of complex agents.

1.3.2 Overview of the research methodology for empirical study and simulation models development

The main aim and knowledge contribution of this research is to advance the capacity of decision-making computational agents used within location choice urban simulative models. As such, there will be a need to design new and improved agent architectures and decision-making mechanisms for the field and test their applicability. Therefore, this research follows a design research paradigm, 'the act of creating an explicitly applicable solution to a problem'(Peffers et al., 2007, p. 47).

The research uses a design science research methodology with a focus on objective-centred solution. The study will design two new computational simulation models with an embedded research contribution surrounding the development of agent decision-making mechanisms. It is therefore imperative to apply a methodology that is specifically aimed at creating a more useful design solution while providing the means to test and validate that claim. The research requires knowledge of decision-making theories that can aid in bringing about the desired solution and will seek to determine the effectiveness of the two new artifacts against what is currently available. There are generally six parts to this methodology. In order of operation these are problem identification, definition of research objectives, design & development, demonstration of use, evaluation and lastly communication (Peffers et al., 2007). The communication part is associated with the publication of the work and therefore will not be explored in future work beyond this thesis.

Firstly, the thesis looks at problem identification. This involves the empirical aspect of the research methodology using a qualitative data analysis method, cross-case analysis, to evaluate and compare agent architectures as well as modelling techniques within a range of urban simulative models. Comparison of the models uses a series of evaluating question on the merits of Agent Architecture. These merit criteria include Autonomy, Mental Mechanism / Attitudes, Adaptation / Reaction, Concurrency, Communication, Collaboration / Teamwork, Agent Abstraction, Clear concepts and Agent-Oriented. A table holds these merits as its row headings with the model names analysed forming the column heading. For a model, achieving a merit to some degree results in a point scored. For example, do the agent have communication capability? Yes(1pt) No(0pt). The method allows for the direct comparison of models not just by sum of score, but effectiveness is specific situations / merits. Unlike quantitative comparison methods, this methodology does not require a screening of inputs, validation of model outputs, determining of uncertainties, sensitivity analysis of inputs or optimisation of variables. Due to the nature of the comparison, model output comparison on the real system is not the aim but an evaluation on its nature and usefulness to the user. This enables the research to identify gaps in what current urban simulative models can achieve given their computational architecture. This also informs the definition of research objectives which revolves around implementing currently missing agent features identified through the cross-case analysis method.

The second part of the methodology, focusing on the development of simulation models, builds on the findings of the first empirical part. Discovered limitations in agent capabilities and their theoretical basis form the gap addressed through the creation of novel simulative models featuring novel complex agents. The agent architecture choices are representative of the decision-making theories and axioms used to dictate agent behaviours. This leads to the research's work in creating three simulative models featuring computerised agents demanding and exchanging space / dwellings in a simulated world. The aim is for these models to be unique in their theoretical and agent architecture framework. The architectures modelled derive from the results of the previous analysis into the current use of agent architectures in urban simulative models. The outcome of the study being a lack of representation of BDI, and cognitive agent architectures provided the challenge for creating these two architectures in parallel with a rule of inference architecture as a representative of the majority of current urban models in order to compare the inputs and outputs of all three models.

The next part of the methodology consists of demonstration. The context for this does not need to be a real-world application but rather a controlled artificial environment to demonstrate the performance of each computational agent model. In order to have a balanced platform for comparison between the models, all experiments have 12 dwelling and 24 household agents competing to move in those dwellings. At the start of every turn, the resident household will choose whether to move to a different location or remain in that household. The 12 dwellings exist across three neighbourhoods each with four dwellings and their own unique features (such as containing a park or a school or closer / further from work). These models aim to be short experiments for conceptualising new agent architectures and behavioural theories thus the number of agents and dwellings need not be in the thousands. The inputs of each model are limited to the variables each architecture requires for the dwelling and agents. The outputs from the model will consist of the price changes of the dwellings over time calculated by excess demand for a dwelling at the end of each turn. Demand will then determine if the value increases or decreases and by how much. The rate of change in price / demand and how that demand spreads across neighbourhoods and dwellings serves as the output. This allows for a comparison between the agent architectures and sensitivity / volatility of demand in each model.

The final part of this methodology is the evaluation. This comprises of observing how effective the different computational agent architectures and underlying decision-theories are at mimicking actual human decisions. This is achieved by creating and running a human role-playing simulation/game laboratory experiment with 24 participants playing assigned imaginary roles that correspond to the computer agent profiles from the three computational models. The location choice decisions of these assigned characters will allow comparison between computational agents and participant decision-making within a housing location choice process. The aim is to achieve external validity and evaluate the application of both new agent architectures and new theoretical basis for urban simulative models.

1.4 Contribution and innovation

This thesis's contributions to the literature are demonstrated by two focus areas. The first covers the empirical analysis of agent architectures/theoretical basis of urban simulative models, specifically agents making decisions on location choice. Identification and knowledge of gaps within this field reveals insight for future research that dwells deep into the fundamental level of building an urban simulation model, specifically the currently unexplored agent architectures that may provide more complex observed model behaviours. The achievement of which will aid in improving urban simulative models as tools for planners, benefitting planning practice and design in general. Secondly, the thesis includes the development of two new disaggregate ABMs to simulate dynamically, the co-evolution of urban location choice and price patterns on real estate. These models provide the means to test both fundamental economic decision-making theories and computer science architectures in respect to their performance and applicability in the field of urban modelling. Therefore, these two focus areas are further refined as contributions of knowledge in four different disciplines between urban modelling, planning and architecture, economics and finally computer science.

Contribution to urban modelling

Contributions to urban simulative modelling are two-fold. Firstly, **the empirical analysis of agent architectures/theoretical basis of urban simulative models, specifically agents making decisions on location choice offers unique insight to new and existing researchers in the field**.

Elaborating on that, in chapter three, the analysis of current urban simulative model agents is presented. Urban simulative models incorporate human systems to various degrees and scales. The interest here was solely in simulative models that include micro-simulations and agent-based interactions within their human system representations. As such, the evaluating variables for the cross-case analysis were the concepts and properties present in the agent architecture. The choice of cases cross-analysed stems from previously reviewed urban simulative model work in published reviews with the exclusion of all models with no micro-simulative aspects. This type of analysis provides a unique insight not only to what already exists in the state of art but the limitations of this area from a very fundamental level, the coded agent architectures.

Secondly, the thesis in chapter 7 demonstrates that the results gained by the experiments, question the theoretical foundations of urban modelling in two ways. **a) A different approach with an expanded theoretical and agent architecture is achievable within the field. b) It is worth exploring and is required to switch away from utility maximisation theory as the basis for decision-making agents.** Elaborating on the second point, the development of two new disaggregate ABMs (in chapter 4) to simulate dynamically, the co-evolution of urban location choice and price patterns on real estate, showcase the potential of different agent architectures. These disaggregated ABMs consist of two new and novel agent architectures in urban simulative models, BDI agent architecture and Cognitive agent architecture. The creation of these simulative models features computerised agents demanding and exchanging houses in a simulated world. The contribution revolves around the models unique theoretical and agent architecture framework and their overall performance when compared to the results obtained through the lab experiment in chapter 6. The outcome of the empirical study in chapter three being a lack of representation of BDI and cognitive agent architectures provided the challenge for creating these two architectures in parallel with a third, rule of inference architecture as a representative of the majority of current urban models in order to compare the inputs and outputs of all three models.

All outcomes and analysis of the new simulation models was validated through an active role-playing simulation. The use of people, role-playing agent roles, making the decisions between choices in the same situation/context as their computational agent counterparts in a controlled virtual environment, allows for a direct comparison of results. This adds some external validity to the computational agents created by providing an initial test of their performance. At the same time, it concludes by showcasing both cognitive and BDI agents outperforming simple logic-based agents, signifying the importance of using these agent attributes and theoretical basis in future research.

Contribution to Planning and Architecture

The work in the thesis contributed to planning practise through the introduction of new tools/improvement of current tools that can aid in the method by which they understand a situation better, allowing planners more advance methods to test scenarios by changing parameters. The first, is a model of BDI agent architecture that introduced desire prioritisation in the decision-making process of agents demanding space. Furthermore, this model incorporated individualism for the agents and the notion of subjective rationality by shifting the weightings of each desire for each agent to be unique to their perspective. To achieve this, the agent's creation drew from the theory of planned behaviour in order to calibrate each desire's appeal to the unique characteristics that make up each agent. The second tool is a model that makes use of cognitive agent architecture from the computer science as a means of including memory storage and representation in the decision-making process of agents demanding space. To achieve this, the agent's creation drew from cognitive theories that include Case-Based Decision theory and consumer behaviour theory to deal with decision-making under uncertainty and cognitive decision-making on subjective housing attributes. Contrary to existing models in the field that currently feature within a planning toolkit, these two unique urban simulation prototypes feature in two distinct ways a new method of modelling agents and their decision-making processes expanding the current utility maximization modelling techniques present in disaggregated urban simulative models. This effectively pushes the capacity of these type of simulations and unlocks the ability to answer more complex questions for the end-users which now form part of current planning practice as evident by the empirical work in the thesis.

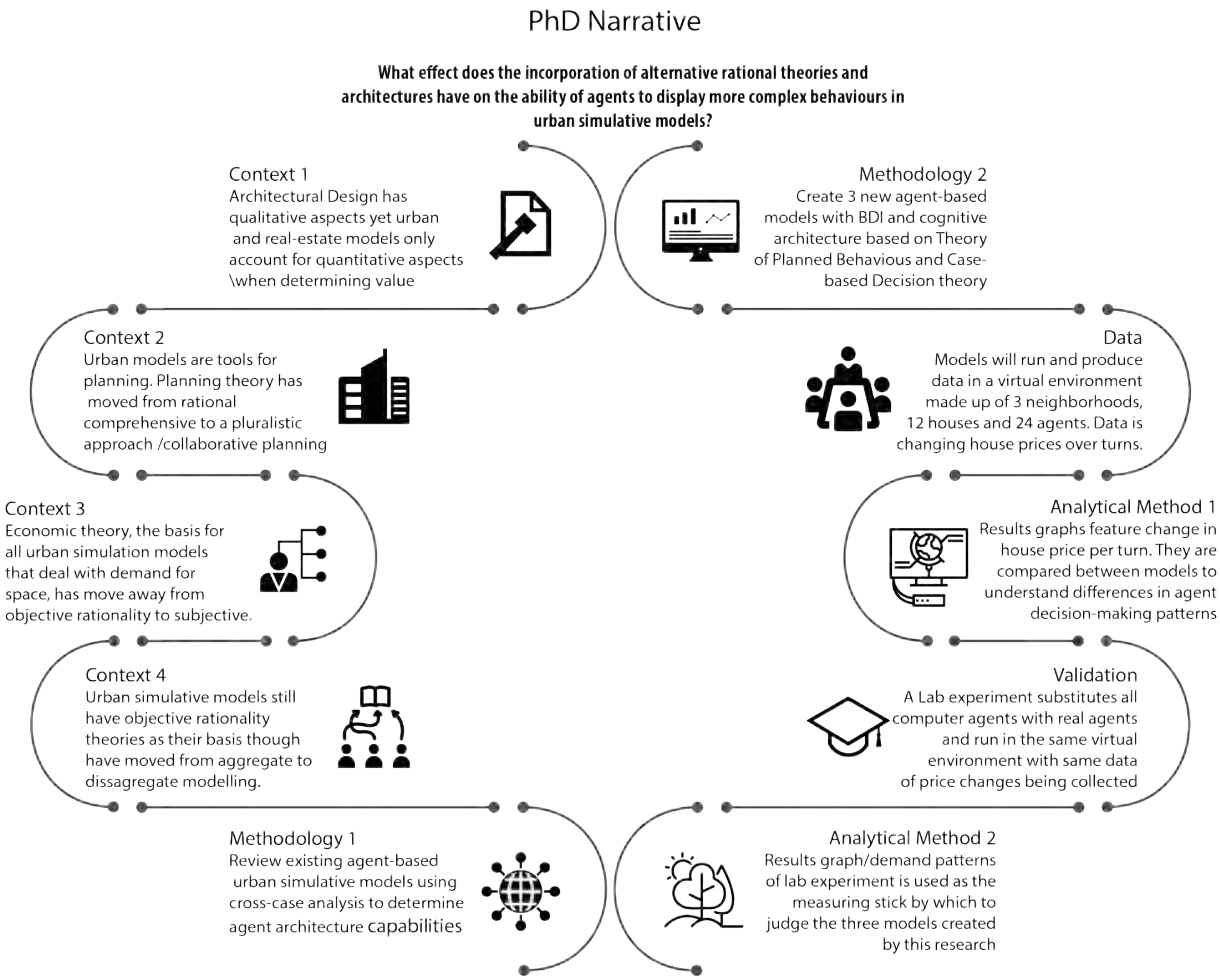
As such, cognitive agents can make decisions based on their context that favour them as individuals rather than a collective, forming different groups within the population, each with their own values and needs. This exhibited behaviour is particularly important as it has the ability to aid communicative planning practice. Cognitive agents can act as context specific stakeholders and unbiased participants of collaborative planning in "live action" demonstrations of open discourse. They can resolve conflicting ideologies without the presence of power dominance as they are untouched by external forces and only focused on their own individual needs given their unique set of context and circumstances. Thus, they allow for the testing of the means with direct indication of end goal effects on different stakeholders improving the quality of planning decisions. Beyond solutions, they can also aid with problem identification through the unbiased interaction between subjective goals/means. In a design context, this knowledge is invaluable as it provides an insight into user preference and needs making any proposal more valuable to that specific population and a better fit for that physical area/space. This design element extends beyond large scale urban planning and policy, into architectural design of buildings and their association to each other, effectively improving the value of those designs through repeat testing and identification of demand born through the subjective means and goals of the population that makes up the social context around it. Therefore, the thesis contributes to planning and architecture/design through once again through the **introduction and testing of these new computational agents which allow designers to both formulate accurate representations of problems and simulate the value of their designs beyond the objective parameters of proximity and size.**

Contribution to Economics

The work contributes to the field of economics through **the testing of different economic theories as the basis for decision-making mechanisms for computational agents vs a direct comparison with real-world decision-making agents in a controlled environment.** The application of Utility Maximisation in the context of urban modelling can be criticised given the results of this study. The research approach followed by this thesis showcased that when compared to real world human decision-makers in the same situation, some decision-making theories fared better than others. The laboratory experiment featured in chapter 6 enabled a direct testing of the performance of three decision-making economic/psychology theories when applied to the field of urban modelling. These theories tested are Utility Maximisation theory which has thus far been the gold standard in the field of urban modelling, Case-Based Decision Theory and Theory of Planned Behaviour. Out of the three theories, the analysis revealed that Utility Maximisation was the worst performing theory while Case-Based Decision Theory was the best performing decision-making theory when applied to an urban modelling context.

Contribution to Computer Science

The contribution to computer science is in the form of a research finding stemming from the **comparison of the potential of different agent architectures when applied to an urban modelling context**. The computational models created as part of this research (logic-based, BDI and cognitive) as well as the validation technique followed (active role-playing simulation), demonstrated that the performance of BDI and Cognitive agent architectures is better than logic-based architectures when dealing with decision-making agents in an urban modelling context. The analysis revealed that Cognitive Agents are the best performing architecture when applied to an urban modelling context given the parameters set out within the controlled experiments/computational models.



Contributions to Knowlege:

1) Contribution to urban simulative modelling:

I have demonstrated that the results gained by the experiments, question the theoretical foundations of urban modelling in two ways. a) A different approach with an expanded theoretical and agent architecture is achievable within the field. b) It is worth exploring and is required to switch away from utility maximisation theory as the basis for decision-making agents.

2) Contribution to Planning and Architecture:

I have contributed to planning practise through the introduction of new tools/improvement of current tools that can aid in undertanding a situation better, allowing planners to test scenarions by changing parameters.

3) Contribution to Economics:

The application of Utility Maximisation in the context of urban modelling can be criticised given the results of this study. The research approach followed by this thesis showcased that when compared to real world human decision-makers in the same situation, other decision-making theories faired better.

4) Contribution to Computer Science:

The computational models created as well as the validation technique followed, demonstrated that the performance of BDI and Cognitive agent architectures is better than logic-based architectures when dealing with decision-making agents in an urban modelling context. Cognitive agents have faired best.

Figure 2: The diagram analyses the context, methods of analysis, data, and validation that this thesis deploys as part of an overarching design science research methodology. This leads to clear identification of contributions to knowledge.

1.5 Thesis structure and organization

Apart from the introductory chapter responsible for setting out the overall research context, outlining research objectives, questions, methodology and contributions to literature, the thesis is organised in six further chapters. Each chapter builds on the subsequent to form the narrative for this thesis.

In chapter two, established research relevant to this thesis is presented to understand the state of the art and inform on potential gaps. Urban simulative models of integrated land use and transport are explored in this chapter with an emphasis on disaggregate modelling. The thesis takes a deep dive into the fundamental theories and operationalized models of theories that make up these urban simulative models analysing them using the ESU-AF1 analytical framework. This provides the prevailing theories and operational models that make up the trends in urban simulative model development. Furthermore, urban planning theories and approaches are discussed forming an understanding of end-user thinking and practical application trends. This leads to a discussion of the research direction and gaps in the literature and a formulation of both the empirical research and simulation model objectives and questions.

In chapter three, the empirical research work investigates the limitations of agent architectures in current urban simulative models. The research design and strategy for the cross-case analysis of models is defined and executed in this chapter with a series of evaluation criteria outlining agent capabilities. The results of the empirical study also make up a part of this chapter leading to an understanding of underlying gaps in model capacities due to agent coding.

The fourth chapter outlines the methodology of the simulation work. The outcome of the empirical study leads to the specification of conceptual models as part of the simulation development work outlined in this chapter. The purpose of each model, their design concepts, subcomponents, behaviours, and feedback are all defined here. The last part of the chapter outlines the implementation platform and programming language as well as the model input data for the simulation work.

The fifth chapter is concerned with describing the simulation model runs, calibrating them and outlining the results. The chapter includes the initial parameter values and number of simulations runs as well as the calibration method for the experiments. Finally, the chapter concludes with the final simulation run results and the analysis of those results in terms of price evolution.

The sixth chapter outlines a laboratory experiment of an active role-playing simulation that substitutes the computational agents with human participants. The participants role-play their given agents in the same context, deciding between the same choices. This acts as the external validity for the project by providing comparable results for the computer agents' performance to be judged on.

The seventh and final chapter of the thesis concludes with a revisit on research objectives and questions discussing what has been achieved and future directions. The chapter also includes a discussion on limitations of the research and what it will take for the work to be implemented in a practical setting with unique data inputs and potential verification hurdles.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Urban simulative modelling will form the starting point for the literature investigation as understanding the current tools and their capabilities for planning use will lead to the discovery of gaps in the knowledge. This gap being the need for improvement on the theoretical basis models as utility theory, implemented with fixed utility attributes does not fully address the complexity of human decision making with ever shifting attribute ranking in a new complexity economics framework. As mention by Brian Arthur on complexity economics, “a solution is no longer necessarily a set of mathematical conditions but a pattern, a set of emergent phenomena, a set of changes that may induce further changes, a set of existing entities creating novel entities” (Arthur, 2015).

The exploration of the urban simulative modelling literature has two facets. Firstly, the origin of these models, what they are, what are their uses range of uses and what is the exact part of them investigated as part of this thesis requires examining. Secondly, unpacking all aspects that make up urban simulative models, what are their basis, how they are placed together, requires an additional level of exploration to determine the points of intervention that any attempt at developing them will need to consider.

Following a complete understanding of all facets of urban simulative models, the final crucial aspect to investigate is planning, its roots and development both in practical application and theoretical thinking. Urban models are essentially tools for planning and their development goes hand in hand with shifts in planning theory and approaches (Batty, 2008). Any attempt to change and develop existing modelling methods and techniques must first be grounded in the shifting needs of the users, the strategic planners.

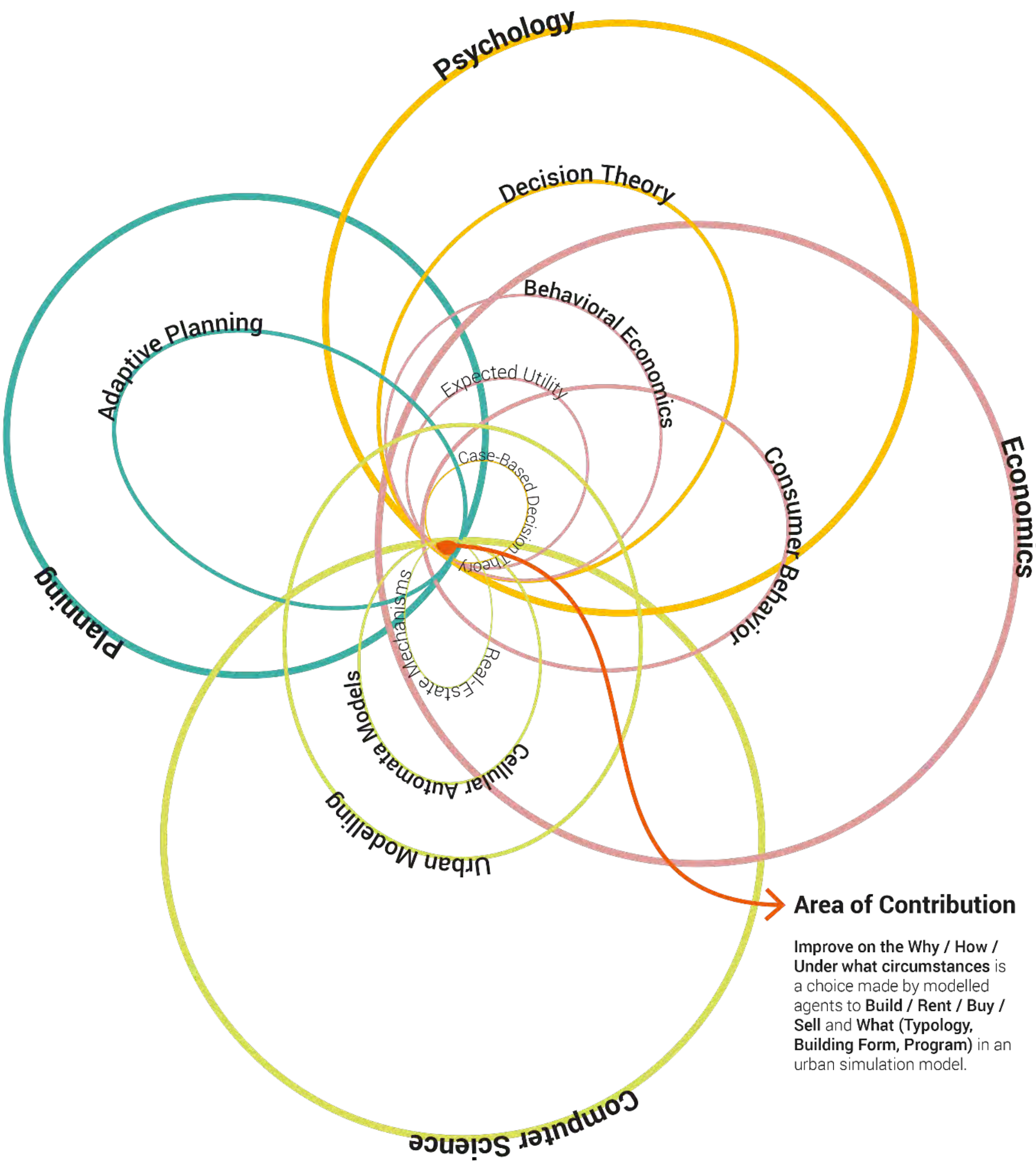


Figure 3: A visual representation of the disciplines involved in the research the area of contribution through visual representation of the various fields.

2.2 Chapter organization

The chapter is split in 5 parts as it runs a literature review of the various aspects related to this thesis and proceeds to identify gaps and formulate research objectives going forward.

The first section (2.3) introduces urban simulation, the definition and use of as well as a brief history. Urban simulation is a form of computer simulation that focuses on the imitation of behaviour in urban systems using a digital model. The simulation uses agents to represent different groups in the urban system, and their interactions with each other create emergent properties of the system. The purpose of urban simulation is to predict, educate, prove, and discover relationships and principles in urban systems. One of the forms of urban simulation is ABM, which originated in social science for understanding city dynamics. ABM focuses on interactions between agents using a set of predetermined behaviours and generates change from the bottom-up. The simulation is not used to prove theorems but rather to experiment and understand consequences from simple interactions of agents in the urban system. The research looks into the limitations of urban simulation models, particularly in the realm of real-estate demand and land value setting. The role of real-estate demand modules is critical in all land use and transport models, as they simulate the decisions of individuals who drive urban change.

Section 2.4 examines the concepts and theories governing simulative urban models (SUMs). SUMs are abstractions of the urban environment that aim to project future states and understand the effects of external influences. The review focuses on the theoretical frameworks of SUM methodologies in urban spatial planning, excluding transport aspects. SUMs rely heavily on specific theory-based inputs and understanding the development and current theories utilized within existing SUMs is crucial for exploring the potential of new uses. The study aims to explore the real-estate demand modelling module within SUMs and its relationship with the wider SUM field. The four-step process of SUMs is comprised of the formulation of a model of one or more urban systems to the simulation-based study of a specific process or phenomenon, consisting of modelling approach (MA), modelling framework (MF), urban model (UM), and urban simulation (US). The notion of operationalized models of theories is used to link theories to SUMs and explore the various theoretical basis throughout the full process of SUMs. The research uses the ESU-AF1 analytical framework developed by researchers to facilitate the incorporation of theoretical assumptions into the process of urban simulation modelling (SUM). The framework helps to identify the specific theoretical inputs at each stage of the SUM process and also helps to understand the choices made between different approaches based on operational models of the theories (OMoTs). In the example of UrbanSim, the MA involves a micro-simulation modelling approach, the MF involves discrete choice modelling, the UM involves the integration of context-specific data, and the US involves the execution of the simulation for a specific purpose. The framework was applied to a collection of simulative urban models reviewed in previous studies to understand the basis for the choice of models and the urban modelling frameworks used. This led to the discovery of trends in the literature that include both development and popularity of models over time, hierarchical decisions and associations of theory to specific OMoTs at different steps.

Section 2.5 explores urban planning theories and approaches by firstly having a short look at planning's long history dating back to ancient civilizations that sought to regulate urban layouts to prevent disastrous events such as fires and epidemics. With the rise of industrialization, urban planning became more complex as urban growth and economic and social development were no longer tied to land ownership and wealth. Conflicts between economic powers and social divisions led to government intervention in the form of urban and regional planning policies that regulate land use. The two forms of government intervention were public spending on environment maintenance and development, and reduced freedom for private landowners to protect all parties. Between 1890 and 1914, institutions of city planning and development plans at city scales emerged, especially in Germany, leading to the birth of the term "town planning." Following on from the formalisation of planning until today, there have been a series of notable theoretical approaches linked to the practice. Rational comprehensive planning is a planning theory that views communities as a collection of constantly interacting and changing patterns that form the shifting nature of society. The planner is meant to guide/control change in these relationships in a rational and objective manner, considering all alternatives and selecting the one whose consequences best fit the desired end result. Critical theory views planning as structured by the dominant power relations of society and sees planners as both the solution and the problem, serving to ensure continued production while striving to protect the exchange value of land as an investment. Neo-liberal planning focuses on better and more efficient societies, with markets viewed as the most efficient way to organize society and planning intervention seen as an arbiter for disputes. Pragmatic planning is a normative approach to planning that opens it up to a greater plurality of voices and opinions, focusing on solving issues rather than achieving goals. Advocacy planning is based on the idea that planners cannot be value-neutral and should embrace their bias, working as advocates of government and other groups while promoting competing plans from different groups. In post-modernist planning, there is a rejection of the idea of absolute truth and instead a focus on celebrating and embracing differences. The five principles of post-modern planning are social justice, politics of difference, inclusive citizenship, redefining community, and moving from public interest to civic culture. Collaborative planning, a result of post-modernism, replaces instrumental rationality with communicative rationality, where objectivity is achieved through free and open discourse among stakeholders. This discourse is guided by six characterizations, including interaction free from domination and strategizing, equality of participants, and the authority of good arguments. Collaborative planning challenges formal rationality and instead emphasizes substantive rationality, taking into account individual values and perspectives to reach agreement. The planner's role is to facilitate this discourse and accept a pluralistic orientation with multiple futures.

Section 2.6 concludes the development of planning theories and approaches and links it back to modelling as tools for planners. The development of planning approaches and modelling approaches is linked to the way city planning shapes the future. Real-estate demand models play an important role in simulating demand for specific locations but their linear relationship with agents often fails to predict multiple outcomes. This highlights the need for a more flexible approach that takes into account shifting values, meanings and actions in society. With a shift away from instrumental and formal rationality towards communicative and substantive rationality, existing modelling approaches need to evolve. The use of complex agents in simulative urban models could help address the shortcomings of traditional approaches and better suit the needs of planners. The thesis here suggests a theoretical potential for these computational agents and provides guidelines for their development.

Section 2.7 reviews previous section and discusses research directions and gaps in the literature. The focus of research in the field of urban simulation has shifted towards disaggregate modelling approaches and away from instrumental rationality in planning. This is due to the subjective nature of decision-making by individuals, which cannot be predicted through empirical generalizations alone. The shift in focus towards subjective rationalities is necessary to incorporate unique tastes and preferences of individuals in urban simulation models. Real estate demand models are a specialized part of urban simulation modelling, and they aim to place value on land and buildings in specific contexts and determine the location choice of households within the simulation. The research aims to add a subjective ontology/epistemology, originally from the social sciences, to real estate demand models. To overcome the limitations of objectivity in agent-based decision-making, complex agents with more intricate behavioural aspects are being created for disaggregate agent-based location choice models. This approach will help to understand demand, control supply, and positively influence policy.

Section 2.8 formally sets out research objectives and research question. The research aims to improve the theoretical basis of agent-based real-estate demand urban simulation modelling and the current agent architecture, with the goal of incorporating more complex agent behaviours. To achieve this, the main research objectives are: 1) classify real-estate demand urban simulation models, 2) conduct a systematic review of real-estate demand models, 3) evaluate current agent architectures, 4) build simplified computational urban simulation models, 5) run a human role-playing simulation experiment, and 6) draw conclusions. The focus is on urban computational simulation and how to incorporate more subjective rationality in the decision-making mechanism through improved agent-architecture. The main research question is: "**What effect does the incorporation of alternative rational theories and architectures have on the ability of agents to display more complex behaviours in urban simulative models?"**

2.3 Overview of urban simulation

2.3.1 What is urban simulation?

The context of this research is urban simulation. A definition of simulation is as follows:

"Simulation means driving a model of a system with suitable inputs and observing the corresponding outputs"(Bratley, Fox, & Schrage, 1987, p. ix).

Although this definition is accurate, it does not explain the variety of purposes for simulations that, according to Axelrod (2007), includes prediction, performance, training, entertainment, education, proof and discovery. There are different types of simulation. These are physical, computational and human simulation. Physical simulation involves physical objects substituted for the real thing in an attempt to imitate some aspects of reality. When those physical objects are human beings, the simulation becomes human. Computer simulation involves the creation of a digital model and is concerned with the imitation of behaviour from one or more groups of entities called agents (Davidsson & Verhagen, 2013). This research will focus only on computer simulation.

2.3.2 Who uses it and why?

In the field of urban planning, simulation exists for the purpose of prediction, proof, education and discovery. A prediction simulation helps improve or validate the theory the simulating model is based on. Proof simulation investigates concepts such as Wolfram's (1994) CA simulation model proving that complex behaviours can arise from a set of simple rules. Discovery simulation aims to discover important relationships and principles that may exist in the urban systems. In an education simulation, the user learns the relationships and principles himself by testing how a change in some variables can affect the outcome. All of these types of simulation are essentially tools for planners that can help them improve their policy-making process. References to urban simulation and modelling in this research fall in the computer simulation definition that includes the above purposes.

2.3.3 How is it used as a scientific method?

Unlike inductive and deductive research methods, a simulation does not prove theorems. Much like a deductive approach, a concrete set of assumptions forms the basis of any simulation. The model's theoretical basis generates these assumptions. The output of the simulation is a set of data that can be analysed inductively (Axelrod, 2007). The difference between simulation and inductive research is the origin of the data, the latter being from real world observations and the former generated from a specified set of rules. Simulation is essentially a means of experimenting to help understand consequences at a large scale arising from simple locally interacting agents. These effects are called "emergent properties" of a system and are often surprising as they can be the consequence of the simplest form of interaction (Axelrod, 2007).

2.3.4 What are the origins and examples of urban simulation?

"Agent-based modelling" is a fundamental type of urban simulation and the focus of this research. It includes a range of agents interacting with each other using a set of predetermined behaviours. Depending on the simulation's research aim, the type of agents used may differ. Each type of agent has a different set of behaviours (Gilbert, 2008). The interactions between the different agents generates the emergent properties of the system while driving change from the "bottom-up" rather than imposed from the "top-down".

When trying to identify the origins of ABM, the question arises of how far back to go. On one hand, it begins with the invention of the computer. The word itself was first recorded in 1613, referring to a person that did calculations. Although the first mechanical computer was invented in 1837 by Charles Babbage called the analytical computer, what we would call a computer today was not invented until 1938. Created by Konrad Zuse, the Z1 was the first electro-mechanical binary programmable computer. From then on, following the theories of Alan Turing and his proposition of the Turing Machine, the industry took flight to what we now know as the modern computer in the form of PC, Mac, IPads, and Smartphones. On the other hand, models do not need to be computerised. A model can exist in a non-digital platform and its computations calculated by a person rather than a machine. This point is made clear by Harris (1965) when he talks about new tools for planners. He does however explain how the invention of the modern computer can help the planner in making decisions by being the "servant of the planner and the extension of his personality" (B. Harris, 1965). If we are to take a functionalist view on planning, ABM is the latest demand for answers to questions that cannot be answered through other means.

When tracing back through all ABM, one of the initial applications of them was done in the field of social science. Particularly in investigating and understanding city dynamics (Chen, 2012). Originally in the form of 2 dimensional grid models called checkboard models, the work of Sakoda's (1971) originally unpublished doctoral dissertation in 1949 (Sakoda, 1949), formulates one of the first computerised attempts in ABM. Sakoda created a grid of 8x8 checkboard as the field of social interaction with the rows numbered from top to bottom and columns from left to right creating a total of 64 cells. He then added 2 sets of 6 pieces, a cross and a square to represent 2 different social groups. The initial position of the groups was at first random on the board with each member of the group having 2 sets of values attached to them that could be either positive, negative or neutral. These values represented the agent's attitude towards other agents of both groups. The model was turn based, with each turn ending when agents of both groups made one move each at random orders. The movement of agents was based on their attitude towards each other and with the ability to go up, down, right or left by one cell or stay in the same cell depending on which was more advantageous to the agent (Sakoda, 1971). The description of the model actually depicts a CA model; however, checkboard models were not classified under the CA framework until 1975 by economist Peter Albin (1975). Following Sakoda, the work of Thomas Schelling (1971) in dynamic models of segregation is another early example of the use of CA models in social sciences. This study however is more about understanding the dynamics of movement rather than the interaction of the agents themselves.

2.3.5 Cellular Automation

The origins of CA models did not begin with these first attempts, as its roots are purely biological. Thomson (1917) in his work on growth and form, from a biological / physics perspective, talks about cell-division and intra-cellular phenomena as the result of conflict between surface-tension and its opposing forces. He explains the cellular growth as a natural rather than computational process. Theorization of organic development simulated computationally was not thought off until the pioneering work of Alan Turing and John von Neumann. Though Turing (1952) theorised on the mechanics of genes determining the anatomical structure of the resulting organism, it was Von Neumann in his work on the general and logical theory of automata who explains the first rules of CA. Though he references Turing's work, he explains how computing automata works (Neumann, 1957). His later work on the Theory of Self-Reproducing Automata (Neumann, 1966) acts as a continuation of those rules and theories.

A Cellular automation is an ABM whose agents are arranged in a specified grid of either one dimensional row, two-dimensional rectangle or three-dimensional box. Each agent adopts a space on the grid and acts as neighbour to other cells both occupied and unoccupied by other agents. The agents follow strict network-based decision rules meaning the actions of individual agents is based on decisions affected by their respective network. The network can be both local and global, but the tendency of cellular automation is to have local networks weigh more than global networks in agent decisions. A turn in a CA model is defined as all agents making a move once. That move may be to move, remain, change or die. The base rules determine how the agent behaves in a variety of neighbour proximity scenarios.

Though the idea of CA originated, from a computational standpoint, in the 1950s, it wasn't until the 1970s when scientist would use the framework for the testing of theories and decisions. An early notable example of the generative capabilities of this model framework was by John Conway and his game of life. Published in 1970s by Martin Gardner (1970) in Scientific America as part of his mathematical games column, Conway's work showed the generative capabilities a grid based model with simple network rules can have. The patterns arising from different starting points began to intrigue scientist in a plethora of disciplines both in hard and soft sciences.

This was especially prevalent in urban studies as cities began to be viewed as complex adaptive systems (Ulysses Sengupta, 2017). Urban dynamics are driven by collective behaviour, where many urban actors' decisions build on previous decisions made by other urban actors (Portugali, 2006, 2018; Portugali & Haken, 2018). CA’s connection to complexity theory was defined more clearly in a series of papers by Stephen Wolfram. His contribution in the class of CA which he named elementary CA (Wolfram, 1994) combined concepts from dynamic systems. In doing so, he classified models into four classes:

I) Stable / uniformity
II) Periodic Oscillation
III) Chaotic
IV) Complex Patterns of behaviour

His discovery of unexpected complexity behaviour in Classes III and IV arising from simple rules (Chen, 2012) began the suspicion of complexity in nature also originating from simple mechanisms. This understanding has allowed for the evolution of simple agents in ABMs for a variety of areas, especially in the urban simulation area.

2.3.6 Cellular Automata in geographical modelling

The first proposed application of CA models in geographic modelling was made by Tobler in his 1975 working paper titled cellular geography. With the evolution and availability of computer systems in the 1980s came the first theoretical approaches to simulating urban systems with CA-based models (M Batty & Xie, 1994; Michael Batty, 2000; Clarke et al., 2005; H Couclelis, 1985; Helen Couclelis, 1989; Engelen et al., 1995; X. Li & Yeh, 2004; Tan et al., 2005; Waddell, 2000a; White et al., 1997; White & Engelen, 1997; Wolfram, 1994; Wu, 2002; Xie, 1996; Yeh & Li, 1998). These modelling methods have developed further during the late 90s and early 2000s as the understanding of the dynamics of urban landscapes advanced. Simple interactions between physical, socio-economic and human factors where the triggers of urban dynamics (Batty, 2005). The interactions included decisions on urban development locations, infrastructure construction, environmentalists' nature protection and top down planning policies (Tian et al., 2016). This has led to define one of the urban modeller's objectives; a landscape system with a variety of environmental characteristics and a self-evolving mechanism independent of human control in order to co-evolve with human systems (Russell & Norvig, 1995).

2.3.7 Current use of ABM in Real Estate Demand models

The focus of this PhD and its aims can be narrowed down to the understanding of demand for forms of build environment in specific location and situations with real estate demand models. This research is not the first to attempt such a thing. Spatial interaction models have incorporated modules that deal specifically with market forces of demand. I-city, for example, determines the value of a plot based on its proximity to other land-uses and amenities (Stevens et al., 2007). This can be classified as a macro-level decision-making simulation, due to the lack of the micro-level interactions that are responsible for driving market forces. The model depicts high-level pattern recognitions of market results. Such models fall in the same trap as many CA-based models that follow strict CA-Theory, which states that emergent phenomena are the product of local interactions. This means that they give no regards to anything happening outside their immediate neighbourhood (Batty, 2000). The macro-level emergent phenomena modelled remove a fundamental aspect of complex systems. The status quo of complex systems is constantly being interrupted with new inventions and innovations. Phenomena such as these cannot be easily modelled through equations and can be best described through the evolutionary dynamics that shape them. Wolfram's vision of simple rule modelling saw these complex dynamics modelled through simple rules; however, they lack the power to explain the actual micro-level decisions driving these changes.

That constitutes a challenge on value setting methodology for land in spatial interaction modelling. An attempt to model development market processes came from Waddell & Ulfrarsson (2003) through the use of a discrete choice real estate development model. This was incorporated with a hedonic regression land price model for the Greater Wasatch Front Area of

Utah. This is part of the CA-based UrbanSim model. This approach incorporates 2 types of models – land price model and real estate development simulation. Both components are based on Random Utility Maximisation theory, hedonic price theory and bid-rent theory of land markets. Real estate development is firmly based on utility maximisation. The assumption is that each cell has a developer and that all possible developments are assessed at each turn. The ones with the highest utility are then selected to be developed in that year (Waddell & Ulfarsson, 2003). The results of this component, in additions to residential location, employment location and external transportation model system, form the yearly changes of the grid cell characteristics. These characteristics become the simulated land prices that influence next year's development decision-making behaviour on location choice.

Microsimulation systems exist in other models such ILUTE (Miller & Salvini, 2001; Systems et al., 2003) and ILUMASS (Moore, 2000). Within these models, there have been attempts to incorporate real-estate pricing modules. These are different from previous aggregate model systems (Barra, 2005; Echenique et al., 1990; Hunt & Abraham, 2003; Putman, 1979). Although progress in disaggregated modelling of urban systems such as residential location choice, business location choice, real estate supply and workplace choice has been encouraging, improvement on realistic price interaction in real estate demand has seen little progress (Wang & Waddell, 2013a). Models such as the Regional Economy, Land Use and Transportation Model (RELU-TRAN) system relies on a Computable General Equilibrium (CGE) framework (Anas & Liu, 2007) working on the assumption of price changing to meet supply and leave no real-estate unsold. It generalises by creating a set of homogenous agents of same tastes and requirements.

This way of thinking has been heavily criticised especially as ABM approaches see the future firmly embedded in heterogeneous agent with spatial resolutions fit for policy interventions. Other attempts at modelling price within an urban simulation was through Zhou and Kockelman (2008). Their use of survey datasets for people moving house in Austin incorporating data such as income, house price and travel cost to workplace added a more realistic view. The model is rooted in random utility maximisation theory when it comes to location choice for agents. Although the theory helps simulate some of the complex behaviours in human decision-making, it also falls in the trap of homogenising taste between agents. Another critique of the model revolves around the lack of consideration in cross-elasticity between alternatives. Price change in one does not only affect demand for its alternative but of other alternatives in the alternative's set (Train, 2003; Wang & Waddell, 2013a). A way to solve the short-term price adjustment for achieving unrealistic equilibrium was solved in Wand and Waddell's model of Disaggregated Real Estate Demand (2013a). This has allowed for a more realistic representation of the price mechanics in the real estate market by keeping supply fixed in the short-term. The model uses a Random-Utility Maximisation theory framework when dealing with agent decision making. The theory seems to be consistent with many land value-setting urban integration models.

2.3.8 Land use models of urban location choice: Emphasis on disaggregate models which forms the area of research for this thesis.

The research investigates the theoretical limitations behind a specific range of urban simulation models. This particular range involves the setting of value and demand for land. For the purpose of grouping these types of models under one term, the thesis uses the name “real-estate demand model” to describe all value-setting urban simulation models. These have relevance to urban planning, architecture and urban modelling. Real estate demand models are important in urban simulation because they form the link between land value and change in specific locations and conditions. They are important in urban planning because the outcome of these models, run repeatedly with a range of alternating parameters, allows for a better understanding of the range of effects a specific decision in policy can have.

The research will compare existing applications of real-estate urban simulation models, not to the real world, but between alternative model versions. The aim is to identify the limitations of each simulation version based on the different types of agents it consists of. The differences in agent types stems from the theories the simulation is based on. The research will expand on this knowledge by basing agent behaviours on an alternative range of behavioural theories. The conclusion of the research will be a theoretical urban simulation model capable of subjective research and non-deterministic outcomes in the area of real-estate demand / land value setting.

2.3.9 What is the current literature surrounding real-estate demand urban simulation models.

There are multiple disciplinary and theoretical overlaps associated with this type of models such as computer science, psychology, behavioural economics and planning. They require a broad literature understanding of theoretical frameworks and concepts across multiple disciplines that deal with agent decision making. The research explores different theories that form the basis for real estate demand models. The theoretical basis in simulative models directly dictates the behaviour of the agents coded. This is due to simulation models having an alternative ontology and epistemology compared to social and natural sciences research. Entities within the simulation represent abstractions or interpretations of reality according to a theory. The simulation runs and the outcome tested against reality in order to gauge the accuracy of the model and understand the limitations of the theory. There is no standard way of creating an ABM for social simulation. Each model has a different purpose, as specific agent architectures are determined for specific research purposes.

At present, real-estate demand models have yet to achieve reality-testing state. The current state of real-estate demand models has provided planners with a platform for predictive and proof simulation. The objective nature of these theories translates to deterministic decision-making mechanisms for coded agents. This limits the effectiveness and possibilities for such models by not allowing the consideration of alternative outcomes and discovery of possible complex relationships arising from chaotic agent behaviours.

2.3.10 The role of demand modules in land use and transport models

If we consider the beating heart of the urban realm to be the people that inhabit it, then all attempts at modelling it, be it a Land-Use Change model, Land-Use and Transportation integrated model, Land-use Cover Change model or Urban Growth model, revolves around the abstraction and simulation of those people. The scale of this varies depending on the model and whether it falls within the macro (aggregate) or micro (disaggregate) modelling framework. The interest for this thesis is primarily the latter and its use of ABM to be exact. However, if we consider notions of self-organisation and emergent from a complexity perspective, applied to the urban realm (Batty, 2012; Batty & Marshall, 2012a; Portugali, 2006), then urban change is driven by the chaotic interactions of people, self-organising following some type of top-down or external influence and subsequently resulting in the emergence of a new urban pattern. In all models previously mentioned, the decisions of these individuals, whether modelled as households, developers etc. or even at an aggregate scale as a collection of individuals, defines any change that occurs within them. Therefore, these real-estate demand modules are an extremely important part of these models and exist in all of them. Investigating historic and current trends in these wider urban models will reveal the development of real-estate models as well as their limitations.

2.4 Urban simulative models: concepts and theories

Simulation models of the urban environment are abstractions of reality that seek to mainly project future states in an attempt to understand the effect of external influences upon the urban realm. Though models vary, the driving force of this change are generally bottom-up interactions or a general rule of law that describes them. Investigating the concepts and theories governing this driving force as well as wider urban model functions will be pivotal in understanding the state of the art for real-estate demand models that act as modules in many of these wider urban models.

2.4.1 Unpacking Urban simulative models

Definition of Simulative Urban Model (SUM) in this Study

There is no consensus on the use of terminology for **simulative urban modelling** as various terms are used to describe a similar set of 'models' within existing literature. These range from 'urban simulation', 'model' and 'modelling package' to 'modelling framework'. Within this research a broad term 'simulative urban model' (SUM) is used to refer to the whole set of spatially explicit and temporally dynamic models of urban systems. These simulative urban models included Land-Use Change, Land-Use and Transportation integrated models, Land-use Cover Change and Urban Growth models. All of which are of interest to this research as they use modules within them that deal with household location choice or, as coined in this research, real-estate demand models.

What was reviewed

Urban models incorporating simulation implicitly or explicitly incorporate theories at various points. The assumptions incorporated from these theories can bias or limit model-based approaches to different degrees. This part of the literature aims to review the range and point of incorporation of theories within 'Simulative Urban Models' (SUMs). The focus in this review is specifically on the theoretical frameworks of SUM methodologies focusing on urban spatial planning, but not including transport aspects. The research does not examine the application of existing simulation models to new contexts. Instead, it traces the use of theories within SUM methodological development over time to understand their role. There are a number of current operational 'computer-based geographical simulative urban modelling frameworks' being used to support urban spatial planning (Waddell, 2000b; Wegener, 2004), reflecting the range of theories utilised. In order to contextualise theoretical frameworks in urban modelling, the research purposefully incorporates methods and theories borrowed from other disciplinary areas.

Why it is important.

Computational urban models have moved on from the initial experiments testing hypotheses based on existing theories of cities. With the move away from aggregation-based models, and the popularity of data based simulative approaches, SUMs have increasingly embraced bottom-up approaches and decentralised urban dynamics (Batty, 2009a). Despite this shift away from tests on generalised theories of cities, the configuration of SUMs still relies heavily on specific theory-based inputs at multiple levels. As an example, simulation-based approaches on the generation of unknowns in 'artificial cities' (and societies) are dependent on the integration of theoretical frameworks and theoretical urban dynamics (Wu, 2002). Hence, any attempt to explore the potential of alternative and new uses needs to be based on a comprehensive understanding of the historic development and current theories utilised within existing SUMs. Due to the inter-disciplinary nature of urban spatial planning, changing use of theories needs to be researched as a co-occurrence with methodological approaches integrated from other disciplines to a land-use change context. The aim of this research is to explore a very specific module within the SUM field, that of household location choice or, as coined in this research, real-estate demand modelling. In order for this module's development and current state in literature to be understand, the research must understand not only its role within a wider SUM but also the development of SUMs in general as they directly influence the choice of modelling approaches taken at the household demand module level.

Unpacking Simulative Urban Models

SUMs can be understood as a four-step process (Figure 4) - from the formulation of a model of one or more urban systems to the simulation-based study of a specific contextualised process or phenomenon - consisting of:

1. Modelling approach (MA)
2. Modelling framework (MF)
3. Urban model (UM)
4. Urban simulation (US)

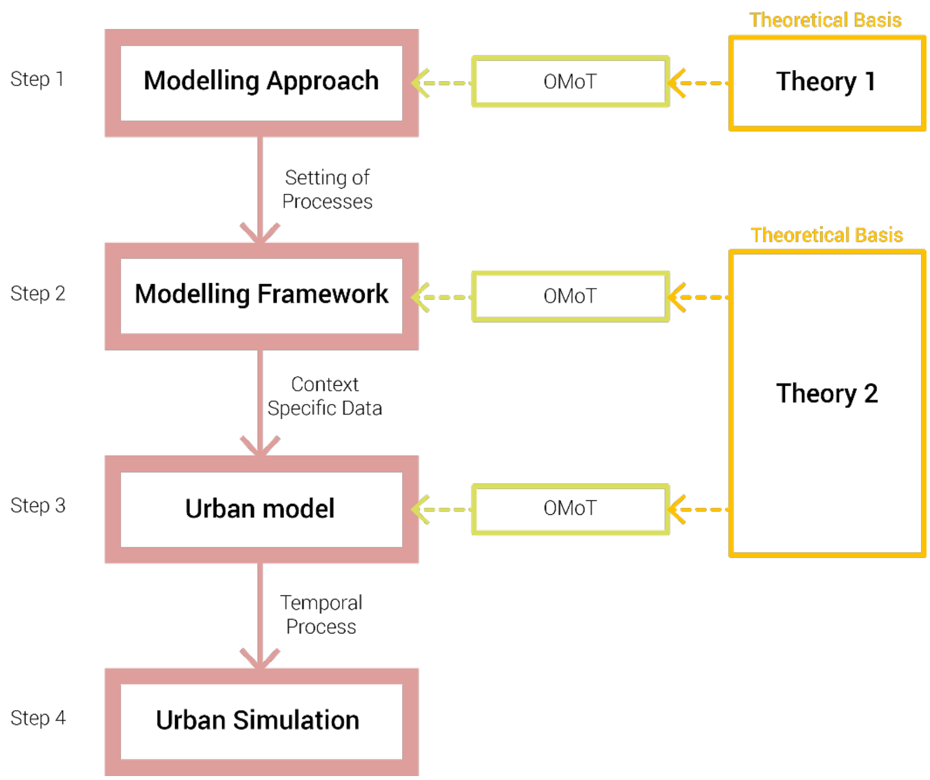


Figure 4: Four-step SUM model related theories through OMoT (operationalised models of theory)

Definition of Operationalised Models of Theories (OMoT) in this Study.

The formulation of a modelling approach (MA), modelling framework (MF) and urban model (UM) includes theories that guide how they are specified. This relationship between theory and SUMs has been explored previously. In contextual literature, a notion of the 'conceptual model' has been used in wider simulative modelling approaches to refer to the relationships between theoretical-conceptual, computer-simulation and target (real) systems (Sargent, 2013). The notion of 'embodiment of theory' is also used, when SUMs are discussed within a deductive reasoning context where a 'model represents some embodiment of theory'. This is the case for both parts of SUMs and SUMs as a whole, but primarily for the former (Batty, 1992). While both notions provide valuable avenues to link theories to SUMs, they are not appropriate - in the context of the aim of this study - to explore and map the various theoretical basis against the full process of SUMs from formulation to simulation. The researchers of the ESU-AF1 framework (made up of Ulysses Sengupta, Eric Cheung & this researcher) utilise the term 'Operationalised Models of Theories' (OMoT) (Figure 4) to facilitate a closer link to specific steps of the SUM process. OMoT refers to a set of theoretical concepts that are 'operationalised' in relation to each step of the four-step SUM process. A wide enough definition of operationalised is allowed in this context to incorporate a variety of theories. OMoT refers to elements involving translation of theoretical concepts into any form that can be mathematically or algorithmically modelled.

2.4.2 The ESU-AF1 analytical framework

As the incorporation of theoretical assumptions can occur at various points in a SUM, the aforementioned three researchers (one of which is the thesis author) developed an analytical framework 'ESU-AF1' (Figure 5) consisting of *four steps* and related inputs. ESU-AF1 facilitates the identification of specific theoretical inputs at each stage of the SUM process. These are positioned alongside the specifications of the model dynamics and contextual detail at each stage.

Step (1) of ESU-AF1 consists of the modelling approach (MA). This step consists of the overall model considerations in terms of type of model and its fitness for purpose. The MA requires choices to be made between different approaches based on OMoTs such as ABM versus Input-Output Model. This step sets the framework and limitations for all subsequent steps. Step (2) of ESU-AF1 consists of the Modelling framework (MF). This step specifies the operations (relations and interactions) between the parts of the UM. The MF consists of the set of assumptions on what elements exist in the model, how many exist and how they interact with each other. These theory-based assumptions - such as Location Theory assuming proximity to town centres affects land-use - are translated through OMoTs. Step (3) of ESU-AF1 consists of the Urban model (UM). This step incorporates context specific datasets to create the details required for the operation of one or more OMoTs in a particular location, situation or geographic context. These datasets are integrated through the use of mathematical models. Step (4) of the analytical framework consists of the Urban simulation (US). This is the step in which the computational aspect of the SUM is executed - over time and for a specific purpose - based on the previous specifications.

As an example, UrbanSim (Waddell et al., 2003) can be understood using ESU-AF1. The MA consists of a micro-simulation modelling approach, the MF involves discrete choice modelling, the UM refers explicitly to the step incorporating context specific data such as for the application of UrbanSim in the Puget Sound Regional Council (PSRC) land use model of the Puget Sound region in the United States. In the final step of ESU-AF1, i.e. US, the PSRC land use model is used for land forecasting through simulation.

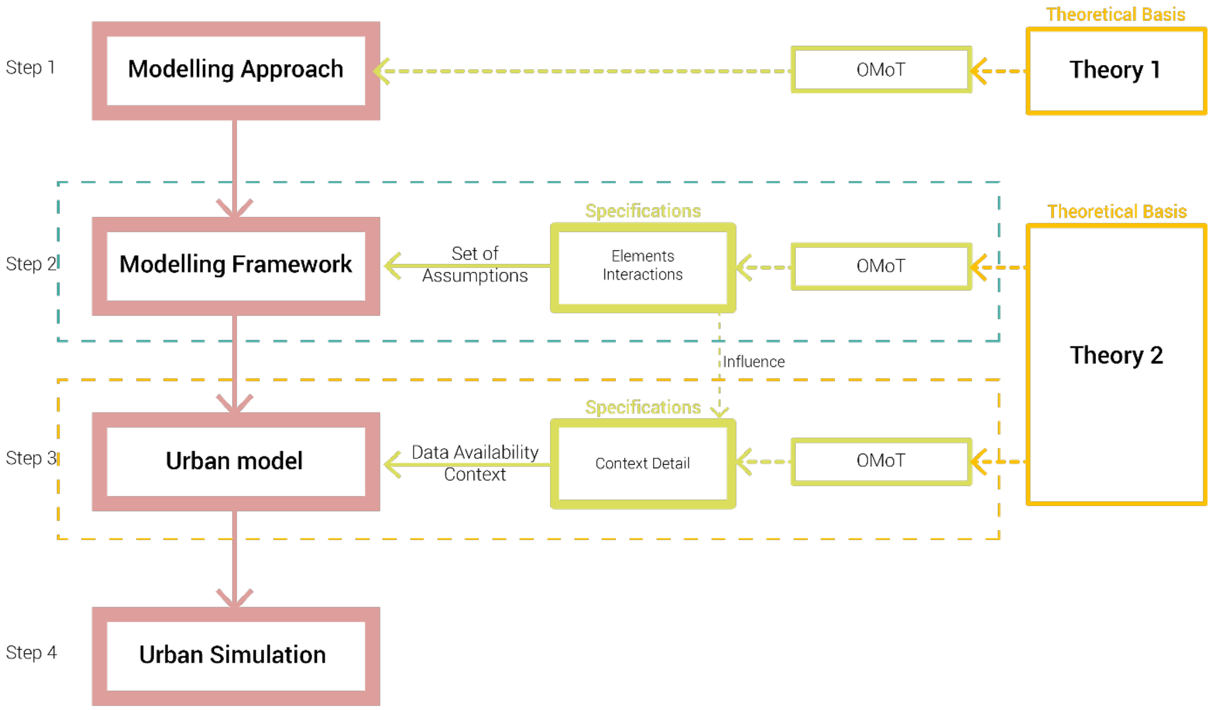


Figure 5: The ESU-AF1 Analytical Framework

There have been over twenty reviews of SUMs within the past fifty years. Three of these had a focus on operational urban simulation models. Wegener (2004) reviewed twenty operational models, Iacono et. al. (2008b) included reference to over twenty models and Silva et. al. (2012) reviewed over sixty models. The reviews provided insights into the shifting trends in modelling approaches and the broad theoretical basis or associations. The researchers of the ESU-AF1 framework (one of which is the author of this thesis) used a collection of simulative urban models featured in the three aforementioned past reviews, analysed through the ESU-AF1 in an attempt to decipher the basis for the choice of models and include a unique collection of different urban modelling frameworks. These simulative urban models included Land-Use Change, Land-Use and Transportation integrated models, Land-use Cover Change and Urban Growth models. The table below list all urban simulative models taken from these reviews.

Name	Author	Year
BabyLOV	White, Straatman and Engelen	2004
Boyce model	Boyce et al	1983
CATLAS	Anas, A	1987
CLUE	Verburg et al	2001
CLUE-S	Verburg et al	2001
CommunityViz	Kwartler and Bernard	2001
CUF	Landis	2001
CUFM	Landis	1992, 1994
CURBA	Landis	2001
CVCA	Silva, Wileden and Ahern	2008
DELTA	Simmonds and Still	1998
DG-ABC	Wu and Silva	
DUEM	Batty, Xie and Sun	1999
FEARLUS	Polhill, Parker, and Gotts	2005
GEOMOD2	Pontius, Cornell and Hall	2001
IIASA	Fisher and Sun	2001
ILUMASS	Strauch et al	2005, 2007
ILUTE	Miller et al	2001, 2004, 2005
ILUTP	Putman	1983
IMREL	Anderstig and Mattsson	1991
INDEX	Allen	2001
IRPUD	Wegener	1982, 1998
ITLUP	Putman	1983
Kim model	Kim	1989
LEAM	Deal	2001
LILT	Mackett	1991
LOV	White,Straatman and Engelen	2004
Lowry model	Lowry	1964
LTM	Pjanowski et al	2000
LUCI2	John	2005
LUCIM	Hoffmann, Kelley and Evans	2002
LUCITA	Lim et al	2002
LUSD	He et al	2004
MALUT	Kii and Doi	2005

MEPLAN	Echenique	1990
METROPILUS	Putman and Chan	2001
METROSCOPE	Larson,Cser and Conder	2000
METROSIM	Anas	1982, 1994
MUSSA	Martinez	1997
PECAS	Hunt and Abraham	2003, 2005
Place3S	Snyder	2001
PLUM	Prastacos	1985
POLIS	Prastacos	1986
PUMA	Ettema et al	2005
RURBAN	Miyamoto et al	1986
SAM-IM	MAG	
SIMPOP	Sanders et al	1997
SLEUTH	Silva and Clarke	2002
SLUDGE	Parker and Najlis	2003
STASA	Haag	1990
STIT	Nuzzolo and Coppola	2005
SYPRIA	Manson	2005
TLUMIP	ODOT, Weldner et al	2002, 2006
TRANSIMS	Barrett et al.	2002
TRANUS	de la Barra	1982
TRESIS	Hensher and Ton	2001
UED	He et al	2008
U-Plan	Walker et al	2007
UrbanSim	Waddell	2002
What if?	Klosterman	2001
WiVsim	Spahn and Lenz	2007

Table 1: All urban simulative models that have been analysed for identification of OMoTs.

Once the dataset was completed, the next step included the identification of supporting operationalised models of theory that comprise set simulative urban models. Operationalised models of theory (OMoT) are all sub models with specific actions that together are responsible for all operations run within a simulative urban model. This process required the reading of all data sources and the careful extraction of all information relating to OMoT.

The identification of theoretical basis / theories that make up OMoTs were selected using two methods. The first method is the extraction of theories explicitly stated in the data document. The second method is theories deduced through the identification of OMoTs that have a set theoretical basis. For example, an economic base model has a theoretical basis of economic base theory and equilibrium theory as the application of it requires that specific perspective on the world.

The identified OMoT and theories were analysed by the researchers in terms of their input in simulative urban models through the ESU-AF1 framework. Each operationalized model of theory has a specific purpose viewed as part of four distinct steps. The first step on ESU-AF1 named modelling approach consists of the most abstracted or overall model considerations that dictates how the urban simulation will work. It includes such OMoT such as ABMs and Input-Output Models. Everything positioned at this level serves the purpose of setting the framework in which all subsequent OMoTs and theories abide by. They are essentially the initial decisions taken when creating an urban modelling framework that serve as the overall description of the type of urban simulation to be undertaken.

The second step includes everything that is specific to the operation of the simulative urban model’s components. These exist at a modelling framework level as the operations that drive change in physical space, activity allocation, human behaviour and socio-economic factors. They are specific to both the action they represent and the choice of step 1 OMoT and theories. The set of assumptions on what elements exist in the model, how many exist and how they interact with each other, are prescribed by the OMoT and theories at this step. It is also worth noting that at the modelling framework step, everything is yet without context that means all equations exist with no specific values but rather with coefficients/abstract constants. The type of coefficients, set by the type of OMoT used, indirectly affects the choices made at step 3.

The third step OMoT and theories exist on the urban model level. They work with the context specific datasets in order to create the context details required for the operation of the OMoT set at a modelling framework within this specific situation. These are primarily comprised of mathematical models.

No OMot or theories exist on the fourth step, the urban simulation. This is due to that step referring to running the model over a specified period thus time being the fundamental consideration of this step.

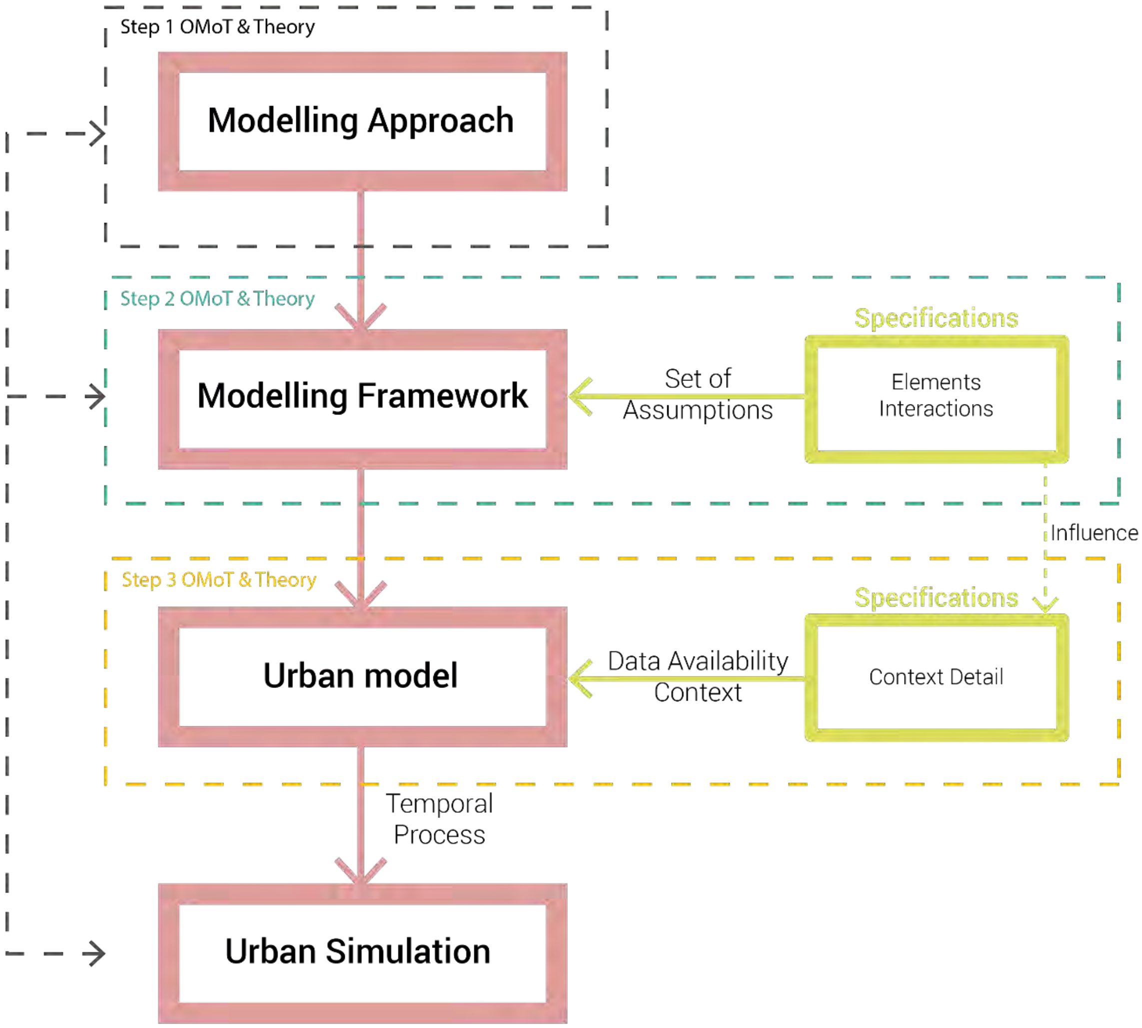


Figure 6: The ESU-AF1 analytical framework showcasing the inclusion of assumptions and data at different steps.

2.4.3 Prevalent theories forming the basis of urban simulative models.

The research and analysis of set model revealed a detailed theoretical breakdown of the models used within them, offering an opportunity to re-examine the work done so far. The identified underlying theories for urban modelling frameworks consist of location theory, micro-economic theory, entropy maximisation, random utility, bid-rent theory, utility maximisation, expected utility, general equilibrium theory, input-output theory, rational choice and economic base theory. This section briefly examines the theories to understand their origin, their use in urban modelling framework and their limitations / assumptions.

Location Theory

Location Theory concerns itself with the geographical concentration of economic activity (Christaller, 1933). Its fundamental assumption is that of people acting in a way that maximises their utility. Losch (1954) deduced this general principle mentioning that, the selection is made when nowhere else does the individual feel better for his choice in terms of cost of moving and loss of surroundings. This also applies to firms in two ways, one is the firm's decision to maximise profit through location choice and the second is the entrepreneur's choice to maximise their utility be it profit or otherwise (Losch, 1954). In an urban modelling framework, the use of theory comes in the form of coded agent decision-making on location choice. An agent takes into account all alternatives and decides on a location purely based on maximising their pre-set utility criteria. This may also be aggregated at a macro-level with location theory acting as reasoning for a mass change in aggregated behaviour.

Micro-economic Theory

Micro-economic theory deals with understanding how individuals and small groups make decisions given a set number of parameters or limitations such as income constrains (Macmillan, 2008; Mas-Colell et al., 1995; Varian, 2010). The theory is broken up into five separate elements. The first is consumer choice of specific goods or action under certain conditions. The second deals with firms, business, and their decisions on type of good production, quantity and price. The third consists of consumer and firm interactions with a focus on how their actions are associated with market changes. The fourth element deals with the demand and supply of production inputs such as labour and raw materials. The last element is that of welfare economics and market efficiency. Agents in urban modelling frameworks base their decision-making on this theory, especially in situations presenting both monetary and non-monetary opportunity costs.

Entropy Maximisation

Entropy Maximisation originates from the principle of entropy, a cross between information theory and statistical mechanics with the purpose of contesting conventional probability theory when assigning an initial probability distribution (Jaynes, 1962). One of the first uses of the theory for urban research was by Wilson (1967). Instead of basing change in an urban setting to human behaviour, the use of entropy maximisation provided a higher scale theoretical justification for spatial interaction models (Wilson, 1970). This allowed for the development of a varying degree of both constrained and unconstrained models of spatial interaction (Ledent, 1985). Its use in urban models has been as an alternative to the direct modelling of agent decision-making.

Random Utility

Random Utility is part of the wider Utility theory concerning itself with determining what decision an individual will make given a set of alternatives. Originally, the theory is based on the random utility model for qualitative choice behaviour developed by McFadden (1973, 1978). The distinction in random utility is the separation of total utility to deterministic and random components of the function (Ben-Akiva & Lerman, 1985). The deterministic aspects, also known as systematic, are representative of the individual’s own preferences while the random components acting as disturbances. These disturbances make up the unique element of this branch of utility theory as in many other applications they are given a value of zero. In an urban model, random utility helps include any unobserved quality associated with an individual’s set of alternatives such as unobserved qualities with the neighbourhood (Bayer et al., 2004).

Bid-Rent Theory

Rent theory started with Adam Smith contemplating on the relationship between rent and the produce of the land. The cost of production and the revenue from the product all determine what the tenant can afford to pay the landlord for rent of the land (Smith, 1776). Following on from this work, David Ricardo (1817) expanded on it adding capital and interest considerations while keeping the same view of rent being a portion of the produce of the land. The theory later evolved in combination with location theory to bid-rent theory to include the relationship between distance from town centre, values of products and land and ground rent (Von Thünen, 1863). Bid-rent theory is therefore concerned with how price and demand for space changes with the land’s distance from central business districts. Retail establishments seek to maximise profit through proximity to business centres, which pushes both demand and price for the land higher. The assumption of the theory is that a higher accessibility means a higher profitability for firms. Bid-rent is the amount the firm is willing to pay for the land. In an urban modelling framework, this variation in willingness to pay based on proximity to other things, determines the variations in land prices.

Utility Maximisation

Determining a measurement for utility is in itself a subjective quantity explored in cardinal utility theory. Utility maximisation is a concept in economics that helps define consumer decision-making by assuming that the individual behaves to maximise the sum of all future utilities (Samuelson, 1937). The concept is a basic assumption in neo-classical economics which believes that consumer behaviour is about utility maximisation (Haddon, 2002). The measure of utility comes in the form of the consumer's perceived notion of value. If a consumer is deciding whether to buy product A or B, assuming both have the same monetary cost, the consumer will choose the product that he perceives has the highest value. In an urban model, utility maximisation justifies agent-decision making when faced with a range of alternatives with similar monetary value.

Expected Utility

Expected Utility theory is a conceptual framework for deductive science in the field of economics, political science and psychology (Shubik, 1984). First published in the "Theory of

Games" paper, expected utility uses the theory of strategy games and related it to economic theory as a means to develop a theory of economic behaviour (Neumann & Morgenstern, 1953). It includes the notion of utility as part of rational choice; a person will make a choice that will be in line with his expected utility rather than against. Expected utility is part of the deterministic area of utility theory. It calculates all the possible outcomes from all the alternatives and then determines the agent's choice based on which alternative yields the best result. Therefore, its usage in urban models comes as a means of identifying the optimal, thereby the most likely, choice for an agent.

General Equilibrium Theory

General Equilibrium theory is a macro-scale theory. It attempts to explain the forces of supply and demand for one or many markets in an economy. The theory was initially presented by Walras (1926) in the book titled Elements of Pure Economics. In this book, Walras breaks down the assumptions for the theory to work and determines the possible usages / circumstances. Both macro-level economic models and micro-level economic models use general equilibrium theory. The difference being the complexity of market structure incorporated in either model with macro-level models using single to few or micro-level models using a plethora of different ones. This is because, the theory seeks to explain the equilibrium price and supply of one good while accepting the interrelated nature of that good with the price, production, growth of one or more other goods and the broader economic values of inflation, interest rates and wage levels.

A model featuring the theory in an attempt to explain real world economics was created by Kenneth Arrow and Gerard Debreu (1954). This model derives the modern conception of general equilibrium and applies it using three interpretations of the theory terms. These are the location of good delivery, the time of delivery and the state of delivery while taking into account the good's unique nature. The critic exists on the assumption of complete markets, which rarely apply in the workings of a real economy; however, the theory helps provide a guide rather than an accurate reading.

Input-Output Theory

The Input-Output method originates from Léon Walras´ general equilibrium and interdependence model (Miernyk, 1965). It is a practical extension of the classical theory of general interdependence, which views the economy of the area in question from a macro-level perspective as a single system. This view enables it to describe and interpret the economy's operation in terms of the structural relationships observed directly by the modeller (Macmillan, 2008). The first theoretical explanation of economic interdependencies came from François Quesnay (1694-1774), in Tableau Économique, published in 1758 (Pellet, 1965). Quesnay's pioneering work of inter-industrial analysis and accounting was recognised by Wassily W. Leontief (1906-1999) who carried on the work and is credited as the founder of input-output theory (Leontief, 1986). An input-output model is a large spreadsheet that contains all the parts that make up the economy and their output. The links and interdependencies of each part are mirrored from their real-world counterparts. The assumption here is that flows between each part are stable in the short term and the dependencies are used to figure out the effect to the economy when a change to a single or more parts occurs (Batty, 2008). The method has the ability to investigate not just the direct effects of a change but the indirect effects as well. This is the reason for its usage in primarily macro scale urban modelling frameworks, to investigate the effects of changes without the need for accounting of individual agent's decision-making.

Rational Choice

Rational choice theory asks decision-makers to compare cost, risk, gains, pain and pleasure across time and space to determine which choice is most beneficial (Macmillan, 2008). The alternative with the highest benefit becomes the rational choice / decision taken. The origins of rational choice theory are elusive as it has taken many forms throughout the years and been incorporated in many theories such as expected utility, utility maximisation and random utility. The argument exists that Bentham's measurement of pleasure and pain for constructing a more rational system, published in 1789, forms the basis for the theory (Burns, 2005). Followed by the principle of utility or greatest happiness principle, it formed the basis for utilitarianism or hedonic utility that sees consumers choosing the option that yields the most pleasure. Other noteworthy economists have created theories for decision-making based on utility and the understanding of the economic man as a rational decision-maker (Neumann, 1957; Simon, 1972; Walras, 1926). The first mention of rational choice theory as a thoughtful deliberation came from Herbert Simon on his argument that rationality is bounded (Simon, 1959). Before Simon, rationality was a concept for choice and a methodology to determine that choice

(Hodgson, 2012). The critic that rationality depends on one's knowledge of alternatives began a debate on the use of rational choice theory. In the social sciences, rationality is a limiting theory due to the objective nature of the decision-making process that "fails to focus on the historically and geographically specific features of socio-economic systems" (Hodgson, 2012).

Economic base theory

The origins of economic base theory date back to the early 1900s as means of explaining regional growth process (Schaffer, 2010). Debates exist as to whether this is an actual theory or a method of analysis (Iossifova et al., 2017). The theory itself was popular with regional scientists who favoured it as the basis for their models during the period of 1950-1985 (Schaffer, 2010). After 1985, Richardson, a then leading regional scientist, wrote an article calling the findings of economic base models as conclusive and not inspiring confidence (Harry, 1985). This has done little to stop economic base research with new publications providing empirical evidence in support of the theory's hypothesis for short-run and long-run regional growth analysis (Lesage, 1990; Lesage & Reed, 1989). The theory states that the economy of a region consists of two parts, the goods and services produced locally for export (basic sector economy) and the goods and services produced locally for internal consumption (non-basic sector economy). There are three assumptions that make up an economic base model; (a) non-basic economic activity depends on basic economic activity; (b) population depends on total employment number; (c) locational attributes affects location choice for households and non-basic sector jobs (Clay & Valdez, 2017).

2.4.4 Prevalent operational models of theory in urban simulative models

Through the identification and positioning within the conceptual diagram, the range of OMoT and theory types conforms to a series of hierarchical decisions. The following section describes the position of OMoT and theories within the analytical framework. Through the analysis of the data, an underlining structure of modelling and theory decision was observed, separated in three steps.

The first step is indicative of the initial decisions taken when creating an urban modelling framework that serve as the overall description of the type of urban simulation to be undertaken. The second step includes everything that is specific to the operation of the simulative urban model's components. The third step's OMoT and theories exist on the urban model level. They work with the context specific datasets in order to create the context details required for the operation of the OMoT set at a modelling framework within this specific situation.

The analytical framework is organised from top, as highly abstract OMoT and theories, to bottom, as context specific. For example, the repast toolkit as well as the transport-demand overall model determine the choices made below them by restricting the availability of subsequent choice. This is due to the criteria of compatibility between themselves and choices made above. Each step acts as a guide to creating the framework with each decision limiting / guiding further decisions. The choice of macro simulation or microsimulation modelling approach will then determine the supporting models for both the spatial and human subsystems which will in turn determine the statistical models used as well as data type needed. All OMoT and theories listed in the analytical framework as well as their position are a result of the analysis made on existing urban modelling frameworks.

Step 1: Abstract OMot & Theories

One of the most important distinctions for a modelling framework is the scale approach, macro vs micro level simulation. From the analysis, the macro-level approaches found include system dynamics, equilibrium model, economic base model and input-output model. This type of OMoTs are informed by the theories of Random Utility, General Equilibrium, Input-Output and Economic Base. Though each approach within this group may include different step two and step three choices, they consistently aggregate human behaviours as opposed to considering individual behaviours. In contrast, microsimulation-modelling approaches, made up of agent-based and cellular-automata models, informed by complex systems theory, allow individual behaviours to exist within the modelling framework. The ecological perspective of patch-matrix-corridor and mathematical ecology still use the microsimulation modelling approach of ABM with a predator prey model. It is however a special case due to having only one modelling framework using this combination of approaches with an ecological perspective originating from patch theory (Gustafson, 1998).

Step 2: Economic Decision and Location Choice OMoT & Theories

Step 2 consists of OMoT and theories with a range of support models that, alongside their theoretical basis, are used to determine choices/ decisions at both an individual and aggregate level. Figure x shows the list of OMoT, which consists of discrete choice model, attraction weights, location choice model, probability choice model, willingness to pay, hedonic price model and multi-evaluation criteria. These models are the applied manifestation of a range of economic and psychology-based theories that includes Location Theory, Random Utility, Utility Maximisation, Expected Utility, Rational Choice and Game Theory. These “models” range in usage depending on the nature of the decision. For example, a discrete choice model is primarily used in a transport related choice while a location choice model is used in a spatial decision.

Within this step, exist a series of OMoT that deal specifically with physical / spatial change for all such operations in the modelling framework. They consist of Lowry Derivative, Offer-Accept, Gravity-Based, Activity Allocation and Artificial Neural Network models. Bid-rent theory and location theory inform these models. The exception to this is the Artificial Neural Network model. In the case of simulative urban models, its usage is limited to setting the transition rules for CA models that drive spatial change.

Step 3: Statistical OMoT and theories

Step 3 OMoT consist of mathematical / statistical models. Applying a modelling framework to a real-world scenario creates an urban model, at the same time; appropriate statistical models determine the value of each variable in the framework’s equations. These statistical models include logit model, mixed logit, multinomial logit, multiple regression, linear regression, hedonic regression and maximum likelihood estimation model. Datasets for urban models include census, government, Survey, GIS and network data. These OMoT sometimes form a population growth model that acts as a limiter to activity growth. Entropy Maximisation theory acts as the basis for it.

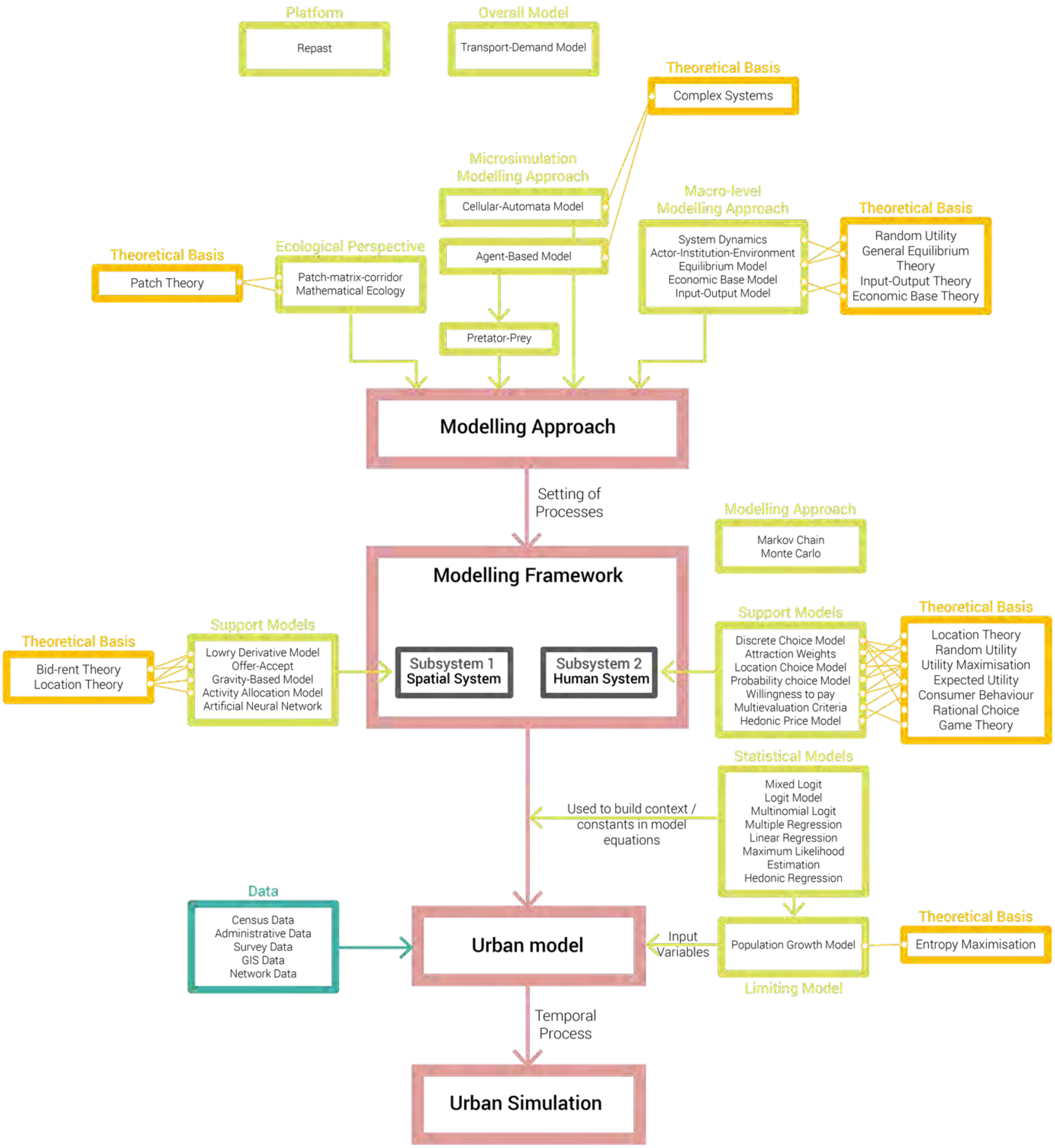


Figure 7: The ESU-AF1 analytical framework with all OMoTs and theoretical basis showcasing their position in each step.

2.4.5 Aggregate vs disaggregate modelling approaches.

The discussion on the hierarchy of theoretical basis / approaches and operationalised models of theory thus far in the literature review, centred on its relation to the ESU-AF1 analytical framework proposed for viewing urban simulative models. Although this has provided a great way of viewing and understanding the pieces that come together at each of the four steps, it lacks the ability to decipher the divergent paths presented with each choice at various steps.

An inherent limitation exists with each decision of an OMoT or a theory. This was explored by creating a decision tree diagram that connects every OMoT and theory to all their possible combinations with other OMoT and theories (See Figure 8). This provides the opportunity to explore how everything is connected. The possible connections are, to the best of the researcher's knowledge, created by analysing descriptions provided in the simulative urban model papers reviewed. The diagram's hierarchical structure is vertical with all choices starting at the top as these OMoT and theories fundamentally carve the path for all subsequent decisions. Some choices provide a richer selection later down the line with others being more limited.

Viewing the connections explored in figure x, some choices such as System Dynamics lead to no place. This is due to its application being a special case in a specific model called LUSD (He, 2005). It combines system dynamics with CA with the former being directly used to providing demand for land-use and the latter identifying land-use supply. Another special case worth mentioning is the predator-prey model used in describing the occupational competition in a spatially structured labour market by Curry (1981) as quoted in Deal (2001).

Interesting findings from this exercise includes how the deviation in scale, macro-level modelling vs micro-level modelling, provides a shift in operational models at a framework level. For example, the majority of macro-simulative approached links with a Lowry derivative model that provides them with a spatialized output through a mixture of location / bid-rent theory and subsequent OMoT. On the other hand, micro-level simulation generally moves to a probabilistic choice model that includes discrete choice modelling and decision theories based on individual utility. The exception to the rule, from a macro-level perspective, is the equilibrium model. This requires a distinction, as an equilibrium approach can exist as part of both a macro and micro-level simulation with a combination of ABM/CA modelling thus explaining its combination to a broader range of OMoT. It is an essential element of economic modelling which the majority of theories connected to OMoT at a modelling framework find their origin. It also becomes evident that the majority of choices end with a statistical model in the form of some sort of regression analysis. This is due to a fundamental need for data processing in order to provide the specific contextual value required for all the variables existing in OMoT equations. It exists as an essential step of transforming a modelling framework to an urban model with specific contextual usage.

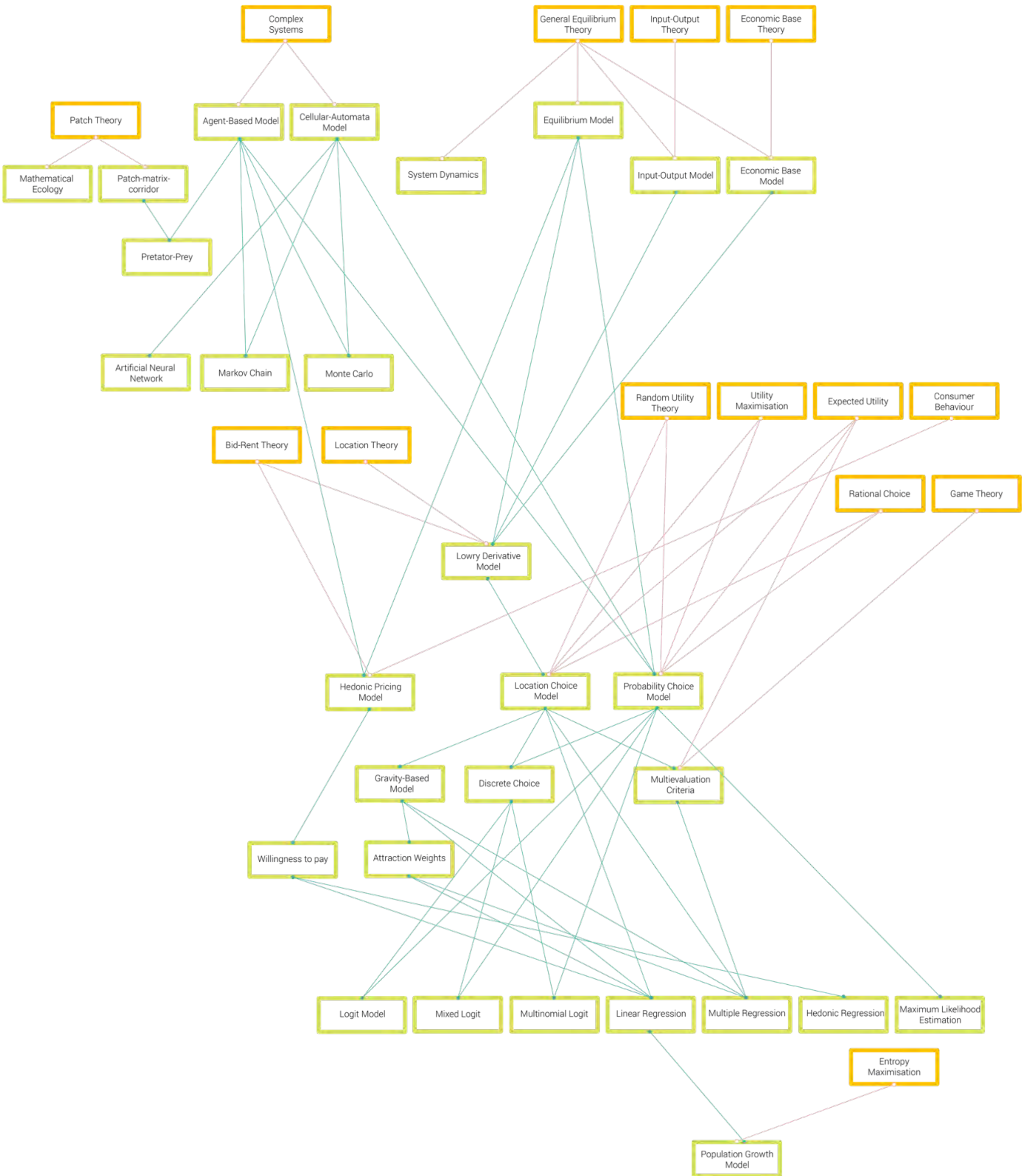


Figure 8: A hierarchical set of decisions and associations between different OMoTs and theories from top to bottom. Red lines indicate theoretical basis associated with each OMoT while blue lines showcase all possible combinations of OMoT following a choice at a higher level

2.4.6 Trends in urban simulative model development

This section splits up all OMoTs in terms of the age of the overall urban model they are used in. This allows the research to establish the overall trend in urban simulative models and therefore the current/future needs/expectations for demand modules in terms of their operation. By age, simulative urban modelling trends show the earlier usage involving the use of location theories and Lowry derivative models followed by random utility urban simulative models and ending with micro-level modelling approaches as the latest addition. It is interesting to note the model generation evolution is consistent with previous review findings (Cordera et al., 2018; Iacono et al., 2008b; Wegener, 2004). The research therefore split the OMoT and theories discovered into three generations.

Gen 1:

The first generation of simulative urban models have been referred to in previous reviews as spatial input-output models, mathematical programming models and spatial-interaction models (Cordera et al., 2018). They date as far back as the early 1950s (Iacono et al., 2008a). These types of simulative urban models use spatial OMoT such as Gravity-Based Models, Activity Allocation models, Lowry Derivative Models and Offer-Accept models to regulate spatial change. They are characteristic for aggregating human behaviour with Location Choice Models, Willingness to pay and Hedonic Price Models. All these components are part of a macro-level modelling approach of Input-Output, Economic Base and General Equilibrium models. The model scale or resolution for these models is mainly regional with theories explaining change and relationships at a macro-economic level. Early urban simulative models of this generation include Lowry's "Model of Metropolis" (Lowry, 1964) with an example of later additions to this category being MEPLAN (Echenique et al., 1990).

Gen 1

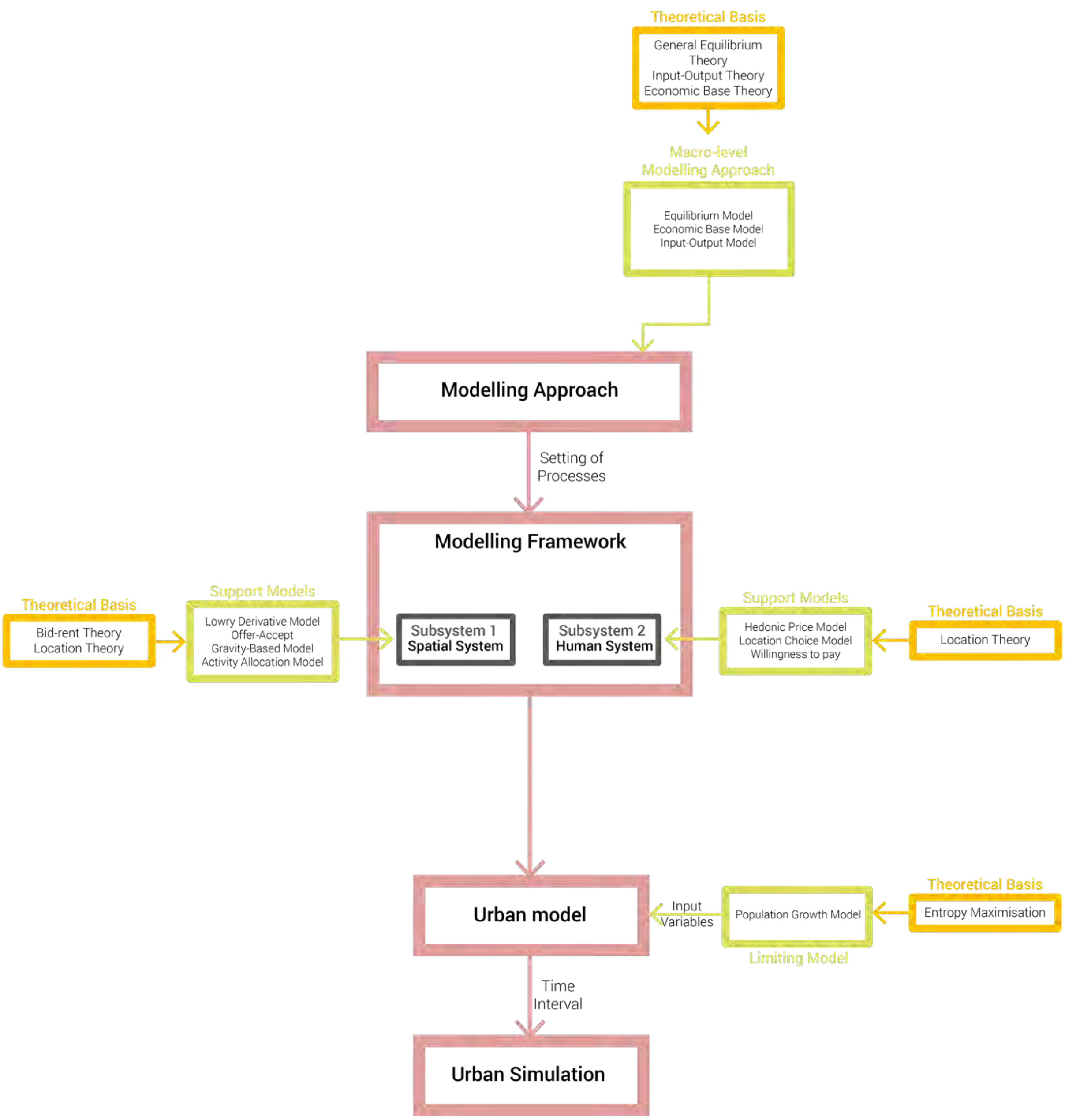


Figure 9: Generation 1 list of OMoT and theoretical basis that are associated with early version urban simulative models.

Gen 2:

These models began to surface in the 1980s and 1990s (Cordera et al., 2018). The work of McFadden (1973, 1978) on modelling choice behaviour using random utility theory with applications in transportation and the real estate market formed the basis for a new generation of urban simulative models. This framework makes use of OMoT such as Discrete Choice Model, Attraction Weights and general Probability choice models to form the decision considerations in order to discover the most probable decision. The exact constants for these equations are determined with statistical models of Linear/Multiple Regression and Logit Models, including mixed and multinomial. The modelling approach includes an equilibrium model that ensures no supply surplus.

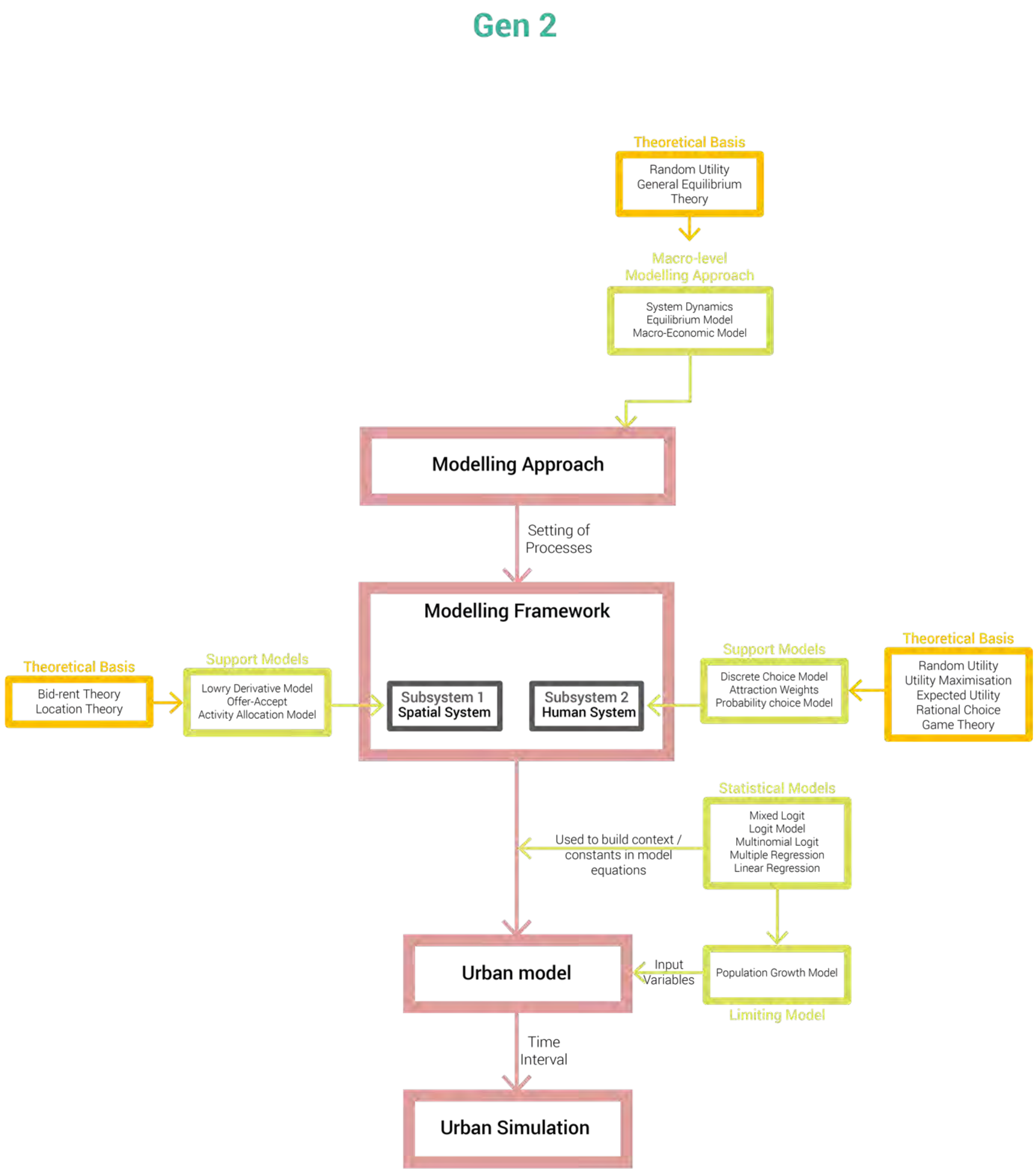


Figure 10: Generation 2 of urban simulative models and their prevalent OMoT and theoretical basis at the time.

Gen 3:

This type of simulative urban models appeared more recently during the 1990s as a response to the increased availability of fast computers and general advancement in computer science (An, 2012). These models follow a complex systems theoretical approach with the use of CA and ABM to achieve a highly disaggregated model with a series of heterogeneous agents interacting with each other, achieving complex behaviours from seemingly simple rules/actions (Wolfram, 1994). The use of a micro-simulative approach has branded this generation of urban modelling its name, microsimulation models (Iacono et al., 2008b). Here we find an exploration of different, more computationally heavy OMoT such as Artificial Neural Networks to determine the exact relationships between land-use and spatial change. Human behaviour and choice is modelled similarly to second generation models but incorporates a wider range of heterogeneous agents with the ability of more aspects influencing decision-making such as consumer behaviour and the concept of rational choice / bounder rationality (Simon, 1972) from the spectrum of microeconomic theory. There is also the exploration of Markov Chain and Monte Carlo models as a means of including a consideration to exogenous factors previously not considered.

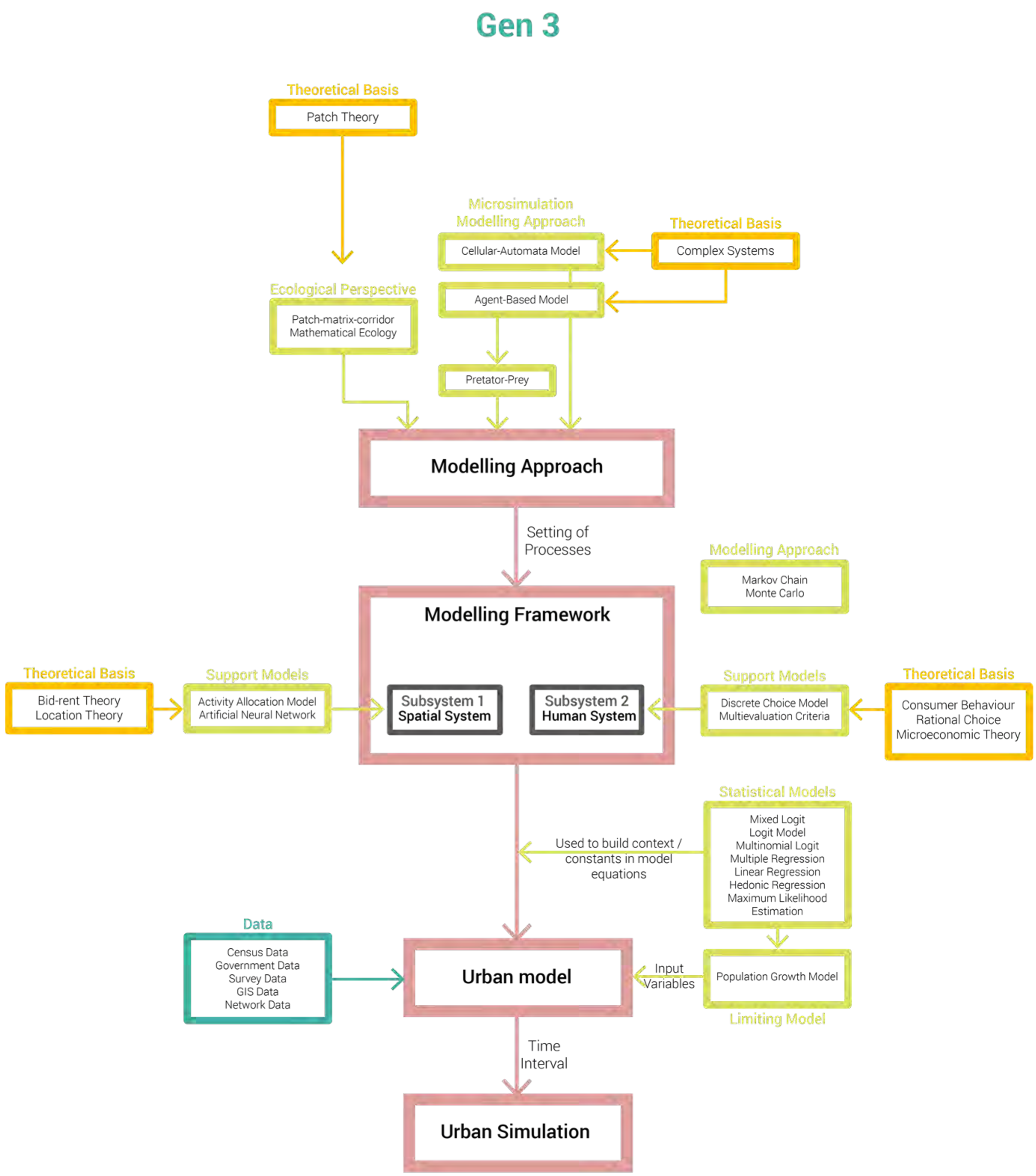


Figure 11: Generation 3 of urban simulative models featuring their prevalent OMoT and theoretical basis at the time.

2.4.7 Concluding thoughts on the evolution of Urban simulative models.

Use of the ESU-AF1 analytical framework demonstrates that (1) some OMoTs and theory types are more commonly or exclusively used in particular steps of the SUM makeup; (2) the choice of OMoT and theory types at higher levels results in a hierarchical or limiting relationship affecting subsequent choice of OMoT and theory types at lower levels; (3) the evolution of SUMs can be understood in terms of three generations (which is consistent with previous reviews), all of which can be analysed using developed framework.

Regarding the first, considering the focus of this thesis being real-estate demand modelling, the module that includes this type of model, within urban simulative models, is mainly covered by economic theory. In particular, utility maximization or random utility theory for disaggregate modelling. These are applied usually using discrete-choice modelling. It is therefore evident through the analysis that decision made within real-estate demand models is currently governed by objective rationality. This is of particular importance for this thesis as the research aims seek to push the field to be in par with current economic theories that deal with subjective rationality.

The second conclusion underlines the limitation of some of these simulative urban models in adopting subjective rationality within their demand modules due to their overall modelling framework. Macro-level models are inherently unable to profit from the contributions of this thesis as they do not use an ABM framework which this research utilizes to push subjectivity within these models. Therefore, going forward, any analysis to further understand the decision-mechanisms within these demand modules will need to exclude macro-level models that do not enable the modelling of interacting urban agents pushing emergent patterns.

The third conclusion highlights the field's push towards disaggregate, micro-level modelling as an overall framework for future simulative urban models. This is of particular importance for this research as it validates the aim of the thesis to further develop decision-making mechanisms for agents in real-estate demand models. This enforces the fact that researchers in the field are pushing for more individual decisions of agents being the driving force for change within these models. This makes any contribution in their decision-making mechanisms, both in terms of new theoretical basis pushing for subjective rationality and new agent architectures capable of modelling such theories, an extremely vital part to research.

2.5 Development of urban planning theories and approaches

Simulating real world phenomena has been an ongoing endeavour by many researchers. When used to understand the course of urban development, the quest enters the realm of planning. The area of urban simulation modelling came about as a tool for planners (Harris, 1965). To understand the ambition of any type of urban simulation, there is a need to situate it within the practice of city planning. A short historical literature review on city planning is needed to grasp how the profession came about, what it deals with and why there is a need for simulative tools.

The profession of city planning primarily concerns itself with shaping the future of urban landscapes. It is, however, impossible to shape the future without analysing and understanding the context first. As such, the context, its state and morphology shaped through decades of conflict and past political, professional and institutional ideologies can only be understood as the consequence of the sum of past planning decisions depicted on the urban fabric (Ward, 2004). Therefore, in order to comprehend city planning, it is imperative to know the way it developed.

The first international Conference of the Planning History Group, held in London in September 1977, formed the first time a group attempted to focus on the last 150 years of planning processes and the reasons that led to the shape of contemporary environments. The aim was simple: to understand the present by analysing the past. The members of the committee aimed to factor in not only different cultural attitudes towards planning but also the environment. Much of the conference's time was spend talking about what was considered the foundation period of modern day planning (1875-1914) (Sutcliffe, 1980). The period involved the rapid rise to urbanisation and industry that came with the industrial revolution and the utilisation of coal as a driving force for production. However, planning existed long before the period of industrialisation. It is worth noting that only elements of what we now consider modern planning practice existed before 1800s. Like everything in nature, adaptation and experience is the driving force for evolution and survival. Disastrous events such as fires, widespread epidemics and floods caused people to rethink about city layouts. From a social standpoint, regulations and control on private housing, layouts of public facilities such as water ducts and pipes were all actions taken by authorities in older civilisations, like the Roman Empire, to encourage prospective residents and businesses. As we look through these changes and developments of planning history, it is equally important to understand why certain ideologies have been superseded (Ward, 2004).

Firstly, we need to define the urban conditions that gave birth to planning ideologies. During the 1700s, the population of London was roughly 575,000 people. By modern standards, it can be regarded as a large city. In contrast, the second largest city was Norwich at that time with a population of 29,000. During 1801 the population of London had risen to 865,000 with other towns like Liverpool and Manchester having populations of 70,000-80,000. By 1891, more than 50% of Britain's population was living in towns of population over 20,000 (Ward, 2004). With the rise of industrialisation, came a new-found complexity and scale to urban planning. Development, both economic and social, was no longer tied to land ownership and wealth. As the urban grew, the associating demographic and economic changes shaped the cities with new spatial structures (Johnson & Pooley, 1982). Districts consisting of offices and shopping areas emerged alongside the integral parts of industry and high-density worker's housing. Outside city centres, the opposite was true. Housing development was more ordered and less dependent on the location of industry. Such residential places for the rich landowners and entrepreneurs' families to live and learn became the first suburban areas. The rise of capitalism and free-market economies brought both social and economic ideological changes that saw urban development being placed in the hands of the market (Sutcliffe, 1980). As such spatial patterns had arisen almost spontaneously that reflected these shifting economic and social demands (Dennis, 1984). That did not last long though as the market proved incapable of resolving conflicts arising from these industrial towns. Conflicts between economic powers of industry and the social divisions that made up their related urban populations. Some form of authority had to evolve, and regulations now came from State level. Planning problems now proved far more threatening to growing cities than ever before, forcing a greater involvement by the State governance locked in an accelerated feedback loop.

In the end, the result from the clashing between government, public and private business institutions gave rise to what we now know as urban and regional planning policies. This is the government's answer to efficient and socially acceptable land use by the immense variety of conflicting functions (Sutcliffe, 1980). The two forms of government intervention through policy came as; on the one hand, public spending on environment maintenance and development being regulated in order to ensure efficient use of public resources and on the other hand, reduced freedom from private owners and landowners in order to protect all parties. These forms of intervention have remained firmly embedded in planning practise since their introduction. So planning policies are effectively planning ideas that have been incorporated in government legislation as officially supported means of action (Ward, 2004).

By the start of the First World War, between 1890 and 1914, institutions of city planning and development plans at city scales have emerged, especially in Germany. In this period came the actual birth of the term 'town planning', an umbrella for the reform movements that now act as the foundations of all modern planning (Ward, 2004). Books had been written on the subject with legislation being passed such as the Saxon Allgemeine Baugesetz of 1900 and the British Town Planning Act of 1909. This was the first step in moving town planning away from the realm of social conscience and co-operative reform to state policy. It formed the basis for professionalising the activities associated with planning and led to the creation of the professional body and qualifying association called the Town Planning Institute in 1914 (Ward, 2004).

Urban planning by now has been firmly embedded within society's functions. The next great advances in legislation did not occur until after the Second World War with the British Town and Country Planning act of 1947 being an eminent example. The rise of socialist governments has also seen planning powers being shifted from their pre-1939 counterparts. Such parts of the world saw the control of all production and environment planning being fully passed to the authority's institution of planning.

Out of the different governance ideologies came debates during the London conference with three distinct interpretations of nineteenth-century planning. The first viewpoint of a liberal-progressive was that of men finding better ways of doing things as time goes by. This certainly resonates well with historical analysis as destruction and evolution go hand in hand. The second interpretation was the Marxists one. The view of planning here was one of neither virtue nor vice as it was looked upon as a part of the institution's structure building on the economic organisation of society. The function of planning here was thought of as means to reinforce the ruling Bourgeoisie parties by both increasing the efficiency of the State and enforcing values and behaviours that contribute towards bourgeois dominance. Lastly, the functionalist view on planning was one of means to an end. A residual activity that society results in to achieve something that cannot be achieved by cheaper more individualistic means (Sutcliffe, 1980).

The importance of the lens of interpretation defines what constitutes as planning. This gives rise to what can be achieved through planning as one idea of it is the architectural form that combines the attractive aspects of a metropolis with the calm comforts of village living. In this research, as the belief is that of supply is driven by demand, a functionalist view is adopted with the existence of city planning as a service came about through the demand of an answer to the social and spatial issues that plagued industrial cities.

From the period of 1915 – 1950, in the field of planning, theories on the subject were dominated by the writings of the Chicago school of urban sociology. The impacts in scholarly research were lasting and raised fundamental issues of social and political policy making in the urban realm. Issues of physical and social redevelopment within cities was discussed by sociologists in the school long before the Great Depression (Park et al., 1925).

They were case study workers, working in the field, gathering and analysing data in the form of observations all in an attempt to discover some kind of pattern within the chaotic complexities of urban communities. Their main concerns were schemes of social change and social planning. As early as 1918, concerns and criticisms of social work were put forth by W.I. Thomas, a scholar of the school.

Park et al. (1925) argues that the city is not just a “physical mechanism and an artificial construction” but rather a product of human nature filled with the customs, traditions and beliefs of the people who inhabit it. Attributes such as physical geography, access to infrastructure and other natural advantages and disadvantages are key indicators of a general future urban plan (Park et al., 1925). As cities grow in size and population, behaviours relating to sympathy, rivalry and economic necessity guide city growth and manipulate the distribution of the population. This is mostly capitalist let, as businesses seek advantageous areas in which to grow and attract the type of population needed to achieve their ambitions.

Indeed, the argument can be made that planning itself is a means to repress the pervasive ills of capitalism in the social-urban while enabling the existence of that very system in the long run. The sociologist's belief at the time was that a surplus economy was needed for a city to exist. This comes in many ways such as natural wealth of resources surrounding cities, major route meeting point for the supply of goods or, with modern technological advances, it could very well be intellectually rich with pioneering ideas and industries. What supports a city depends on the services it provides (Harris & Ullman, 1945) hence why the diversification of economic activities distinguishes each city, giving it its own character. However, trade was not the only believed support for city centres. Religious and social functions were also considered as being an integral if not a main reasoning for city existence (Harris & Ullman, 1945). The notion of the social complexities driving city character was firmly embedded in the early 20th century planning beliefs.

City organisation was viewed as the product of the size, concentration and distribution of the population. They believed in the neighbourhood as being the smallest local unit within the social and political organisation of the city. The belief was that local interests and associations bring forth local bonds which in turn unites the neighbourhood. As the current system of political involvement revolves around the location of residence, neighbourhoods become the basis of political control (Wirth, 1938). The city itself is portrait as a series of socially and economically differentiated neighbourhoods. Their individuality stemming from the tensions, interests and sentiments of their inhabitants (Zorbaugh, 1929). This school of thought understood city dynamics, the ecological progression and advance of the urban, as the means of rendering a population unstable in their beliefs and divided in their interests forcing a change within neighbourhoods and communities. In other words, people's change in behaviour and mentality as a collective, forces a change in the city. In complexity theory, this is referred to as bottom-up, self-organisation of agents, having an upwards structuring effect that establishes a new emergent pattern (Sengupta, 2017).

This school of thought however came under intense scrutiny during the late 1960s. One such scrutiny by Castells argues that all manners of urban studies under the lens of urban sociology are false as the questions raised simply concern society at large and not the build environment (Scott & Storper, 2015). In a later publication, Castells described the work done by the Chicago School as nothing but an over-complicated ideology on "the fundamental nature of capitalism as a framework of social organisation" (Scott & Storper, 2015). Along with other scrutineers like Harvey (1975), the city was now viewed as a stage for class struggles based on land markets as the driving force for wealth distribution in higher classes and the associated political claims from lower class citizens on their urban resource rights. The idea of what a city is continued to evolve to the point where it was no longer considered as worthy of analysis but as a mere random geographic entity of diverse economic, social and political phenomena (Saunders, 1981).

The views of the Chicago School have indeed been strongly discussed and moved on from but the notion of the social in cities has now been firmly embedded within the literature. In fact, current views on the subject firmly embed the social and economic as major driving forces in cities. West and Brown (2004) compared scaling laws in various cities. The research found that population size is the major determinant of characteristics within the city. These characteristics consist of space per capita, socio-economic activity and economic specialisation. Each of these characteristics has their own scaling relationships with size / population of the city. These relationships have been documented and compared (Bettencourt et al., 2007) leading to a greater understanding of urban growth and its consequences.

One of the characteristics refers to the Economic & Social activities diversifying, becoming more interdependent, and resulting in new forms of economic specializations. This leads to the economic theory of economies of scale defined as the average cost of resources per output decreasing due to the increased rate of specialisation. After a certain point of city growth the opposite can happen, diseconomies of scale, which is the opposite effect to economies of scale. As the size of the city grows, the average cost of resources per output grows due to an ever-increasing inefficient use of resources. This is a direct result of the law of diminishing marginal return assuming you have a fixed variable, for example space / resource. The law of diminishing marginal returns states that after a certain point the extra output per person goes to zero and even negative which in city terms refers to the state of stagnation and eventual collapse (Layson & Layson, 2015). It can be understood with the simple example of owning just one spade (fixed variable) and employing workers (flexible variable) to dig holes with it. One worker may get tired and require a lot of breaks during an eight-hour work day meaning he may dig just two holes. Employing two workers may raise their time of rest by switching around, making them able to dig six holes. That means that the extra output per person by adding one more worker to the spade is 1 hole. If you keep adding more workers to that one spade the extra output per person will start to go towards the negative as people get in the way and efficiency suffers. This is where the need for innovation comes from; to further increase the efficient use of the resources and space that cannot increase at the same rate as population.

This phenomenon of urbanisation is likely to increase as higher profitability and excellence attracts more people / talent to the cities further pushing the need of innovation with a feedback mechanism that constantly accelerates that need while at the same time intensifying and diversifying social and economic activity (Bettencourt & West, 2011). This relates to research work on the city as a complex system with no clearly defined optimal state and in constant flux (Batty, 2012; Batty & Marshall, 2012b, 2012a; Sengupta & Cheung, 2013; Sengupta, 2017; Weinstock, 2013). The emphasis should be placed on the process rather than the product as there is no stable equilibrium but only a constant move towards one. Innovation and wealth creation are essentially the drivers of growth within cities and often at an uncontrollable rate. This ever-increasing growth rate is unsustainable, constantly leading towards an eventual state of stagnation and collapse. In order to avoid this impending future, an innovative response must occur within the city, a major qualitative change has to manifest ensuring the dynamic of the city remains within the wealth & knowledge creation phase as opposed to a state of recession (Bettencourt et al., 2007).

This constant move of equilibrium, the constant need of innovation driving to new cycles of wealth creation and growth, has its own Achilles' heel that can lead to disastrous potential outcomes. As population increases, the time between innovative cycles necessarily decreases. This leads to the problem of sustaining continuous growth, necessitating the rise of an ever-accelerated state of innovation and adaptation within the city (Bettencourt & West, 2010). This idea of maintaining sustained growth and the making right decision going forward has plagued planning practice for a century now. In their quest to attain this, planners have developed a number of planning theories that would guide the way they both view problems and the way by which to approach/solve them. These planning theories are constantly evolving ever since the perception of planning practice however, given the link between planning approach evolution and urban modelling evolution, there is a need to gain an overview at the predominant planning theories of the last century.

2.5.1 Rational comprehensive, systems theory planning

Early theories in planning revolved around a rational process. Though there were many methods by which to make a decision, the output was an explicit and objective form of decision-making by planners (Allmendinger, 2009). Systems theory was one such rational process that viewed communities as a collection of geographic, social, political, economic and cultural patterns that are constantly interacting and changing, forming the shifting nature and conditions of society (Ratcliffe, 1974). According to Ratcliffe (1974), the planner was meant to decipher the nature of these relationships and guide/control a change in their composition. Essentially the planner was the decision-maker, considering all alternatives, the end results he seeks to achieve and the possible courses of action available. The planner then identifies and evaluates/predicts the impact of each alternative in terms of total situation change with each course of action adopted. This results in the planner selecting the alternative whose probable consequences best fit the desired end result (Meyerson & Banfield, 1955).

2.5.2 Critical Theory planning

Critical theory in planning arose as a development of Marxist theory after the latter's interpretation in the soviet union proved that it failed to naturally bring about freedom and democracy (Allmendinger, 2009). Marxist's perspective of planning is that of a largely market-led endeavour with public interest being coterminous with the market. Therefore, if the role of the state is to regulate capitalism, then planning and the market work in collaboration (Allmendinger, 2009). This relationship is best described by Healey et.al. (Healey et al., 1988) as they examine if the system itself is inherently biased towards certain group's interests. They provided a view of planning as structured by the dominant power relations of society such as a constant economic drive to achieve better profits and the conditions that safeguard the means of future production (Healey et al., 1988). The conclusions showcased how the state actively serves to ensure continued production through the promotion of the interests of some producers while simultaneously striving to protect the exchange value of land as an investment, facilitating "the use of the build environment as a store value for capital" (Healey et al., 1988, p. 245). Essentially, planners are viewed as both the solution and the problem with their attempts to create social stability and spirit of community though not aimed at improving the lives of residents but improving the efficiency of labour (Harvey, 1985).

2.5.3 Neo-liberal planning

Neo-liberal theory focuses on better and more efficient societies. The dominant aspects of this theory are the dominance of market mechanisms, the importance of individual freedoms and the role of the state (Allmendinger, 2009). Markets are viewed as the most efficient way to organize societies (Hayek, 1944) with all policies aimed at creating the conditions for markets to work more efficiently. Therefore, planning or government intervention as it is otherwise know, is aimed as an arbiter for disputes and intervene only to set the rules within which individuals are free to pursue personal ends and desires (Allmendinger, 2009). Within neo-liberal planning there are two main alternatives to strict planning control. The first include major reforms to land-use control with an emphasis on the market and the second on structural reforms with different degrees of control addressing different spatial requirements (Allmendinger, 2009). There are different approaches to these though there are common principles by which a neo-liberal planner may approach a problem. These are a) rule of law that includes a system based on tribunals, covenants, third-party insurance b) centralization that includes a centrally directed approach with no local discretion and c) market orientation that has minimal regulation and the provision of information to help the market make investment decisions (Allmendinger, 2009).

2.5.4 Pragmatism planning

Pragmatic planning sees some of the first attempts at including a normative dimension to planning with a more democratic approach that opens planning up to a greater plurality of voices and opinions. Forester (Forester, 1989) argues that argument and talk matters as it is a means for planners to firstly understand the interests, perceptions and commitments of others and secondly show/convey their ideas, expose dangers and open up fruitful opportunities for action. Lindblom (Lindblom, 1977) proposes a pragmatic method to promote incremental decision-making while simplifying complex problems. These include the limitation of analysis to a few familiar alternatives, combining values and policy goals with empirical analysis of problems, focusing on solving issues rather than goals to achieve, trial and error learning, analysis of multiple options and their effects and finally, fragmenting of analytical work to many partisan participants in policy-making (Allmendinger, 2009). The role of the planner in pragmatic planning shifts to acting on ideas and beliefs that make sense and to helping others act while accepting that public interest is impossible to aggregate.

2.5.5 Advocacy planning

Advocacy planning is mainly based on the works of Paul Davidoff that proposed a number of arguments for the role of planners and the importance of a pluralistic approach (Allmendinger, 2009). He argued that planners cannot be value-neutral and therefore should be honest about the values that led them to a particular decision. He advocates for planners to embrace this bias and work for organisations that mimic them, engaging as advocates of the interest of government and other such groups (Davidoff, 1965), arguing their client's position. Furthermore, Davidoff (1965) calls for the idea of competing plans from different groups all seeking different desirable future outcomes. Some of the plans will directly contradict the planner's own plan, though instead of rejecting them, the planner would instead counter them. The advantage of this approach is threefold - firstly it serves to better inform the public of all alternatives, secondly forces competition between planning groups and lastly force others with a critical position that opposes council plans to prepare their own (Allmendinger, 2009). Advocacy approach to planning acknowledged a pluralistic perspective on public interests therefore any decision made should be the outcome of competing ideas while simultaneously addressing power inequalities.

2.5.6 Post-modernist planning

Post-modernist planning stems from the idea that there is no such thing as an absolute truth. Post-modern planning is difficult to define as it is split within two categories. The first critics planning through a post-modernist lens in attempt to arrive at a new set of principles. The second approach seeks to develop a framework (Allmendinger, 2009). Sandercock & Lysiottis identified 5 principles for planning to move towards a postmodern and pluralistic form

(Sandercock & Lysiottis, 1998; Sandercock & Lyssiotis, 2003). The first is social justice which seeks to move beyond looking at inequalities in the material and economic realm and consider oppression and domination as new ways of preventing diversity. The second is politics of difference that is based on an inclusionary commitment through discussion, enabling positive aspects of difference to shine (Allmendinger, 2009). The third is the question of citizenship as an inclusive term that needs to be constantly reinterpreted and refined. The fourth is the idea of community and how it shouldn't be defined purely on territorial geographic boundaries. The last principle is from public interest to a civic culture. Moving past the idea of a homogenous public interest into a heterogenous public interest. The argument here is one of inclusion and pluralism through a collaborative approach. Post-modernism sees planners focusing on celebrating and catering to differences by rejecting objective knowledge and understanding that public interest is fragmented and atomistic.

2.5.7 Collaborative planning

Collaborative planning follows on from the principles of post-modernism and the critic of modernity with the rejection of instrumental rationality, substituting it with what Habermas (1984) terms as communicative rationality. This type of rationality rejects the notion of scientific objectivism, where the professional decides/decipher what are the best courses of action. Instead, it pushes for a new type of objectivity, bore by a consensus of different stakeholders through free and open discourse (Allmendinger, 2009). This discourse needs to adhere to six characterisations that embody the idea of communicative action:

"1) Interaction free from domination (the exercise of power)

2) Interaction free from strategizing by the actors involved.

3) Interaction free from (self-) deception.

4) All actors being equally and fully capable of making and questioning arguments.

5) No restrictions on participation.

6) The only authority being that of a good argument" (Allmendinger, 2009, p. 204)

Here planning is challenged to not only follow formal rationality, use of formal procedures to achieve given ends, but to consider substantive rationality that embodies individual perceptions of value, ideas and morals about those very ends (Darke, 1985). Essentially, collaborative planning breaks down scientific objectivism with a focus on free and open discourse to reach agreement with the planner's role being the introduction of other ways of thinking as they accept a pluralistic orientation with different futures with no overarching meta-narrative regarding the existence of a public interest (Allmendinger, 2009).

2.6 Development of planning approaches and modelling approaches

Understanding what city planning is and how the practice of planning shapes the future reveals a link with urban models as they are considered tools for planners, helping them investigate and propose solutions to planning problems (Batty, 2009b). Therefore, there is a need to look at the tools of planning, specifically the simulation of urban environments.

Real-estate demand models are very important when simulating the potentials of demand for specific location in certain conditions. However, the deterministic, linear relationship state of agents in current modules fails to anticipate more than one outcome. "Society has a habit of shifting values, meaning and actions” (Allmendinger, 2009, p. 4). This makes it impossible to have a universal theory of society and decision-making of its agents as there are constant shifts that cause the original grounds that birthed the theory to change, rendering it unusable. This is why, in the current practice of city planning, a tool with fixed utility attributes for its agents cannot fully explore all of the potential possibilities and allow for more informed decisions to be taken.

With planning practices shifting away from instrumental rationality towards communicative rationality, as well as from formal rationality to substantive rationality, signals the need to evolve existing modelling approaches. Predictive simulative urban models that do not allow for agents with pluralistic/subjective perspectives when making decisions, no longer embodies the needs of planners as end-users. The table below showcases the theoretical critic of different planning approaches. For each one of those approaches and critics, the thesis offers the means through the use of more complex agents in simulative urban models to counter them. This is a theoretical potential of such computational agents that the thesis proposes could help planners/end users of these models bolster the shortcomings of their approaches. They are meant as a guideline for this thesis in the prospects of the new computational approaches developed as part of it. For if simulative urban models are tools for planners, developing these tools in a manner that best suits their users forms a necessary part of their development.

Planning Theory

Critique & Complex Agent Potential

Systems Theory/ Rational Theories	Models of systems used too simple / descriptive to capture complexity of a city. Model relies on mathematical values to measure effect of one aspect to others	Cities are not linear with predictable behaviour but instead made up of irregular behaviours. Qualitative aspects exist and their effect is difficult to quantify due to their subjective nature	Due to the nature of cognitive agents, qualitative issues can be explored & can better capture complexity of the system. The more complex the agent used the less the degree of abstraction
Neo-Liberal Planning	Does not account for context as some issues require more or less intervention by the state	Markets are seen as not able to achieve optimal results due to the power of some strong players manipulating the mechanics	Complex agents can simulate a more comprehensive market response to proposed interventions. Understanding market failures through complex agents acting as independent actors reduces uncertainty
Pragmatism	Powerful forces at work could mean planning only produces further inequality as planners identify more with protocols of professional expertise than the citizens	Being practical in the face of power inequality is difficult leading to issues of ideal speech	Placing a normative element based on an unbiased plurality of voices and opinions using complex agent profiles can more impartially assess societal needs
Advocacy Planning	Problem in choosing between different competing plans as planner is inherently non-neutral/driven by the idea that theirs is the only truth	There are a multitude of world views / perspectives which usually makes planners unable to account for all.	Complex agents can aid in understanding different stakeholder views generating outcomes that showcase the effect on each. With clear winners and losers decisions on plans can be less biased.
Post-modern	Problem bridging post modern / post structuralism theories to on the ground planning	Planning practises have an issue in drawing the line between sectoral boundaries in a planning with everything in mind approach	Complexity is seen as the synthesis of modern & post-modern thinking delimiting the range of time and space understanding. Complex agents allow for greater understanding infusing elements of positivist modelling
Collaborative Planning	Issue separating ends from means. Even if communicative rationality is used to determine end goals, the means are not defined and revolve around formal procedures that take precedent over end goal values. Issues with problem identification and definition as incomplete information on context, values, alternatives prevents ideal speech	Pluralist nature of the world is irreducible with existence of complex mix of cultures and discourses even through communicative rationality a clear agreement may not be possible between all parties. Power in societies is unequally distributed meaning no undistorted communication is possible due to the existence of domination, repression and ideology	Complex agents as context specific stakeholders act as unbiased participants of collaborative planning in a "live action" demonstration of open discourse resolving conflicting ideologies without the presence of power dominance. They allow for testing of the means with direct indication of end goal effects on different stakeholders improving quality of decisions. Can help with problem identification through unbiased interactions between subjective goals/means.

Figure 12: Diagram showcasing the issues with each planning approach and the potential of complex agents to aid in the process.

2.7 Discussion of research direction and gaps in the literature

2.7.1 A shift towards disaggregate modelling approaches and a shift away from instrumental rationality in planning approaches.

The reliability in the empirical generalizations is what allows for an intended result based on estimated actions by individuals to have validity (Gerth & Mills, 1946). The fundamental issue with judging/predicting an individual's decision in any situation heavily relies on whether the empirical generalization by which the prediction scenario's rules are based on, were constructed under a "subjective" rationality or "objective" rationality. The distinction here is important because an objective rationality choice is scientifically, factually correct or right. The decision maker himself on the other hand, directly influences the correctness or justification for a subjective rationality choice. In essence, the subjective choice for the individual has none to limited empirical grounding facts but relies on the perceived notion of the individual's own perception of right and wrong.

Such subjective rationalities are what account for choices of taste or for choices under uncertainty. The Bayesian approach to apply a probability to all choices/scenarios only works under objective probabilities where all choices are clearly identifying and have measured likelihood or value. Here lies the gap in measuring value and demand for land/space in urban simulative models. In many cases, the demand for land is justified from survey data of homeowners and their activities in a particular period in time. This enables the empirical generalization for space choice of individual agents/homeowners in urban simulative models. The issue here is the subjectivity in this decision. Though empirically assessed, the validity only stands for that moment in time for that particular population making decisions on those particular spaces. This become an issue if we consider urban simulation as a co-evolving tool for planners alongside planning theory and practise (Batty, 2008). Planning has shifted from a rational comprehensive approach, where the planner's view is perceived as the objective truth in all situations. The focus now is a collaborative communicative rationality approach (Allmendinger, 2009), where the planner understands there is a plurality of perspectives and his is not the objectively correct. As such, urban simulation tools need to adapt to enable the representation of individuals with unique tastes and preferences.

2.7.2 Understanding and modelling housing location choice decisions

Real estate demand models are a specialised part of urban simulation modelling and can manifest as modules for bigger integrated land-use and transportation models. These models fall within the umbrella of spatial interaction models that houses a range of different urban simulation models such us urban growth and land-use. Real-estate demand models aim to obtain values of real estate / land in specific locations and conditions. The term itself is not a clearly defined one. It includes a series of simulative models that deal with any part of placing a value, monetary or otherwise, on a land parcels or buildings in specific contexts and determining the location choice of household agents within the simulation. In this research, the term has been adopted (Wang & Waddell, 2013a) as a means of bridging the various existing studies and define the area of urban simulation that the work will contribute in.

Real Estate Demand simulative models form a small portion of the spatial interaction-modelling umbrella. They incorporate economic concepts and behaviours while being simplifications / abstractions of reality. This is why in many of the already existing real-estate demand models the rationality of the agents is objective. The entities and their interactions are interpretations of theories in the digital world. This research aims to add a subjective rationality, originally from the social sciences, to an engineered digital system. The ambition is that current limitations associated with the level of objectivity in agent-based decision-making can be overcome with this new approach of complex behaviours applied through different agent architectures and theoretical basis. This will in turn strengthen the importance of real estate demand models as understanding demand users may be better able to control the forces of supply through positive interventions of policy. In architecture, supply of design services is only provided when demand exists. Planning shares the same belief especially when looking into how the profession came to be as a means to protect the interest of all parties, further explored within this document. Knowing the shifting demands in the urban economy, planners can help guide, through policy, the way to a desired future city-state.

2.7.3 The need for creating complex agents for disaggregate agent-based location choice models.

As previously stated, urban simulation tools need to adapt to enable the representation of individuals with unique tastes and preferences. To overcome this issue, urban simulation must once again turn to its theoretical basis of economics. The evolution of economic theory predominantly in the area of consumer behaviour established how a range of internal determinants, relating to one's own motivations, and external determinants, relating to outside factors have the possibility to influence decision-making on an individual level (Gibler & Nelson, 1998). The subjective rationality behind consumer behaviours relating to land/building/space choices overcomes the issues with current theoretical applications of expected utility, random utility and utility maximisation in urban simulative models. These issues, primarily centred on trying to create objectivity in an otherwise subjective rational choice, have historically been justified as a necessity in order to create a scientific method by which to predict future states. The limitations of this approach have been heavily criticised as it lacks any transferability and offers no way of accounting for disruptions that can cause changes in the empirical patterns observed.

Though the new wave of urban simulative models builds on the notion of disaggregated modelling with more intricate behavioural aspects for agents and decision-mechanisms/variables there still exists a 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). There are limitations on the reliance of empirically-derived relationships (Verburg et al., 2002) and a lack of impact of demographic changes to demand for dwellings (Ettema, 2011). Furthermore, Ettema mentions 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). These issues, coupled with a call for the advantages of disaggregated behavioural approaches (Vorel et al., 2015), all adds to the need for more advanced behavioural agents. In short, urban land-use models have a lot to benefit from ABM with intelligent agents (Huang et al., 2014). However, to the best of this researcher's and other researchers knowledge, currently there are no geographical spatial applications of advanced cognitive behaviours and agent architectures (Heppenstall et al., 2016).

2.7.4 Incorporating previously unused theories and agent architectures for urban agent decision-making mechanisms, expanding the scope of urban simulative model development and application.

In light of the limitation/gap outlined in the section above, the research will borrow from social science-based theories and a range of social science-based disciplines such as psychology and behavioural economics in an attempt to identify potential ways to improve agent behaviour in space demand models. The reason for exploration in these areas is to harvest what the natural progression of theoretical thinking in the disciplines that traditionally form the basis of real estate demand models has yielded. These concepts include notions of cognition, judgment and decision-making processes, consumer behaviour and the role of experience in decision-making. These then need investigating in terms of the agent architecture attributes needed to implement these theories.

The perception of importance and priorities being unique to each agent adheres to the concept of subjective rationality. An individual may value some things differently from someone else while maintaining a rational perspective. There are a number of behaviour theories explaining individual factors and their influence in a rational choice. As part of the methodology for this research, these theories will need to be identified and explored/adapted in test models to understand their capacity in terms of their existing alternatives.

The adaptation of new theories comes with the issue of creating a computer model that allows those behaviours to exist within it. Here lies potential issues as existing agent-based urban simulative models that incorporate real-estate demand modules may lack the necessary agent architecture capacity to enable new theories to exist within them. Therefore, there is a need to firstly understand the capacity of existing agent architectures used within real-estate demand models and then, if there are gaps in agent attributes, formulate new models based on new to the field agent architectures that incorporate new theoretical basis for more complex agent behaviours.

2.8 Formulation of research objectives and questions

2.8.1 Empirical research objective and questions

The research aims to improve upon the theoretical basis of agent-based real-estate demand urban simulation modelling and the current agent architecture with the hopes to implement more complex agent behaviours. The clear goal here is an attempt to incorporate new theoretical basis for real estate demand models following the inclusion of, new to the field, agent architectures.

To achieve this goal, the thesis has set out the following main research objectives:

1) Classify what are real-estate demand urban simulation models.

2) Undertake a systematic review of real-estate demand models that analyses their theoretical basis, model scale, decision factors and spatial interaction model.

3) Evaluate current agent architectures in use for real-estate demand models and assess any limitations that may exist.

4) Build simplified computational urban simulation models for real-estate demand with a range of theoretical basis for agent decision-making processes.

5) Run a human role-playing simulation/game laboratory experiment with 24 participants playing assigned imaginary roles to externally validate the models.

6) Draw conclusions through comparing results from computational models and role-playing simulation

The term real-estate demand was concocted by this research in an effort to establish a term for all models and modules that would be investigated. A 'Real-Estate Demand' urban simulation model is part of the spatial interaction model family that incorporates a range of different urban simulation models such us urban growth and land-use. The main characteristic of this model is the ability to assign value, both monetary and otherwise (demand), to buildings/land/plots (space).

This definition adequately describes all models and modules that abstract real-estate markets and their processes. This enables the research to move towards a review of real-estate demand models in an attempt to understand the current literature around them.

The research retains its focus on urban growth and change. However, considering that simulations have an alternative set of ontologies and epistemologies from "real-world" research, the decision was made not to mix field-based research with computational simulation. This is because simulation ontology and epistemology, particularly for space simulations, are derived from the choice of how reality is abstracted into a computational model and form the basic concerns during the development of an agent-based system (Raubal, 2001). Specifically, within an agent-based system, ontologies are theories on how different classes of objects within the simulation exist and are related to each-other (Chandrasekaran et al., 1999). Epistemologies within a simulation determine the agent's knowledge and beliefs (Raubal, 2001). Both ontologies and epistemologies within an ABM are effectively determined through the choice of agent theories which the thesis explores in chapter 3 and are concerned with modelling ‘the agent’s processes of perception, cognition, and action in a plausible way’ (Raubal, 2001, p. 653).

The thesis will focus solely on urban computational simulation and contribute to knowledge in this domain. Real estate demand models are important in urban simulation because they allow for a greater understanding of land value (both monetary and non-monetary) arising from microeconomic agent decisions in specific locations and situations. The use of urban simulation models continues to grow parallel to an increasing need to understand complex urban transformations. Previous models have been criticised from a social science/soft science perspective due to their reliance on pure rational reasoning. My research will explore the incorporation of behavioural theories driving the agent decision-making aspects of real estate demand urban simulation models.

This leads to the research question for this PhD:

What effect does the incorporation of alternative rational theories and architectures have on the ability of agents to display more complex behaviours in urban simulative models?

This research question, the inquiry into the limitations of current urban simulative models, limited to their agent architecture, is a direct response to both the current planning practice needs and the ambitions of urban modelers.

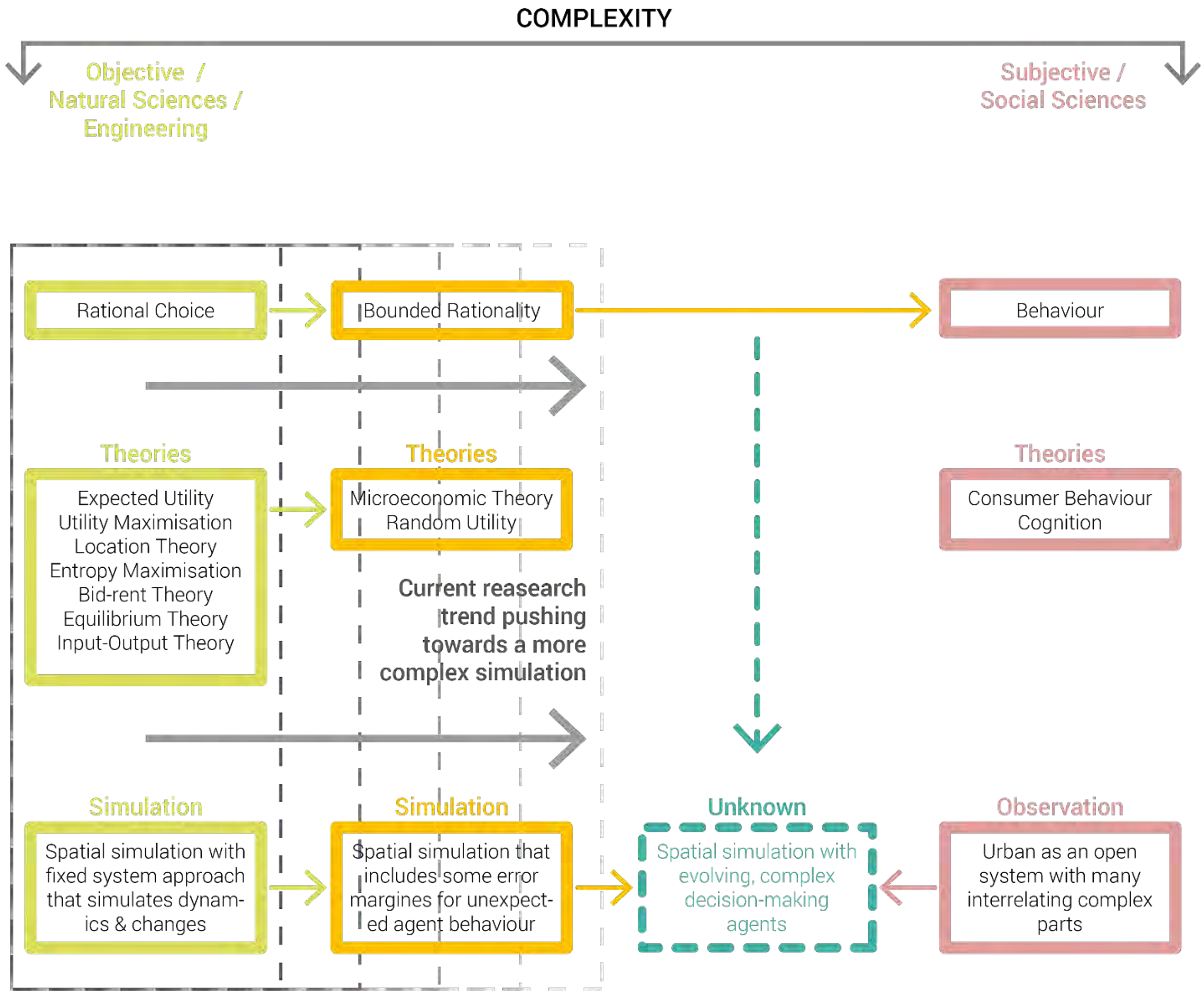


Figure 13: Diagram showcases the trend of urban simulative models, pushing for more complex and subjective decision-making within their simulations.

2.9 Chapter summary

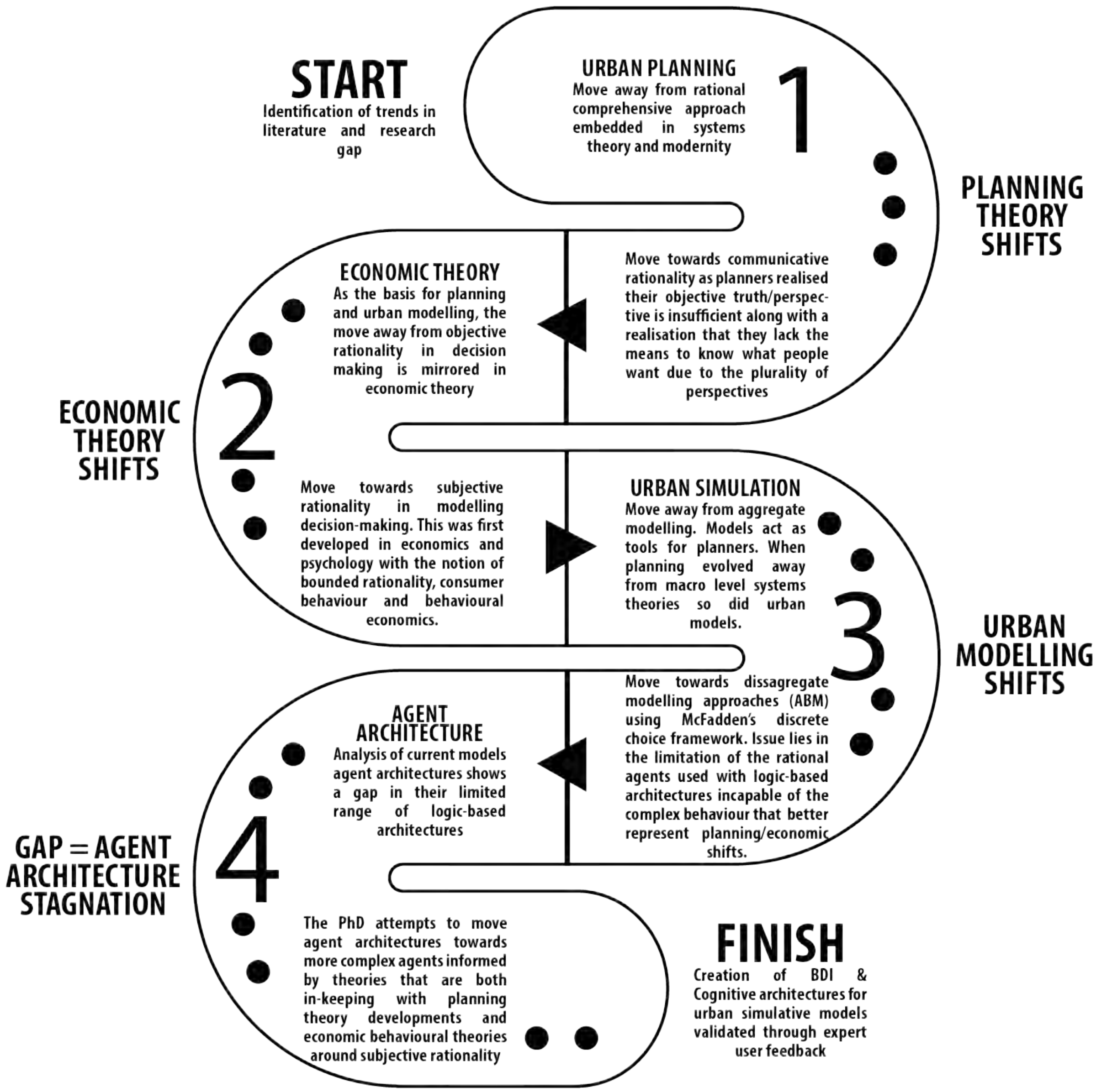


Figure 14: Diagram summarises findings in the areas of urban planning, urban simulation and economic theory. The resulting findings point towards the need for more complex agents incorporated in urban simulative models.

This chapter focused on a literature review of three main disciplines, urban planning, urban simulation and the theories (predominately from economics) that dictate urban simulative models. This analysis revealed an overarching shift in all three fields towards considerations of the individual in their own ways. Urban planning theories have evolved away from rational comprehensive approaches embedded withing systems theory and modernity. The field has moved towards communicative rationality instead as planners became aware that their objective truths and perspectives are insufficient. They lack the ability and means to know what different people/demographics desire due to the plurality and often conflicting perspectives. In parallel, urban simulative models, which are in fact tools for planners, have also moved away from aggregate modelling and macro-level simulations. The move towards disaggregates modelling and microsimulation took advantage of McFadden's discrete choice framework to create ABMs that allow for logic-based agents to be heterogenous with different desires based on different objective decision-making theories. These took advantage of the evolution of theories in economics, which forms the basis for these models, which evolved from macro-level theories such as location theory, bid-rent theory and economic-base theory to more micro-level theories of decision making notably random utility and utility maximization. These theories are based on objective rationality and form the basis of a new generation of real-estate demand models. However, there seems to be a lack of subjective rationality in modelling decision-making in real-estate demand models which the field has moved towards with consumer behaviour, behavioural economics and bounded rationality.

These findings and field knowledge provide the basis for the creation of a methodology that seeks to move real-estate demand modelling in both their agent architecture and theoretical basis towards more complex agents' behaviours. This attempt will be informed by theories that are both in-keeping with current trends in both planning theory developments and economic behavioural theories around subjective rationality.

CHAPTER THREE: RESEARCH METHODOLOGY FOR COMPARATIVE STUDIES— MODEL SELECTION, DATA COLLECTION, ANALYSIS METHODS AND RESULTS

3.1 Introduction and Overarching Design Science Research Methodology

The main aim and knowledge contribution of this research is to advance the capacity of decision-making computational agents used within location choice urban simulative models. As such, there will be a need to design/develop new and improved agent architectures and decision-making mechanisms for the field and test their applicability. Therefore, this research follows a design research paradigm, 'the act of creating an explicitly applicable solution to a problem'(Peffers et al., 2007, p. 47).

Design has many ambitions and definitions that are often contradicting each other with some placing the emphasis on the end product (Julier, 2000) while others on the activity of design (Sanders, 2008). This dichotomy in perceptions may stem from the word itself being both a verb and a noun. Frankel & Racine consider both aspects and argue that 'design is an activity for planning and implementing new products, which includes the by-products of the processes involved such as drawings, models, plans, or manufactured objects'(Frankel & Racine, 2010, p.

3). This means that the process of designing new computational agents within this field constitutes but one aspect of the research undertaking.

The scientific design research methods set out in the 1960s are further separated into different types of design research. Buchanan (2001) noted that depending on the design problem, the research needed may be viewed as clinical, applied or basic. He was not the first to attempt to categorise different types design research with Frayling (1993) notably calling for a differentiation between research for, through and into/about design. Both Buchanan's and Frayling's taxonomies have been interconnected (Frankel & Racine, 2010) with clinical associated to research for design (establishing conditions, processes, specifications and data that designers can use to achieved desired end results (Downton, 2003)), applied associated with research through design (action-reflection approach with an emphasis on creating design knowledge and not the project solution (Findeli, 1995)) and lastly basic associated with research about design (work undertaking a design inquiry to determine experience of designers and users alike (Buchanan, 2007)).

This thesis will undertake design research, with a particular focus on futures using unique design processes that are specifically geared towards it. These involve forecasting, speculative design with a look at specific elements in isolation. The creation of these agents will need to be separated from context in an attempt to generate new solutions and knowledge through design experimentation (Sevaldson, 2010). This type of research is both informed and contributing to new and existing theories and practices (Sevaldson, 2010) that transcend disciplinary boundaries. The design of these agents will require a look at agent architectures (computer science), decision-making theories (economics and psychology) and finally knowledge of the field of application (urban modelling for architecture and planning).

The particular focus of this speculative design research is simulation which constitutes a means of researching future possibilities and scenarios. Acknowledging the role of simulation as a useful research tool to develop an understanding of future context and demands, its development and use merits the association to research for design. This is justified as it seeks to speculate about future possibilities, to design potential outcomes, and/or to test multiple different design outcomes. The process includes both a robust computational coding framework generated within the computer science discipline and the integration of human behaviour within the simulation.

Given the need for a design research paradigm, this thesis will adopt a design science research methodology as proposed by Peffers et al.(2007). This constitutes a commonly accepted framework for successfully undertaking design research that will aid in both the recognition and legitimisation of the work, its objectives, processes and outputs. It involves 6 activities that are integral to the methodology.

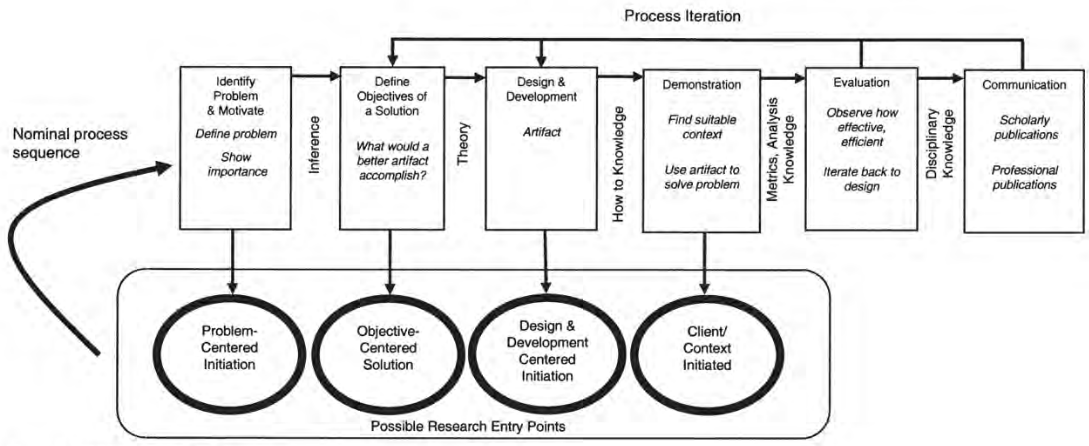


Figure 1. DSRM Process Model

Figure 15: Diagram showcasing design science research methodology as proposed by Peffers et al.(Peffers et al., 2007,page 54).

The first activity is problem identification and motivation. This involves the definition and justification of both the research problem and the solution. This includes both knowledge of the state of the art and the problem as well as the importance of its solution. In this thesis, though the literature review has revealed a need for the development of more advanced heterogenous agents within real-estate demand urban simulative models as a means to justify the solution, the extent of the problem has yet to be revealed as that will require an analysis of existing models outlined and carried out in this chapter.

The second activity is concerned with the definition of objectives for a solution. These include rationally inferred objectives from the problem definition and can be both quantitative (better than current) and/or qualitative (supports solutions to problems not currently addressed) (Peffers et al., 2007). The objectives for this thesis are clearly defined in chapter 4 prior to the development of a solution.

Design and development are the third activity which includes the development of an artifact. In chapter 4 the thesis will seek to develop two new computational simulation model with an embedded research contribution surrounding the development of the agent decision-making mechanisms of the field. This includes the design of both the desired functionality of the model as well as the architecture of the agents followed but the completed creation of it. The process requires knowledge of decision-making theories that can aid in bringing about the desired solution. The thesis will seek to design a third artifact based on current solutions to the problem (i.e. existing agent theories and architectures currently in use in within urban modelling) as a means to determine the effectiveness of the two new artifacts against what is currently out there.

The fourth activity, demonstration, uses the artifact created to solve one or more instances of the problem (Peffers et al., 2007). In chapter 5 the thesis will use the artifacts to run simulations that showcase their ability to be used to solve the problem, in this case, the ability of different complex computational agents to make location choice decisions. This step aims to demonstrate not only the ability of the artifacts created to fill the role of a real-estate demand model but to also showcase differences in results between the three computational models created.

The fifth and perhaps most important activity, evaluation, requires the observation and measure of the extent by which the artifact created supports a valid solution to the stated problem (Peffers et al., 2007). In chapter 6 the thesis will seek to evaluate and validate the results obtained in the demonstration by comparing the observed results of the three artifact demonstrations to a real-world equivalent. This method will include relevant analysis and comparison techniques (active-roleplaying simulation) that seek to measure the effectiveness of the results while considering the objectives set out in activity two. Based on the outcome of this activity, the methodology allows for the choice to iterate back to activity 3 and improve the design of the artifact to better perform. This thesis will not be doing so, opting to design a proof-of-concept solution and leave further improvements in subsequent projects. This is mainly due to the nature of the research, since the testing of the artifact is in itself a contribution to knowledge and any iterative process would sever the integrity of the process.

Lastly, the final activity is communication. The entirety of this thesis and particularly chapter 7, will fulfil the final step of this methodology as it seeks to communication ‘the problem and its importance, the artifact, its utility and novelty, the rigor of its design, and its effectiveness to researchers and other relevant audiences such as practicing professionals’(Peffers et al., 2007, p. 56).

All six activities will be undertaken by this thesis in the subsequent chapters. This chapter will primarily focus on activity 1, problem identification and motivation. In order to understand the existing capacity of agent-based urban simulative models there is a need to define the models of interest to this research. As previously stated, this particular range of decision-making agents involves the setting of value and demand for land or “real-estate demand models”.

This research focuses on the decision-making mechanisms of agents for location choice within a range of urban simulation models which include land-use change, land-use and transportation integrated models, land-use cover change and urban growth models. As such all models chosen for comparison will include prevalent examples of models from this area.

This chapter will define what are agents, agent theories and agent architectures as an introduction into the computational coding processes that are needed to create the abovementioned real-estate demand model agents. Subsequently, the chapter will set out a methodology for the comparison of agent architectures across a series of the most prevalent models in the field found using some key searches in the web of science. The comparison will reveal insight into the capacity of current models to accommodate more complex behaviours of agents as well as potential areas of improvement within the agent architecture itself.

3.1.1 Defining agents.

There is no widely accepted definition for an agent (Chin, Gan, Alfred, & Lukose, 2014;Nwana, 1996). For this research we will use Wooldridge's widely cited description of an autonomous software entity situated in a specific environment with the ability to monitor and respond proactively and reactively autonomously or through agent communication in a constant attempt to achieve certain goals/tasks on behalf of the user or other agents (Wooldridge, 2009).

Agents have a set of characteristics, which fall within two categories, a weak notion of agency and a strong notion of agency as related to Artificial Intelligence (AI). Weak notions of agency include the characteristics of Autonomy, Social Ability, Reactivity and Pro-activeness. Autonomy is the ability to operate without direct intervention by either the user or other entities as well as the ability to have some control over the agent's own actions and internal state (Conte &

Castelfranchi, 1995). Social Ability includes agents that have the capacity to interact with either humans or other agents through a communication language (Genesereth, 1994). Reactivity means agents have a perception of their environment and the capacity to respond appropriately and timely to changes that occur in it (Wooldridge & Jennings, 1995). Pro-activeness means agents not only respond to changes in their environment but can exhibit goal-directed behaviour by taking initiative (Wooldridge & Jennings, 1995).Strong notions of agency include traits such as knowledge, belief, intention, obligation and even emotion (Bates et al, 1994). Other attributes include Mobility, Veracity, Benevolence, Rationality and Learning Capacity. Mobility is the ability of an agent to move around an electronic network. Veracity or trustworthiness is the assumption that an agent will not knowingly communicate false information. Benevolence is the understanding that agents will always do what is asked of them. Rationality is the knowledge an agent will act a way that achieves their goals and never in a way that prevents their goals from being achieved. Learning capability is the ability to learn and adapt their actions accordingly. Strong notions of agency help in increasing the complexity of agents and their decision-making mechanisms. Their use and inclusion is very important in overcoming the lack of cognitive agents in current real-estate demand models, capable of adjusting their behaviour during the decision-making processes over time where both external conditions and the experience of the decision maker are in constant change (Ettema et al., 2005).

3.1.2 Defining Agent theory.

In the previous section, the research introduced characteristics that describe agents and their capacity. The combination of these dictates the type of agent architecture that exists for the model. It is tied to the agent theories that provide the specification for agents by formalising the representation of agent properties (Wooldridge & Jennings, 1995). Agent theory is the blueprint for how an agent should behave prior to its creation/build.

Agent theorists can consider agents as intentional systems. In this sense, an explanation or prediction of human behaviour exists through the understanding of the attributes of people's attitudes. For example, I will take my umbrella because I believe it will rain. There are grades of intentional systems, first order and second order (Dennett, 1987). First order grade refers to agents having traits of beliefs and desires while second order refers to agents having beliefs and desires on beliefs and desires. There is a variety of these traits for agents, commonly referred to as attitudes, split between information attitudes and pro-attitudes. Information attitudes includes all of the agent's information on the world it occupies. Examples of such attitudes include belief (what it thinks the world is) and knowledge (what it knows the world to be). Pro-attitudes are more related to activities as they exist as a way to guide agent actions. Examples include Desire, Intention, Commitment and choice.

All agents require one information attitude and at least one pro-attitude (Wooldridge & Jennings, 1995). This is an important point when cross-analysing different architectures as the pre-set attitudes dictate the type of agent architecture present in the model as well as how well it digitally represents the human behavioural theory it's based on. With the development of the agent theory framework for belief, desire and intention agents (Rao & Georgeff, 1993, 1991), there is a consideration on the notion of realism. How can an agent's belief about the future or a future state of the world affect its present desires and intentions (Rao and Georgeff, 1997)? Such agent theories allow for the existence of social plans within digital agent societies (Rao et al., 1992). Hence, when analysing the various urban simulative models, there needs to be a focus on the agent's capacity for mimicking social behaviour through their agent theory and architecture.

3.1.3 Defining Agent architecture.

Agent architecture is the move from specification to implementation, how all these agent properties get build in a computer system. It is intended to support decision-making process by being the foundation of agent reasoning mechanisms (Chin et al., 2014). It encompasses techniques and algorithms supporting a decomposing set of components and how these components interact (Maes, 1991). Agent architectures have two main categories explored in this research, classical and cognitive. Classical architecture can be further split into logic-based, reactive, BDI (belief, desire, intention) and hybrid.

Logic-based agent architecture relies on representing the environment and agent behaviour with symbolic representation. The agent's reasoning mechanism is modelled by a set of deduction rules called rules of inference. The decision-making process occurs through these rules of inference as a set of if statements with the best possible action returned if a specific statement stands. In the case that a statement does not stand, the return is a special, null action. Due to the syntactical manipulation of the symbolic representation being the process of logical deduction, this type of architecture can be considered as theorem provers (Chin et al., 2014; Shardlow, 1991).

Reactive architecture involves the direct mapping of situations to actions for the agent's reasoning mechanism. As the environment changes, the agents respond through stimulus-based actions. A key idea here is that intelligent behaviour can be generated without explicit representation and abstract reasoning (Brooks, 1991). This is reminiscent of Wolfram's (1994) findings with 2D CA models with complex behaviour emerging from simple rules of interaction between agents.

BDI architecture is based on Bratman's practical reasoning (Bratman, 1987). Practical reasoning is reasoning towards actions, essentially the process of figuring out what to do. The agent derives its own knowledge, reaches their own conclusions using own agent's beliefs and knowledge. Achieving this practical reasoning is through the three mental attitudes that this type of architecture has.

Belief is what the agent thinks the world is. A set of internal knowledge on the environment usually represented in a Boolean statement (Caillou et al., 2017). Belief synergises with an agent behaviour called perception that runs at each iteration allowing the agent to update its belief and desire base. Desires are what the agent wants the world to be. It is the motivation or possible options to carry out actions with the objectives the agent wishes to accomplish in mind. The objectives are stored as a set of desires. These desires are realised when the belief matches the desire. They can have priority values allowing for a choice between ranges of them. They may be dynamic with super desires, and sub desires creating a roadmap with mini objectives in order for the agent to fulfil its ultimate goal. This attitude links with the agent behaviour of plan. The agent has a set of plans, behaviours defined to reach specific desires. A plan is either instantaneous or persistent with priority values making their choice dynamic between several possible plans. Intentions are the agent's commitments towards a desire or belief, what it actually does in order to fulfil its goals. As a result, intentions are action inducing, what an agent has chosen to do. Current intention determines the plan chosen. Intentions have the ability to be on hold when there is a rise of sub-desires making them stackable. The last item on a stack of intentions is the one active while all others are on hold.

Cognitive architecture, based on a stream of cognitive science, help construct intelligent agents for modelling human performance. What sets it apart is the three distinct characteristics that this type of agents have (Langley & Choi, 2006). Firstly, agents have short/long-term memory for storing the agent's beliefs, goals and knowledge. Secondly, agents have representation of memory and their organisation. Lastly, there are functional processes that operate on the memory structures. Memory and learning are the two key components in developing cognitive architecture.

3.2 Chapter organization

In this chapter, the introduction has set out the overarching methodology adopted by the thesis (design science research methodology) and proceeds to identify the performance of current agent architectures used within urban simulative models, specifically focusing on the modelling of human behaviour in real estate demand models.

Section 3.3 sets out the initial identification of method for the first part of the methodology. The research adopts a comparative research design approach with a qualitative analysis of simulation models to compare their capabilities and identify potential gaps. The research seeks to assess existing models on their agent architecture capacities and the extent of their ability to implement different/more complex agent behaviours. The research will gather the evaluation criteria from computer science disciplines and assess the models based on the coding method of the agents and the ability to implement different behaviours. The research will not be gauging the accuracy of the simulations, but rather the extent of their capacity to answer the questions set by the user.

Section 3.4 sets out the evaluation criteria for comparing urban simulative models that include micro-simulations and agent-based interactions in human system representations. The criteria will be based on the concepts and properties present in the agent architecture. The evaluation methodology involves creating tables or analysis displays to cross-analyse a set of chosen urban simulative model cases. The evaluation questions will focus on the merits of agent architecture, based on the variables: Autonomy, Mental Mechanism, Adaptation / Adaptability, Concurrency, Communication, Collaboration / Teamwork, and Agent Abstraction. The variables will be scored on a scale of 0 to 10, with 10 being the highest score. The information will be reduced and stacked in a meta-matrix display for comparison and pattern finding across all cases.

Section 3.5 showcases a table displaying the results of the agent-based urban simulative model analysis. It compares 11 different models, represented by the columns, based on 7 different variables, represented by the rows. The models are then compared based on beforementioned scores to see which models have higher levels of control or features in each category.

The summed-up conclusions of the cross-case analysis, in terms of current lacking agent attributes, are as follows:

1. cognitive agents using memory storage and representation
2. collaboration between agents to achieve goals
3. belief, desire, intention agents (BDI)
4. pro-activeness traits

3.3 Identifying the limitations within the agent architectures:

3.3.1 Research Design: Comparative

One of the aims of the PhD is to investigate what are the current limitations of urban simulative models. More specifically, what are the limitation surrounding the modelling of human behaviour in deciding on dwellings, space and land in real-estate demand models? This is an important aspect of a simulative model due to the complexity and unpredictability of individuals and the accuracy of translating that to a digital platform being the source of criticism for the wider urban simulative modelling world.

In order to answer this, a comparative research design approach is required with a method that compares and rates the current approaches of modelling human behaviour in urban simulative models.

3.3.2 Quantitate vs Qualitative analysis of simulation models.

This research compares simulative models on their capabilities while aiming to create new models to address potential gaps. Quantitative approaches to evaluating simulation models uses a series of statistical techniques at five different stages of the model (Kleinjnen, 1996). These stages are as follows:

1) Validation: Simulation output compared to real system to determine accuracy. Statistical technique used depends on the available data from the real system.
2) Screening: Sequential bifurcation using aggregation and sequential experimentation identifies the important inputs for the simulation.
3) Sensitivity: Regression analysis or other techniques help create a detailed analysis of inputs. This analysis reveals many things such as potential interactions between inputs for gauging resultant effects of extreme value inputs.
4) Uncertainty: Inputs can have a range of values with no precise measurement. This results in uncertainty of values. Techniques like Monte Carlo sampling help deal with this issue.
5) Optimisation: In order to optimise controlled inputs such as policy variables, the modeller can use a range of techniques such as Regression Analysis or Response Surface Methodology.

This type of quantitative 5-stage evaluation methodology is useful for validating and comparing a series of predictive models to gauge their effectiveness / accuracy. This research however does not seek to gauge the accuracy of simulations but the extent of their capacity to answer questions set by the user. As such, the methodology needed to achieve this is a qualitative comparison of models. Using a qualitative comparison, existing models will be assessed on their agent architecture capacities, directly answering the question set by the research of whether they are able to implement different/more complex agent behaviours.

3.3.3 Research Strategy: Qualitative

ABM, as a method, plays a major part in helping researchers understand the dynamics of complex systems especially when modelling natural and social systems/human-environmental systems (Axelrod, 1997b; Batty, 2005; Benenson et al., 2002; Bousquet & Le Page, 2004; Clifford, 2008; Crooks, 2007, 2010, 2014, 2015; Crooks, States, et al., 2018; Crooks & Hailegiorgis, 2014; Dawson et al., 2011; Filatova, 2014; Fontaine & Rounsevell, 2009; Grignard et al., 2016; Heppenstall et al., 2012; Huang et al., 2014; Jager & Joachim Mosler, 2007; Le et al., 2012; Matthews et al., 2007; Parker et al., 2008; Parker et al., 2008; Parker et al., 2001, 2002; Polasky et al., 2011; Schlüter et al., 2012). The literature showcases the fundamental importance decision-making models have as research tools especially in ecological, geographical and social sciences (Crooks, States, et al., 2018; Heppenstall et al., 2019). This rise in popularity brought about certain issues with using this research method. The first issue stems from poor documentation of reasoning behind agent decision-making within the models. The second issue lies in lack of sufficient/transparent description and communication of models in a way that allows for reproducibility by other researchers (Müller et al., 2013).

In order to overcome such shortcomings, attempts made in both the social and land-use sciences, tried to set a protocol for the communications of ABM (Grimm et al., 2006, 2010; Hare & Deadman, 2004; Parker et al., 2008; Richiardi et al., 2006). In many ways the ODD (Overview, Design Concepts and Details) protocol (Grimm et al., 2006, 2010) has seen some success in describing social-ecological model. Attempts were made to use the ODD protocol for Land use cover and change models (Polhill, Parker, Brown, & Grimm, 2005) concluding to positive results however proposing refinements in definitions of terms in the protocol. This gap in the ODD protocol was addressed in an extension of the protocol called ODD + D (ODD + Decision) with the intent to facilitate a clear and comprehensive description of ABMs with particular emphasis on the theoretical and empirical foundations of the human decision choices within the model (Müller et al., 2013). Though this protocol could become the foundation in the qualitative assessment of ABMs proposed by this research, many of the structural elements within the ODD+D protocol is not of interest to this research. The research interest in purely the agent-architecture would not benefit from descriptions on implementation details, initialisation, theoretical and empirical backgrounds etc. As such, the research has opted to gather the evaluation criteria from the computer science discipline as the fundamental coding method of the agents form the main interest for this research.

In the computer science domain, there is no formal qualitative comparison methodology for simulations (Dam & Winikoff, 2004; Jung & Fischer, 1998; Lin et al., 2007; Mualla et al., 2018; Rohlfing, 2016; Sudeikat et al., 2005). There have however been attempts to create such a methodology (Dam & Winikoff, 2004; Lin et al., 2007; Sudeikat et al., 2005). These methodologies focus on evaluating and comparing agent architectures as well as the modelling techniques used. As the study of the research is on the agent-behaviours, this type of evaluation methodology is appropriate. An analysis of these attempts revealed a number of common practices on which to build. These common categories used in previous examples includes:

Agent Architecture:

1. Autonomy
2. Mental Mechanism / Attitudes
3. Adaptation / Reaction
4. Concurrency
5. Communication
6. Collaboration / Teamwork
7. Agent Abstraction

Commonly, in these computer science methodologies for qualitative comparison, a table holds the merits above as its row headings (see table 2 below). The model names are the column headings. For a model, achieving a merit to some degree results in a point scored. For example, do the agents have communication capability? Yes(1pt) No(0pt). The methodology allows for the direct comparison of models not just by sum of score, but effectiveness is specific situations/merits. Unlike quantitative comparison methods, this methodology does not require screening of inputs, validation of model outputs, determining of uncertainties, sensitivity analysis of inputs or optimisation of variables. Model output comparison on the real system is not the aim but an evaluation on its nature and usefulness to the user.

Merits	Model A	Model B	Model C
a			
b			
c			
d			
e			
f			

Table 2: Generic qualitative comparison of simulations table

3.3.4 Qualitative Data Analysis Method: Cross-Case Analysis

The type of methodology used by the computer science domain, outlined above, is reminiscent of the social-science method of cross-case analysis that this research chose to use. The choice of a cross-case analysis method has three reasons. The first is the ability of the method to deepen the understanding and explanation (Glaser & Strauss, 1967) on the current agent architecture facilitating human interaction / behavioural element in urban simulative models.

The second reason for this method is that it enables the identification of negative cases or cases outside the norm (Miles et al., 1994). The last reason is the fact that unlike the attempts made in computer science, cross-case analysis is an established method with a proven track record. The categories commonly used in computer science methodologies also form the merits in this research cross-case analysis.

3.3.5 Type of cross-case analysis: Mixed strategy

There are generally three strategies of undertaking cross-case analysis, a case oriented approach, a variable-oriented approach and a mixed strategy (Miles et al., 1994). For this research methodology, the choice is a mixed strategy. It offers a method of stacking comparable cases each with a standard set of variables. Matrices and other displays help analyse each case in depth, similar to the qualitative comparison of the method used in computer science. After each case is understood in depth, the information is stacked in a "meta-matrix" that further distils the information permitting a systematic comparison.

Eisenhardt (1989) amongst others form examples of this approach. Ragin (1989) calls for a synthesised approach or mixed strategy for cross-case analysis. This led to the creation of a Boolean approach to analysis that sees each case's variables having binary data on a "truth table" that then helps identify patterns of multiple conjectural causation. This form of a data display gave rise to the qualitative comparative method. Although at first glance, the qualitative comparative method seems appropriate for the research aim, it actually fails to complement this research due to the limitation a yes or no data structure gives. Therefore, the research uses a case-oriented display in its stead containing first-level descriptive data on all cases, ordered by the main variable across all cases. It thus coherently arrays the basic data for a major variable across all cases (Miles et al., 1994).

Building the display is the first obstacle; it involves the ordering of cases. Two choices exist here, ordering through main variables or data sources. As all sources for this research are the published work on the simulative models, ordering through the main variable will be used which warrants the choice of case-oriented display. The second hurdle is entering data into the display. This requires the coding of the material into a list of standard variables while summarising materials found in the initial matrix. Drawing conclusions is the final obstacle. This will require the noting of patterns that exist in the display/table after its completion.

3.4 Evaluation criteria

Though human behaviour is a complex subject to understand, it does not stop modellers from simulating human systems in an urban environment. A series of assumptions allows for an abstraction of reality to create a digital representation of the human entity. Urban simulative models incorporate human systems to various degrees and scales. A macro-scale simulation makes strong assumptions on causalities with human behaviour, existing only as patterns in a digital environment. They do not attempt to include the micro-interactions that bring about the emergent patterns observed at larger scales. These types of models are excluded from the evaluation of this methodology. The interest here lies in simulative models that include micro-simulations and agent-based interactions within their human system representations. As such, the evaluating variables for this cross-case analysis are the concepts and properties present in the agent architecture. These include Land-Use Change, Land-Use and Transportation integrated models, Land-use Cover Change and Urban Growth models.

The choice of cases to be cross analysed stems from past reviews (Wegener, 2004), (Silva & Wu, 2012), (Iacono et al., 2008b), (Acheampong & Silva, 2015), (Huang et al., 2014) of urban simulative models and include a unique collection of different urban modelling frameworks with the exclusion of all models with no micro-simulative aspects. There have been over twenty reviews of SUMs within the past fifty years. Four of these had a focus on operational urban simulation models. Wegener (2004) reviewed twenty operational models, Iacono et. al. (2008b) included reference to over twenty models and Silva et al. (2012) reviewed over sixty models. The cases chosen from the five reviews include CommunityVIZ (Kwartler, 2001), MUSSA (Martínez, 1996), SYPRIA (Manson, 2000), PUMA (Ettema et al., 2005), MALUT (Kii & Doi, 2005), LUCITA (Deadman, 2005), SIMPOP (Lena Sanders et al., 1997), AGENT ICity (Jjumba & Dragićević, 2012), HoMES / ILUTE (Rosenfield et al., 2013), ILUMASS (Strauch et al., 2005), D.ETTEMA PAPER (Ettema, 2011), EUGM(Khajavigodellou et al., 2014), URBANSIM(Wang & Waddell, 2013b), TLUMIP(Abraham & Hunt, 2005), RELU-TRAN(Anas, 2013; Anas & Liu, 2007), PECAS(Abraham & Hunt, 2007; Y. Li et al., 2017), SE3M (BLUM)(Clay & Valdez, 2017), RLCM(Vorel et al., 2015), ILUTE(M. Habib et al., 2011; Miller & Salvini, 2001), CLUE-S(Verburg, 2010).

3.4.1 Agent Evaluative Criteria

In order to compare the models, as part of the research, the methodology will consist of the creation of a series of tables also referred to as analysis displays in cross-case analysis methods. The first display will be the writing down of all information that befits the pre-set variables for each case study. The information from the initial display gets re-analysed and reduced. The new information is stacked comparatively in a “meta-matrix” display for the purpose of comparison and pattern finding across all urban simulative model cases.

The evaluation questions of the table are the merits on agent architecture, commonly used in computer science qualitative analysis methodologies, listed in section 3.3.3. The Agent architecture depends on the theoretical basis of the model that in turn dictates agent behaviours. To enhance the evaluation process to fit the focus of the research, an expansion of the variables with a wider range of scoring must be included as part of the methodology. A preliminary table of evaluation and scoring created below will act as the comparison mechanism between models, which includes a standard set of variables.

Variables	Scoring
Autonomy: Agent decision do not require user input and are based on agent's own inner state (Lin et al., 2007)	0= Agent has no control over its activities 5= Agent has some self-control features but still relies on external input for some decisions / proactive / reactive activities 10= Agent has control and is responsible for all of its own activities with no need for external input / command.
Mental Mechanism: Agent has mechanism to realise intentions by achieving goals	Internal Architecture: Agent architecture used to determine range of Attitudes 1= Agent has a reasoning mechanism based on a set of inference rules / logic based/ symbolic representation 1= Agent has direct mapping of actions to environment changes / reactive 1= Agent has belief, it has a world view / perception 1= Agent has desires, motivation or options the agent has to carry out actions in order to achieve a desired world state 1= Agent has intention, commitment towards a desire and belief, auctioning to bring about the desires 1= Agent has memory storage, long / short term memory storage of world state 1= Agent has representation of memory / learning capacity, realising if a choice made was to its satisfaction or level of satisfaction
Adaptation / Adaptability: Ability of an agent to adjust activities according to a dynamically changing environment	0= Agent has no response to a changing environment 5= Reactive, agent perceives their environment and timely responds to changes to it 10= Proactive, agent does not only respond to environment changes but exhibit goal-oriented behaviour by taking initiative and pro-actively adjusting actions in anticipation for change.
Concurrency: Agent can perform multiple tasks at the same time	0= Agent can only perform a single action at a time 5= Agent can perform a number of tasks in a single family of activities at the same time 10= Agent can perform a range of tasks in a range of activity families at the same time
Communication: Agent has methods or mechanisms or protocols that enable / define agent interactions	0= Agent has no defined interactions with other agents 5= Agent has capacity for interaction with same type of agent 10= Agent has capacity for interaction with same & different type of agents
Collaboration / Teamwork: An agent has methods to cooperate with other agents to achieve goals	0= Agent has no capacity for collaboration 5= Agent has capacity to collaborate with same type of agents to achieve goals 10= Agent has capacity to collaborate with same and different type of agents to achieve goals
Agent Abstraction: Methodology has theory to describe agents using high-level abstraction	0= Agent behaviour is not informed by theory 5= Agent behaviour is informed by high-level abstraction of reality (maybe some aspects informed by theory?) 10= Agent behaviour is informed by a low-level abstraction of reality (maybe all aspects informed by theory?)

Table 3: Evaluation matrix and scoring to determine agent architecture capacity for existing models.

Existing models will have their capabilities assessed using the above table's variables. The resultant table will help identify gaps in agent capability. This will allow for a discussion on the creation of new models with an alternative set of behavioural theories specifically targeting the specific shortfalls of the current urban simulative model literature.

3.5 Results of Case-Study / Agent-Based Urban simulative model Analysis

All cases were analysed, and their scoring entered into display tables to enable comparisons. The first display listed all the information befitting pre-set variables for all case studies (This can be found in the appendix).

The creation of a meta-matrix display, a distilled version of the information, enables an easier comparison and the formulation of trends running through the dataset. To generate this meta-matrix, the initial display information was distilled to the point were only the numerical values of the variables is entered for each case study. The table shown below forms the result of the exercise:

Variables	**Autonomy: Agent decision does not require user input and are based on agent's own inner state (Li*n et al*>, 2007)**	**Mental Mechanism: Agent has mechanism to realise intentions by achieving goals**	**Adaptation / Adaptability: Ability of an agent to adjust activities according to a dynamically changing environment**	**Concurrency: Agent can perform multiple tasks at the same time**	**Communication: Agent has methods or mechanisms or protocols that enable / define agent interactions**	**Collaboration / Teamwork: An agent has methods to cooperate with other agents to achieve goals**	**Agent Abstraction: Methodology has theory to describe agents using high-level abstraction**
Source	0= Agent has no control over its activities	Internal Architecture: Agent architecture used to determine range of Attitudes	0= Agent has no response to a changing environment	0= Agent can only perform a single action at a time	0= Agent has no defined interactions with other agents	0= Agent has no capacity for collaboration	0= Agent behaviour is not informed by theory
	5= Agent has some self-control features but still relies on external input for some decisions / proactive / reactive activities	1= Agent has a reasoning mechanism based on a set of inference rules / logic based/ symbolic representation	5= Reactive, agent perceives their environment and timely responds to changes to it	5= Agent can perform a number of tasks in a single family of activities at the same time	5= Agent has capacity for interaction with same type of agent or non-direct interactions	5= Agent has capacity to collaborate with same type of agents to achieve goals	5= Agent behaviour is informed by high-level abstraction of reality (maybe some aspects informed by theory?)
	10= Agent has control and is responsible for all of its own activities with no need for external input / command.	1= Agent has direct mapping of actions to environment changes / reactive	10= Proactive, agent does not only respond to environment changes but exhibit goal-oriented behaviour by taking initiative and pro-actively adjusting actions in anticipation for change.	10= Agent can perform a range of tasks in a range of activity families at the same time	10= Agent has capacity for interaction with same & different type of agents	10= Agent has capacity to collaborate with same and different type of agents to achieve goals	10= Agent behaviour is informed by a low-level abstraction of reality (maybe all aspects informed by theory?)
		1= Agent has belief, it has a world view / perception					
		1= Agent has desires, motivation or options the agent has to carry out actions in order to achieve a desired world state					
		1= Agent has intention, commitment towards a desire and belief, auctioning to bring about the desires					
		1= Agent has memory storage, long / short term memory storage of world state					

		1= Agent has representation of memory / learning capacity, realising if a choice made was to its satisfaction or level of satisfaction					
SIMPOP	10	1, 0 ,0 ,0 , 0, 0, 0	5	5	5	5	5
MUSSA	5	1, 1, 0, 0, 0, 0 ,0	0	0	5	0	5
CommunityViz	10	1, 1 , 1, 0, 0, 0, 0	5	0	5	0	5
PUMA	10	1, 0, 0, 0, 0, 0, 0	5	5	5	0	5
SYPRIA	10	1, 1, 0, 0, 0, 0, 0	5	0	5	5	5
ILUMASS (IRPUD	5	0, 1, 0, 0, 0, 0, 0	5	5	0	0	5
LUCITA	10	1, 0, 0, 0, 0, 0, 0	0	5	0	0	5
OPUS / UrbanSim 2013	10	1, 0, 0, 0, 0, 0, 0	0	0	5	0	5
RLCM 2015	10	1, 0, 0, 0, 0, 0, 0	0	0	0	0	5
ILUTE / 2013	10	1, 0, 0, 0, 0, 0, 0	5	10	5	0	5
ettema 2011 (closest to cognitive agent)	10	1, 0, 1, 0, 0, 1, 0	5	0	5	0	5
UrbanSim (2003)	10	1, 0, 0, 0, 0, 0, 0	0	5	0	0	5
ILUTE 2001	10	1, 0, 0, 0, 0, 0, 0	0	5	5	0	5
PECAS 2003	10	1, 0, 0,0, 0 ,0 ,0	5	0	0	0	5
Abraham , Hunt 2005	10	1, 1, 0, 0, 0, 1, 0	5	0	5	0	5
SE(3)M / BLUM	10	1, 1, 0, 0, 0, 0, 0	5	0	0	0	5
Kii 2005	10	1, 1, 0, 0, 0, 0, 0	5	0	5	0	5
RELU-TRAN	10	1, 0, 0, 0, 0, 0, 0	5	0	0	0	5
Agent iCity	10	1, 1, 0 ,0, 0, 0, 0	5	0	0	0	0

Table 4: Meta-matrix display/table showcasing the scorings following the analysis of a range of existing real-estate demand models.

Using the meta-matrix display/table above, different trends and gaps were identified. The first variable on the table, autonomy, is sufficiently represented in almost all cases. This may be due to the inherent nature of ABMs and microsimulations to feature autonomous entities. The second variable, mental mechanisms, in contrast to the former, features a poor representation of the majority of available traits. It is evident that nearly all models analysed use the same agent decision-making mechanisms that are based on a set of inference rules/logic based/symbolic representation. Only a small amount of these has additional aspects added on these rules of inference. Only two models by Abraham and Hunt (2005) and Ettema (2011) feature memory storage which is an aspect of cognitive agent architecture although they do not feature a prominent representation of memory as a driving force for agent decision-making. It is also evident that a good representation of models exists that include reactive agents with direct mapping of actions to environment changes. This is further evident in the adaptation variable of the table where the majority of agents do include some sort of adaptive mechanism for the agent to respond to changes. However, none of the models reviewed feature any pro-activeness traits for the agents. In terms of the concurrency variable, only some cases feature agents able to do multiple tasks at the same time. Furthermore, only in one case (Rosenfield et al., 2013) are those agents able to accomplish a range of tasks in a range of activity families at the same time. The fifth variable, communication, shows a majority of cases having agents with the capacity for interaction or non-direct interaction with same type of agents. None, however, allows for the direct interaction between different type of agents. This specific shortcoming of the cases has featured in the literature as a pathway to improvement. incorporating negotiation between developers and potential buyers in a dynamic context (Ettema et al., 2005). The next variable on the table, collaboration, is heavily underrepresented in all cases with only two featuring aspects of cooperation between same type agents and none between different types of agents. The last variable of the table, abstraction, similar to autonomy, acts as a necessary step in the design of models and therefore well represented at a high-level abstraction. The issue with this variable in the table, lies in the lack of use of low-level abstraction of reality and may be attributable to the theories informing the decision-making mechanisms of these models.

The summed-up conclusions of the cross-case analysis, in terms of current lacking agent attributes, are as follows:

1. cognitive agents using memory storage and representation
2. collaboration between agents to achieve goals
3. belief, desire, intention agents (BDI)
4. pro-activeness traits

3.6 Chapter Summary

The lack of demonstration of cognitive and BDI architectures in decision-making processes for agent location choice presents an interesting gap in theories for the literature. Agent architecture choices are representative of the decision-making theories and axioms used to dictate agent behaviours.

Utility maximisation, the most widely used theory in these scenarios, acts as a rule of inference with each determining factor having a stable attached weight to it and all factors featuring in a utility formula that decides on the agent's choice based on what the modeller perceives as objectively good reasoning. The notion of a rational agent making objectively good/the best decisions forms the basis of classical economics. Many macro-economic and micro-economic models depend on rationality as a behaviour style seeking to make the best choice given their goals, time limits and imposed conditions or constrains (Simon, 1982).

Urban simulative models overly depend on this assumption for agent decision-making. Specifically, with the focus of this research being demand and choice of location (dwelling, land and space), decision-making theories such as utility maximisation, expected utility and random utility make-up almost the entirety of the literature. It is a fundamental aspect of agent choice-making mechanisms that lends itself to an easier calibration and validation process.

The limitations of this approach have gathered critic especially on the notion of rationality. Herbert Simon, introduced the notion of bounded rationality (Simon, 1972) that some economists view as an attempt to explain irrational behaviours observed in reality. Instead of viewing a scenario as "the agent had no reason for choosing the wrong solution but…", the researcher chooses to see the perspective of the subject and denoting that "they had good reason for choosing this solution because…"(Boudon, 1989). This was later named as subjective rationality, described as a product of misunderstanding between the complexity of the real world and the cognitive capacity of the subject (Boudon, 1989). Weber (1968) talked of the importance of considering the reasons of a choice and the avoidance of a narrow rationality definition as to prevent viewing behaviour as irrational so frequently.

This aspect of an agent's judgement of what they perceive to be true, correct, good or valid influencing the "best choice" to make, features in decisions concerning location choice in agent-based urban simulative models only as an over abstraction. Agents are devoid of the cognitive capacity to learn from their own actions and alter their perceptions in a similar manner to the real-world people they represent. The psychology discipline has long established that in the real world, "decisions occur in sequences and information available for later decisions is likely to be contingent on the nature and consequences of earlier ones" (Slovic & Lichtenstein, 1977, p. 489). Reasons for this lack of inclusion in real estate demand models ranges between the inherent decision-making theories, the reasons for simulating location choice, the ease of achieving the simulation goals and the agent-architecture restrictions imposed on the implementation of such models. In fact, psychologists have concluded that traditional decision models, based on rational choice, have failed in their attempts to represent human values as "people's preferences are often constructed in the process of elicitation" (Slovic, 1995, p. 364). They call for models of far greater complexity to describe and explain such actions (Slovic, 1995). Therefore, these shifting perceptions of good may form the key that allows agents to make decisions on more qualitative aspects of a product, in this case a location/building/land/space.

The results from the cross-case analysis demonstrate that existing real estate demand models lack capacity in four areas. These are the lack of cognitive agents using memory storage and representation, lack of collaboration between agents to achieve goals, lack of belief, desire, intention agents (BDI) and lack of pro-active traits.

The first conclusion on the lack of cognitive agents forms a question on how such agent architectures can allow for a different type of decision-making theory to exist within urban simulative models. These will be a response to decisions made under uncertainty when classical methods are problematic as clear objectively good decisions become fuzzy. It is also worth noting that the concept of utility maximisation exists in many forms and the implementation of it in agent-based urban simulative models exists in a very specific way. It is therefore possible, with an adoption of a different agent architecture, to elevate the use of utility maximisation and achieve a different result allowing for subjective reasoning amongst an artificial agent population.

The identified limitations of agent architecture capacity shed light on a fundamental issue in fulfilling two specific demands/calls from modellers. The first is the lack of cognitive agents capable of adjusting their behaviour during the decision-making processes over time where external conditions and experience of the decision maker are in constant change (Ettema et al., 2005; Heppenstall et al., 2016). The second is a lack of agents for simulating housing search and choice while incorporating negotiation between developers and potential buyers in a dynamic context (Ettema et al., 2005). This latter would incorporate co-operation between agents and prioritization of objectives and desires. The limitations suggest avenues for further research in agent-based urban simulative models with an important role associated to underlining theories of agent decision-making for location choice.

CHAPTER FOUR: SPECIFICATION OF A METHODOLOGICAL FRAMEWORK TO SIMULATE URBAN LOCATION CHOICE USING BDI AND COGNITIVE AGENT ARCHITECTURES

4.1 Introduction

The literature review, specifically the ESU-AF1 application on urban simulative models, revealed a limited theoretical basis for decision-making agents. This finding, alongside chapter 3's cross-case analysis results on agent architecture, helped identify a potential gap. These findings provide the basis for advancing into the second activity related the design science research methodology, the definition of a solution's objectives.

In light of the limitation/gap in agent architecture, this chapter explores a range of social science-based theories and a range of social science-based disciplines such as psychology and behavioural economics in an attempt to identify potential concepts for agent behaviour in real-estate demand models. The reason for exploration in these areas is to harvest what the natural progression of theoretical thinking in the disciplines that traditionally form the basis of real estate demand models has yielded. These concepts include notions of cognition, judgment and decision-making processes, consumer behaviour and the role of experience in decision-making. These are then compared to agent architecture attributes needed to implement these theories.

We can break behavioural decision theory down to two parts, normative and descriptive. The normative part deals with prescribing actions based on the beliefs and values of the individual. Descriptive seeks to describe these beliefs and values and understand how they infer in the observable response (Slovic & Lichtenstein, 1977). Since the decisions in the development market happen as a sequence of tasks, it is important to study how the task specification changes over time and how information, available for later choices, depends on the outcomes of previous decisions (Slovic & Lichtenstein, 1977).

The identification and classification of subjective decision-making theories will act as part of a methodology to help create a subjective and evolving decision-making process for agents in real-estate demand urban simulation models. The next part of the design science research methodology contained within this chapter, includes the design and development of the artifacts. In this case, this involves the creation of two models that will serve as the testing beds for the identified theories. A third model will be created using existing theories and existing architectures within the field, in order to provide results for comparison between the new agent architectures and theories versus the existing ones. The creation and processes of these models is described using the ODD+D protocol (Müller et al., 2013) as it provides an excellent and standardised way to communicate the ABMs to other researchers as part of the methodology’s activity 6 (communication).

4.2 Chapter organization

This chapter includes the development and creation of the artifacts as part of the overarching design science research methodology. Section 4.3 outlines the different theories chosen to be incorporated as the basis for the conceptual models. The first one is the Theory of Planned Behaviour (TPB), a psychological theory that explains human behaviour based on three factors. TPB holds that individuals' intentions to engage in a behaviour are a product of their attitudes toward the behaviour, the social norms surrounding the behaviour, and their perceived control over the behaviour. TPB assumes that individuals who hold positive attitudes toward a behaviour, perceive supportive social norms, and feel confident in their ability to carry out the behaviour, are more likely to form stronger intentions to engage in the behaviour. This theory will be applied to decision-making for complex agents by using the "if-then" logic statements as guides for the agents' behaviour, aligning the meaning of intention in TPB with the meaning of action in a BDI architecture.

The proposed cognitive agent architecture for the real estate market will be based on a combination of Case-Based Decision Theory and Consumer Behaviour Theory. Case-Based Decision Theory views decision-making as a result of past experiences, where decisions are based on past results that happened. Consumer Behaviour Theory highlights the importance of the consumers' internal database for decision-making and the use of decision rules. The proposed agents will use a lexicographic decision rule, where the alternatives are compared based on the agent's perceived importance of different attributes associated with the dwellings. The agent will alter its priorities based on experiences and evaluate its choice after each round.

Section 4.4 describes the ODD+D protocol that will be used to document the ABMs created by this research. This protocol helps to communicate the ABMs in a clear and concise manner and reduces the risk of poor communication. The protocol includes structural elements with guiding questions to aid in the description of the ABM. These structural elements cover topics such as the purpose and entities of the model, the decision-making process of agents, individual learning and sensing, interaction among agents and collectives, and heterogeneity.

Section 4.5 describes the creation of the first model under consideration in this study, based on BDI (Belief, Desire, and Intention) agent architecture from computer science. The aim is to use this architecture to incorporate the prioritization of desires in the decision-making process of agents seeking space. The model incorporates individualism and subjective rationality by adjusting the likelihood of each desire being acted upon, which is unique to each agent and based on the theory of planned behaviour. The agents prioritize their desires based on their unique situation and the weight they assign to each desire, with the most important desire being acted upon first. The model's decision-making is influenced by market price changes, the emergence of detractors, and attractors. Detractors emerge from low-income neighbourhoods, and attractors emerge from high-income neighbourhoods and same demographic agents. This model adopts the theory of planned behaviour as a means of allowing individual subjective choices based on the agents' perceptions.

Section 4.6 includes a description of a theoretical and empirical background for a model of cognitive agent architecture in the real estate market. The model is based on the combination of Case-Based Decision Theory and Consumer Behaviour Theory, which allows for decision-making under uncertainty when a person has incomplete knowledge of all variables involved in the decision process. The agents in the model have two unique attributes: memory storage and memory representation. The memory storage includes experience in the market, family situation, and the ranking of the value of each attribute associated with the dwellings chosen. The memory representation includes needs and wants, a listing of potential alternatives, and determinants of demand, such as motivation for purchase, personality traits, social class, and family.

Section 4.7 describes the third model created; it includes a logic-based architecture that seeks to maximize the agent's utility by choosing a dwelling. This model uses the theory of ordinal utility, where each housing attribute is assigned a preference based on the goals or desires it achieves. The model is conceptual, and the agent data is artificially constructed to represent the effects of changes in the agent architecture on emergent patterns. The agent decision-making is driven by a set of logic statements and the agent's utility is constantly maximized by trying to achieve their most preferred desire from a list of desires. The model takes into account attractors and detractors that emerge from changes in the market price for dwellings and average income level of residents within a neighbourhood. The agent's understanding of safety and the price of a house constantly change due to other agent decisions and allows for adaptation of the housing choice.

Section 4.8 outlines the choice made by the research to code the three models using Python as the programming language, without using any libraries or packages such as Mesa or Agentpy. This was because the unique nature of the models required custom coding, rather than using a pre-existing framework. The models were created using a basic self-created framework and were coded on PyCharm and run on the console within the program. The inputs were entered within the code, and the outputs were exported to csv files for future analysis.

The choice of Python was due to several reasons including its simple syntax that is easier to learn and use, its widespread use in education, the availability of libraries and frameworks for web development and data science, and its flexibility as a language that is not optimized for one particular aspect of computational processes. This makes the research more accessible to other researchers, easily implementable, and easily expandable in the future.

Lastly, section 4.9 outlines the limitations of using an artificial environment for the simulation rather than a real-world scenario. The artificial environment, made up of 12 houses and 24 agents, is controlled and determined by the researcher. As a result, the data produced may not accurately reflect real-world behaviour and decision-making processes. This limits the practical applications of the models and their usefulness for predicting real-world outcomes. However, the conceptual and controlled nature of the simulation allows for a comparison of the performance of different theoretical bases and agent architectures, which is the purpose of the research.

4.3 Theories of decision-making for more complex agent behaviours

The perception of importance and priorities being unique to each agent adheres to the concept of subjective rationality. An individual may value some things differently from someone else while maintaining a rational perspective.

There are a number of behaviour theories explaining individual factors and their influence in a rational choice. These include the Social Ecological Model that assesses the relationships between individuals, social groups and the environment or community to predict behavioural outcome. Social Learning Theory that explains behaviour as a product of observing and imitating those with direct influence, reinforcement and punishment. Theory of Reasoned Action / Theory of Planned Behaviour that assesses the process preceding behaviour based on expectancy and intentions. A decision to behave in a certain way is the result of the likelihood of specific outcomes. It considers intentions as the best predictors of behaviour assuming that if an individual plans something, they are more likely to do it. The Transtheoretical Model/Stages of Change views individuals residing at a given stage in relation to specific behaviour change; precontemplation, contemplation, preparation, action, maintenance and termination. The stage an individual is residing on directly influences the likelihood of behaviour change (Thomson & Ravia, 2011). On the other end of the spectrum there are evolution of existing utility theory that seek to capture notions of subjective rationality. These are led by behavioural economics and consumer behaviour.

4.3.1 Theory of Planned behaviour

The first theory this research chose to incorporate is the theory of planned behaviour. This consideration for an agent theory forms the means of allowing individual subjective choices on desires being acted upon based on the agent's own perceptions. In accordance with the theory, intentions are a product of three processes(Ajzen, 1980, 1991).

Behavioural Attitudes include how a person thinks and feels about the behaviour and is further split into two groups, affective attitude and instrumental attitude. Affective Attitude considers if the behaviour is enjoyable or not while Instrumental Attitude considers if the behaviour is beneficial or harmful or not.

Subjective Norms include the support given by significant others or members of the agent's social group and are again split into two groups, injunctive norms and descriptive norms. Injunctive Norms consider if others encourage the behaviour or not while Descriptive Norms consider if others in my group engage in set behaviour or not.

Perceived Behavioural Control is the third process and essentially separates the Theory of Reasoned action and the Theory of Planed behaviour as the latter identifies the value of control as an important variable. Whether a person is capable and confident in executing set behaviour plays a central role in their intention and actual behavioural outcome. It also assesses the capacity of a person to overcome fears and barriers.

If all three above processes exist in a positive manner for the individual, then a person will form stronger intentions and be more likely to engage in the behaviour.

Gollwitzer, Scaal and Taylor (1998; 1995) have expanded theory of Planned Behaviour to include a stage between intention and the resulting behaviour called implementation intention. The hope is to move someone with the intention to actually doing that behaviour (nudging).

Implementation intention is a plan the individual makes which includes a description of what will be done and the where (place) and when (time) to perform the behaviour. It is a specific, individualised plan created by the individual. The when and where in which the goal behaviour (the what) is enacted form the contents of this plan. It is posed in the format "if (situation A arises), then (behaviour B to be enacted)." This results in situational cue prompting actions that no longer consider planning or thought.

The addition by Gollwitzer, best implements itself to a situation where the researcher deals with actual people and not computerised agents. However, the format by which the intention is posed lends itself easily for implementation in the rules that govern agent behaviour. The logic statements may act as guides for the agents negating the leap from intention to implementation. In a BDI architecture, intention has the meaning of action / implementation while in the theory of planned behaviour; intention does not necessarily mean action. By using the plan posed by implementation intention in the format of "if a happens, then behave in b way" intention in the theory becomes a given action in the computerized agent. It therefore aligns the two meaning of intention from both the architecture and behavioural theory to be synonymous with action.

For example, if we take Jim as a generic agent deciding whether to a) enter the real estate market and b) rent a house. Suppose that Jim is not actively engaged with the real estate market as he lacks both knowledge and experience however, he is well aware of the fact that his current house if too far away from work. His friends do not encourage joining the market as they recall their own bad experiences. Jim knows that even if his friends dislike the real estate market, they all moved house in the last year. Jim also has low perceptions of behavioural control as his experience causes a lack in confidence in his ability to navigate the market. He will have to rely mostly on his friends to come, view the properties with him, and advise him going forward. In this example, Jim has conflicting behavioural attitudes and social norms with a mixture of positives and negatives. What makes the probability of Jim entering the real estate market lean more heavily on the negative is the last aspect of the theory of planned behaviour, the perception of behavioural control. As Jim relies on his friends to come with him to view the properties, give him advice and in general make up for his lack of experience and knowledge, there is a distinct lack of control in decisions, scheduling and so on. Given all three processes of the theory lacking an overwhelming positive outcome, Jim would have a negative intention given the circumstances deciding not to enter the market at this time. In a similar way, the BDI architecture will use the theoretical framework to figure out the intentions to be implemented, weighting on desires and the resulting intention given a specific set of desires.

4.3.2 Case-based Decision Theory and Consumer behaviour

Creating a cognitive agent as a decision-maker in the real estate market requires a new set of theoretical frameworks. As such, the conceptual underpinning of the cognitive agent architecture model will include a mixture of Case-Based Decision Theory and Consumer Behaviour Theory.

Case-Based Decision Theory revolves around the idea of people choosing courses of action based on their performance in similar past situations (Gilboa & Schmeidler, 1995). In case-based decision theory, what actually exists in the memory of a coded agent is only past results that actually happened. Each result has information only on the action chosen and the subsequent outcome. This serves as a more realistic way of coding decisions in urban simulation models as the notion of bounded rationality (Simon, 1959) stands true in such a theory. Knowledge is not perceived to be perfect, as the information that make up the process of judgement is found lacking and allows for more conflicting and complex decisions to be taken.

Understanding when an agent/consumer seeks new information as part of a rational problem solving, judgment and decision-making process, there is a need to explore consumer behaviour. Part of behavioural economics, consumer behaviour literature expands into the real estate market. Decision rules for consideration when performing any kind of judgment and decision-making process are as follows:

1) A consumer can only consider a product whose existence is known and is perceived to satisfy his needs (Gibler & Nelson, 1998). This means that whether a household is considering dwellings to buy, their choices are limited on the extent of their knowledge.
2) Consumers can make a purchasing decision using either compensatory or non-compensatory decision rules.
    a. Compensatory rules rank all alternatives with their important attributes and a selection is made on the product that scores the highest.
        i. Simple additive rule: Selection is made on the product that has the largest number of positive attributes (Alba & Marmorstein, 1984).
        ii. Weighted additive rule: More complex as each attribute's importance is also factored in the decision-making computation.
    b. Non-compensatory rules set minimum requirements for all choices. If a product does not meet these minimums, then it is simply not considered.
        i. Conjunctive decision rule: Minimum acceptable levels are set for all important attributes and all choices not meeting these are eliminated. If no product meets the minimum standards then a consumer will either change what constitutes a minimum or change their decision rule altogether (Grether & Wilde, 1984).
        ii. Lexicographic rule: All attributes in a choice parameter are ranked to their perceived importance. The consumer then compares all choices in

terms of this most important rank. The highest scoring choice is then selected. If two or more choices score equally high on the most important attribute, they proceed to be judged on their ranking of the second most important attribute followed by the third and so on until the tie is broken (Gibler & Nelson, 1998).

3) A combination of decision rules may be applied in a given choice scenario.
4) The more dissimilar the alternatives the more abstract the evaluation criteria will be (Johnson, 1984, 1989).
5) Experienced consumers have a more defined list of what attributes are important to compare alternatives with while first-time buyers are more likely to be influences by external sources when assembling their set of criteria for decision-making (Bettman & Sujan, 1987).
6) Decisions made may be less than optimal as comparable attributes in combination with the number of attributes and lack of perfect knowledge becomes too complex to comprehend.

In Case-Based Decision Theory, the agent judges all action on the result of previous solutions to similar problems. In the same way, consumer behaviour sees them first search their internal, historic database for information to both frame and judge the problem (Punj, 1987). For this research, the agents follow a lexicographic rule when comparing alternatives. The agent develops their own perception of value for different attributes associated with the dwellings based on case-based decision theory. They then proceed to rank each available choice based on their perceived most important attribute which is subjective. All highest scoring choices are then compared to the second most important attribute and then the third and so on until a clear optimal choice from the set of alternatives emerges. The agent then proceeds to buy that dwelling. During the course of the round the agent evaluates their choice and stores that experience in their memory, ultimately altering their perception of what they prioritise in dwelling attributes.

4.3.3 Agent architecture requirements for identified theories.

In the previous section, the research set out two unique behavioural/decision-making theories from economics and psychology that represent the evolution of existing theories currently used in urban simulative models. The application of any agent theory in a computer model, specifically ABMs, requires a matching capacity from the agent architecture in order to accommodate its peculiar needs. The table below features the theories discussed above as well as some prevalent theories in household location choices for urban simulative models. The needed agent attributes for each agent decision-making theory identified in the table will enable an understanding of required urban simulative model capacity in terms of the agent architecture. The application and testing of these theories alongside novel agent architectures for the field, form the main solution objectives as part of this thesis' design science research methodology.

State of the Art	Theories relevant to Planning – Scenario Analysis	Capacity	Agent Architecture Models/Attributes
Objective (Existing Theories)	1.Utility Maximisation 2.Random Utility	1.Rules of inference 2.Sampling models (logit etc)	1.- Logic-based Architecture 2.- Logic-based architecture
Subjective (Proposed Theories)	1.Case-based Decision Theory/Consumer Behaviour 2. Theory of Planned Behaviour	1.Memory representation / storage 2. Belief, Desire, Intention capacity	1- Cognitive architecture 2- BDI architecture

Table 5: Table of comparison of required agent architecture capacity for current and proposed decision-making theories.

4.4 Specification of conceptual models

Although the ODD+D protocol (Müller et al., 2013) was not adopted for the review of existing agent-based real-estate models due to elements of it not being necessary for this research, it does provide an excellent way to communicate the ABM creations of this chapter. Using standard approaches to document ABM models helps mitigate risks of poor communication (A. Crooks, Heppenstall, et al., 2018) and helps establish the method as a valid and accurate research tool. Therefore, this research has adopted the ODD + D protocol and used the structural elements in the table below to aid in the methodological description of the three proposed ABMs.

Structural Elements		**Guiding questions**
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?
		I.i.b For whom is the model designed?
	I.ii Entities, state variables and scales	I.ii.a What kinds of entities are in the model?
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterised?
		I.ii.c What are the exogenous factors/drivers of the model?
		I.ii.d If applicable, how is space included in the model?
		I.ii.e What are the temporal and spatial resolutions and extents of the model?
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?
II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?
		II.i.b On what assumptions is/are the agents' decision model(s) based?
		II.i.c Why is/are certain decision model(s) chosen?
		II.i.d If the model/submodel (e.g. the decision model) is based on empirical data, where do the data come from?
		II.i.e At which level of aggregation were the data available?
	II.ii Individual Decision-Making	II.ii.a What are the subjects and objects of the decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included?
		II.ii.b What is the basic rationality behind agent decision-making in the model? Do agents pursue an explicit objective or have other success criteria?
		II.ii.c How do agents make their decisions?
		II.ii.d Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?
		II.ii.e Do social norms or cultural values play a role in the decision-making process?
		II.ii.f Do spatial aspects play a role in the decision process?
		II.ii.g Do temporal aspects play a role in the decision process?
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?
		II.iii.b Is collective learning implemented in the model?

	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?
		II.iv.c What is the spatial scale of sensing?
		II.iv.d Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?
		II.iv.e Are the costs for cognition and the costs for gathering information explicitly included in the model?
	II.v Individual Prediction	II.v.a Which data do the agents use to predict future conditions?
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?
		II.vi.b On what do the interactions depend?
		II.vi.c If the interactions involve communication, how are such communications represented?
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?
		II.vii.b How are collectives represented?
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?
	II.ix Stochasticity	II.ix.a What processes (including initialisation) are modelled by assuming they are random or partly random?
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)
III) Details	III.i Implementation Details	III.i.a How has the model been implemented?
		III.i.b Is the model accessible, and if so where?
	III.ii Initialisation	III.ii.a What is the initial state of the model world, i.e. at time t ¼ 0 of a simulation run?
		III.ii.b Is the initialisation always the same, or is it allowed to vary among simulations?
		III.ii.c Are the initial values chosen arbitrarily or based on data?
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?
	III.iv Submodel	III.iv.a What, in detail, are the sub models that represent the processes listed in 'Process overview and scheduling'?
		III.iv.b What are the model parameters, their dimensions and reference values?
		III.iv.c How were the sub models designed or chosen, and how were they parameterised and then tested?

Table 6:The ODD + D protocol including the guiding questions from Muller (Müller et al., 2013, p. 39)

The structural elements and guiding questions will form the descriptors for the three ABM models created as part of this chapter. Some structural elements such as those of implementation will not be included due to the nature of the models described being conceptual adaptations of unique agent architectures situated in an artificial environment and not the real world for testing purposes. Therefore, some of the structural elements of the ODD + D protocol are not applicable in this case and hence omitted from model descriptions in this chapter.

Overview

Purpose

One of the aims of this research involves the creation of new simulative models featuring computerised agents demanding and exchanging dwellings in a simulated world. The aim is for these models to be unique in their theoretical and agent architecture framework. The architectures modelled derive from the results of the previous analysis into the current use of agent architectures in urban simulative models. The outcome of the study being a lack of representation of BDI and cognitive agent architectures provided the challenge for creating these two architectures in parallel in order to compare the inputs and outputs of both models. A third model based on existing logic-based architecture and existing utility theories will be created as a control to judge the results of the other two in terms of existing models.

Entities, state variables and scales

In order to have a balanced platform for comparison between the models. All of the experiments will have 12 dwelling and 24 household agents competing to move in those dwellings. At the start of every turn, the resident household will choose whether to move to a different location or remain in that house. The 12 dwellings exist across three neighbourhoods each with four dwellings and their own unique features (such as containing a park or a school or closer / further from work). These models aim to be short experiments for conceptualising new agent architectures and behavioural theories thus the number of agents and dwellings need not be in the thousands. The inputs of each model are limited to the variables each architecture requires for the dwelling and agents. The outputs from the model will consist of the price changes of the dwellings over time calculated by excess demand for a dwelling at the end of each turn. Demand will then determine if the value increases or decreases and by how much. The rate of change in price / demand and how that demand spreads across neighbourhoods and dwellings serves as the output. This allows for a comparison between the agent architectures and sensitivity / volatility of demand in each model. All agents, houses and neighbourhoods maintain the same attributes across both models other than a limited set of unique variables present for agents related to the architecture and theory requirements.

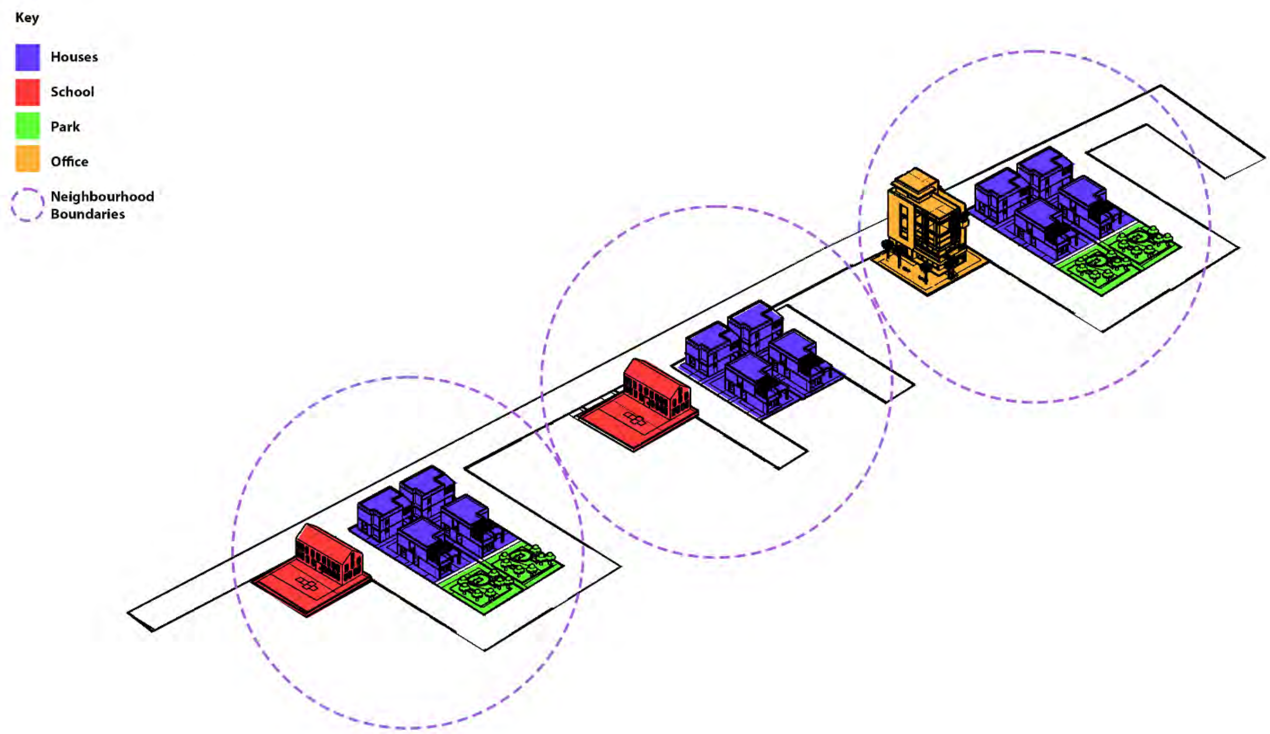


Figure 16: Illustration showcases the virtual environment that includes a set of 3 neighbourhoods, made up of 4 houses each and a combination of Park, Office and School as amenities in each neighbourhood.

Neighbourhoods dictate a number of select choice criteria for the agents. This is because they have attributes that include whether they have a park located in them or a school or are in close proximity to agents' workplace. Each agent in all simulations has an affinity for proximity to these amenities and therefore evaluations of housing choices include considerations of the neighbourhoods. In addition, neighbourhoods include a safety rating. This is a product of the notion of relative poverty being a major determinant of crimes in accordance to studies made with the use of the GINI coefficient (Tsai, 2005). Inequality being the cause of crime and detractor. This means that the average income of the neighbourhood in relation to the agent's own income determines whether the neighbourhood is safe. The use of this relationship for safety functions purely as a means of attraction and detraction in socio-economic and demographic levels allowing for an interaction between the agents themselves. This means that other agents in a proximity around a single agent, influence their utility, preferences/taste or desires depending on the agent architecture. All 3 neighbourhoods have a list of 4 houses in them each and both the houses and the neighbourhood's other attributes are the same in all simulations/models.

Houses have a series of attributes that includes the neighbourhood they are in, the number of rooms (bedrooms) they have, their starting price, their current price, an identity number and an owner. As previously mentioned, depending on the neighbourhood they are in plus the agents currently located in that neighbourhood, certain housing criteria made up of proximity to park, work or school, and the safety factor of the house gets determined. All 12 houses have these attribute be the same in all simulations/models. Current price for each house is set at £100000 for all of them regardless of attributes. This is to allow demand to dictate price formation from the same starting point. It enables a much better comparison of price changes in the market acting as the emergent pattern of agent interactions without an initial influence of housing price bias.

Agents have a core of attributes that is the same for all models, but they are the only class have additional attributes unique to each model due to the theoretical background of these models and their requirements to operationalize within a model. In this section all common attributes will be listed and explained while any additional attributes will be mentioned here but elaborated upon in their respective model sections. Common attributes include an identity number for the agent, income level, number of children and the house the own if any. The income level of the agent directly influences the affordability of the house based on its current price. This is measured using an online tool on mortgage affordability by the money advice service in the UK (Money Advice Service, n.d.). This enabled an estimate of income to mortgage availability that dictates the affordability of houses. If the house current price is too high relative to the agent's income, then the house is not affordable. The number of children directly influences the suitability of houses in terms of number of bedrooms. Agents with a large family will find a house with only 2 bedrooms not suitable to their needs and so on. In addition to these core attributes BDI agents also have four additional attributes specific to the agent architecture that are behavioural attitude, social norm, perceived behavioural control and current desire. The first three are Boolean in nature and relate to the theoretical basis of Theory of Planned Behaviour. The last one is unique to the architecture as BDI agents by nature prioritise desires and, in this case, this attribute states the current desire prioritise by the agent for this turn. Cognitive agents also have a further sever attributes unique their agent architecture. The first six are the agent's experience/tastes and relate to the agent's memory on suitability, affordability, safety, proximity to work, proximity to school and proximity to park. These are all set at the same amount at the start of the simulation for all agents allowing them to form their own experiences and tastes as they move from house to house and evaluate what they perceive to be good or bad. The last additional attribute for cognitive architecture is the active trait. This dictates if the agent has an affinity for physical exercise that may dictate their experiences. The logic-based architecture agents of the third control model have one additional attribute that is similar to the BDI architecture in that it is the utility the wish to improve for that round. Given that these agents are utility maximisers, they constantly seek to improve their lowest performing utility and therefore set themselves that goal at each round.

Process overview and scheduling.

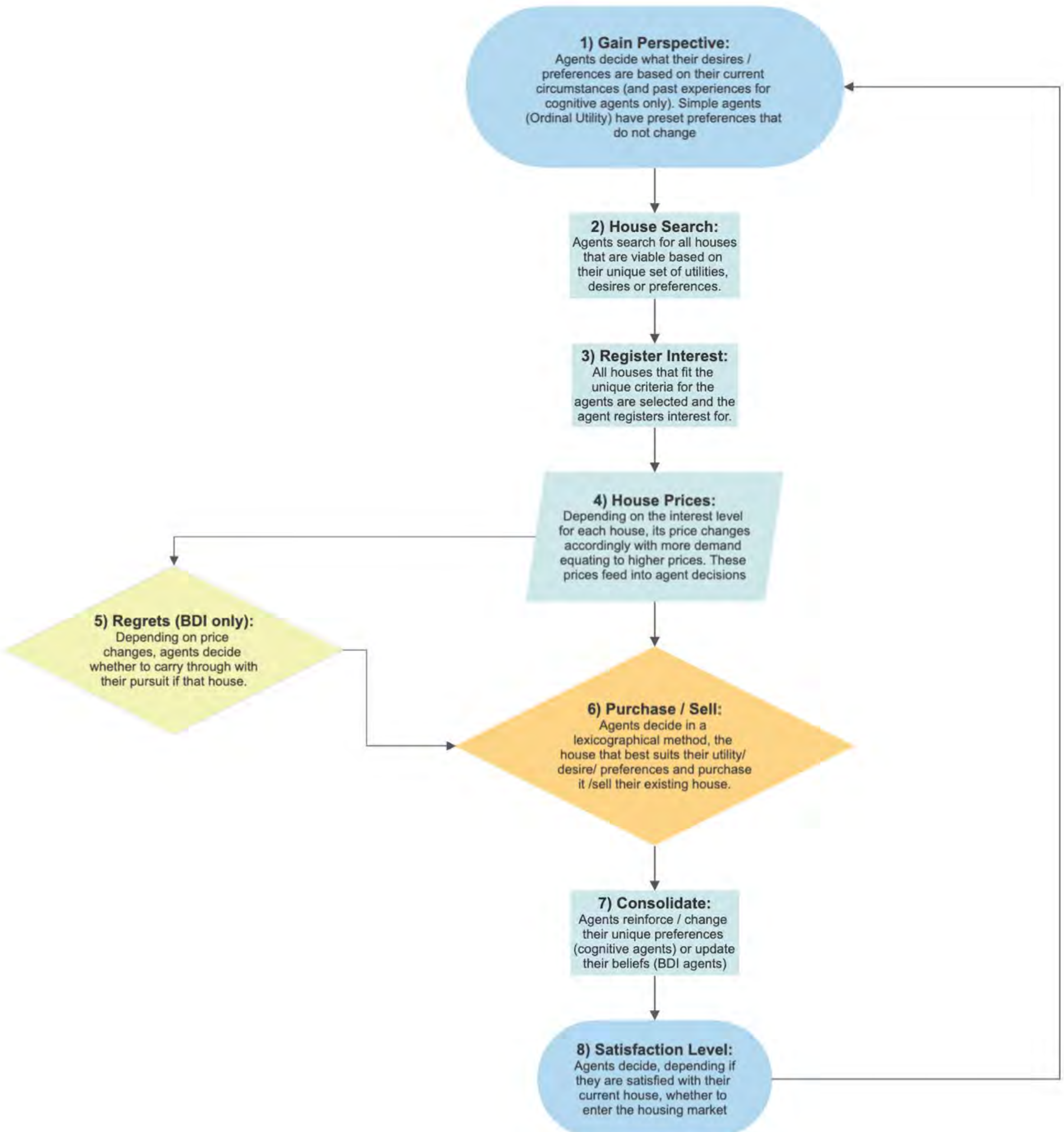


Figure 17: Overview of steps taken by the simulation during a single turn and what choices are made by the agents at each point.

In all models, the agents follow a set of steps at each turn. The first step includes gaining perspective. Agents decide what they wish to pursue in that round. They do this differently in each model as different architectures have different ways for the agent to evaluate their current situation. In cognitive architecture, the agent decides what their preferences, ranking them in order of most important preference to least important. In BDI architecture, the agent chooses among a series of competing desires. The chosen desire is the one they will pursue to bring to fruition this turn. In the last model, the control model using utility agents, preferences are pre-set and do not change. What the agents seeks to do here instead is maximize their utility by upgrading their house to be more in line with their pre-set preferences thus improving their situation.

The second step is housing search. Here agents look to the real-estate market, cycling through the list of houses. Based on their current demands for housing attributes, agents select all houses that suit their needs for this turn. Again, this is slightly different for every agent architecture as the means of the most desirable criteria selection differs. In cognitive architecture, this is guided by the updated agent preferences for this round with the most important preferences being the deciding factor on the initial housing choices. In BDI architecture, based on the most important desire chosen for pursue by the agent, all houses that do not meet the needs of that desire are removed from the list. In the control model, utility agents choose purely based on their unique set of general utilities. For example, if the house they live in now lacks in a specific area of their utility, their next round choice of houses will prioritise to improve that aspect of their utility.

The third step includes registering interest in the houses they shortlisted in step two. This means that all houses that fit the unique criteria for the agent are selected, and the agent registers an interest for those houses. This is the same in all models and leads to step four, which is adjusting market value for houses. Based on the amount of interest accumulated in that round by the collective of agents, house prices increase or decrease. The real-estate market in these models, due to there being an artificial over-demand thanks to limited supply of house, is controlled by the forces of demand as there are only 12 houses but 24 agents seeking a house. Even though not all agents are seeking a house each turn and not all houses go up in the market due to the agents not choosing to change house, at any given turn there are at least 12 agents seeking a house. This is done in an attempt to allow demand to manage the prices in a free market enabling the research to investigate, without interference from other market forces, the pure effect of adaptive agent decision-making on housing demand in the form of price shifts per turn.

Step five is unique to BDI agents and it directly links to their theoretical basis. This step is called regret and is a direct response to shifting house prices. BDI agents have the capacity not to follow through with their intention to bring about their prioritized desire if they perceive that the house price has increased to the point of not being affordable or their house has depreciated to the point of not being worth selling in the current market.

Step six involves agents, in the market for a house, deciding between available houses and purchasing their choice. In all models, housing choices are made in a lexicographical method consistent with consumer behaviour theory. All attributes of the house are ranked to their perceived importance. The agent then compares all choices in terms of the most important attribute to them. The highest scoring choice is then selected. If two or more choices score equally high on the most important attribute, they proceed to be judged on their ranking of the second most important attribute followed by the third and so on until the tie is broken (Gibler & Nelson, 1998). Though the lexicographical method is maintained in all models, each agent architecture has its own way of distinguishing the most important house attribute/criteria for that turn for that unique agent. Similar to step 2, cognitive architecture agents make their choice based on their ranking of preferences/taste, BDI architecture agents make their choice based on that turn's prioritised desire and logic-based architecture agents belonging to the control model of utility agents make their choice based on their pre-set utility preferences (trying to improve their lowest scoring utility). Step 6 also involves all agents that have successfully purchased and moved into a new house, selling their previous property at current market value.

Step seven consists of the consolidate phase. Here all agents come to terms with their actions in this round. This is different in every architecture due to their nature of how they adapt to changing conditions. In cognitive architecture, the agent assesses every criteria/attribute of their new house as well as their own current situation and updates their unique ranking of preferences/taste. In BDI architecture, the agent again assesses their new choice/situation and updates their belief also known as their worldview. In the third logic-based architecture for the control model, agents calculate how the impact this choice has had on their utility scorings.

Step eight, the final step for the turn is the satisfaction level step. Here agents decide, depending on whether they are satisfied with their current choice of house and their needs are met, whether or not to enter the housing market. This step determines whether in the next turn they will pursue steps 1-8 again or if they will remain inactive for that turn other than to reassess their satisfaction at the end of the turn as the market value of their choice house changes, their neighbours change and the overall neighbourhood safety changes.

During a single turn, every single one of the models takes these general steps with the exception of step 5 that is unique to BDI agent architecture. There are some differences as to how each agent architecture deals with the steps, as elaborated in the sections below. The models aim to test at a controlled environment, the different capacities of both subjective rationality-based theories and the agent architectures needed to operationalise models of those theories.

Housing Market Demand Equation:

Inelastic Demand:

```
def interest():
    initialinterests = []
    for agent in agents:
        if ((agent.currentdesire() != "content")):
            if agent.house_suitable() == False:
                for house in houses:
                    if house.r - 1 >= agent.ch:
                        initialinterests.append(house)
```

```
        else:
            pass
```

Interest changing price:

```
    for house in houses:
marketmulti = interest().count(house)*0.05
house.pc = house.pi * (1+marketmulti)
```

The code above determines the house price changes as a product of demand. All accumulated interest on a house from all agents for that turn. The market assumptions include a perfectly inelastic supply as each house consists of unique attributes which extends to no change in quantity provided when price changes. Therefore, shifts in demand and competition for the limited supply have a more direct effect on price. Though land markets are relatively inelastic in supply by nature, this is an exaggerated case to observe the effects of agent decision-making more easily on housing prices. This is achieved through a linear relationship between the amount of interest (a.k.a. demand) for a house and percentage of price shift. The equation that controls that is:

$$pc = pi * (1+ (ti*0.05))$$

Where pc is the new current house price, pi is the initial house price at the start of the round and ti is the total amount of interest/demand for the house in that turn. This enables the observation of all decisions made by agents due to their theoretical basis and agent architecture, without interference from other sources, as an emergent pattern of price shifts in the real-estate market.

All models run for thirty turns at a time to enable an effective computer experiment. The basis for this consists of a practical guide suggesting number of turns should be 10d where d is the input dimension (Loeppky et al., 2009). In this case, the model on a broad level has three inputs in the form of neighbourhoods, houses and households. As such, 30 runs enable a reduced average error in results and allows for clear indications on results and patterns.

4.5 Overview of Model 1

BDI agent architecture works with belief, desire and intention as three separate processes. For this specific simulation, the agent is primarily focused on choosing a dwelling, moving to it and selling their previous dwelling. In this case, beliefs stand for an agent’s current perception of their dwelling, the dwelling’s context, their situation and the neighbourhood’s average income level. Desires in this case consist of an agent’s expression of what they would wish to change about the world or more accurately, the beliefs it perceives to be unacceptable. More specifically, an agent may have desires such as moving closer to work, further away from a school or to another neighbourhood with a different average income level. Choosing between conflicting desires to action becomes an interesting dilemma. This is where the theory of planned behaviour comes in. Using this theory, each desire has a separate likelihood of being acted upon that derives from each agent's own behavioural attitudes, social norms and perceived behavioural control. The actions to achieve the dominant desire make up the collection of intentions. These are the fundamental implementations of desires to actual behaviour.

4.5.1 Theoretical and Empirical Background

The first model to be conceptualised, attempts to make use of BDI agent architecture from the computer science domain as a means of introducing desire prioritisation in the decision-making process of agents demanding space. Furthermore, this model incorporates individualism for the agents and the notion of subjective rationality by adjusting the likelihood of each desire being actioned upon by each agent to be unique to their perspective. To achieve this, the agent's creation draws from the theory of planned behaviour in order to calibrate each desire's appeal to the unique characteristics that make up each agent. This step links back to the purpose of the models, the creation of more complex behaviours within urban simulative real-estate models. It seeks to address what psychologist have observed for years, that people's preferences are not set and are often constructed ad hoc based on the current set of information (Slovic, 1995).

As previously mentioned, the agents prioritise the desire to pursue by listing all current desires in accordance with the weighting each agent gives to every desire based on the unique situation they are in at the time. The most important desire is on top of the list, which forms the next one chosen to pursue. In pursuing that desire an agent will have a specific tolerance to act upon it based on their unique perspective. In this way, the completion of multiple desires occurs in an orderly fashion based on importance as opposed to randomness and the desires shift into intention depends on the agent's own personal opinion of the desire/action. The perception of importance is unique to each agent and adheres to the concept of subjective rationality. An individual may value some things differently from someone else while maintaining a rational perspective.

There are a number of behaviour theories explaining individual factors and their influence in a rational choice. These include the Social Ecological Model that assesses the relationships between individuals, social groups and the environment or community to predict behavioural outcome. Social Learning Theory that explains behaviour as a product of observing and imitating those with direct influence, reinforcement and punishment. Theory of Reasoned Action / Theory of Planned Behaviour that assesses the process preceding behaviour based on expectancy and intentions. Decision to behave in a certain way is the result of the likelihood of specific outcomes. It considers intentions as the best predictors of behaviour assuming that if an individual plans something, they are more likely to do it. The Transtheoretical Model / Stages of Change views individuals residing at a given stage in relation to specific behaviour change; precontemplation, contemplation, preparation, action, maintenance and termination. The stage an individual is residing on directly influences the likelihood of behaviour change (Thompson & Ravia, 2011).

This research adopts the theory of planned behaviour for its agents as a means of allowing individual subjective choices on desires being acted upon based on the agent's own perceptions. In accordance with the theory, intentions are a product of three processes(Ajzen, 1980, 1991) behavioural attitudes, subjective norms and perceived behavioural control. These form a part of the assumptions that the agent decision model is based on. They exist as attributes for the individual agent and depending on the value, dictate the likelihood of the agent acting upon a certain desire.

As this is a conceptual model, the basis for the model data does not lie in the real world. The agent data, which includes all house, neighbourhood and agent attributes, are artificially constructed to represent the effects of changes in the agent architecture and subsequently the decision-making mechanisms on emergent patterns/model outcomes.

4.5.2 Individual Decision-Making

The model being a BDI agent architecture has at its core a set of beliefs, a set of desires and a set of intentions for the agents to operate. The resulting effect of the agent decision-making circles back to influence future decisions as feedback loop through the generation of the emergent patterns listed below:

1) Market Price changes for dwellings (average or individual)
2) Detractors emerge through the state of neighbourhood (income level of residents)
3) Attractors emerge from high average income neighbourhoods and same demographic agents

For this work, attractors and detractors are a product of the notion of relative poverty being a major determinant of crimes in accordance to studies made with the use of the GINI coefficient (Tsai, 2005). Inequality being the cause of crime and detractor. This means that the average income of an area in relation to the agent's own income is directly proportionate to the attractiveness of set area to the individual agent. This emergent pattern forms the agent's perception of safety of a location and is one of the spatial aspects that play a role in the decision process alongside dwelling's proximity to work, school and park. Out of the four spatial aspects, safety is also one of two temporal aspect that exists in this model as it shifts in accordance with what agents move into which neighbourhood and what their individual financial circumstances are. The second temporal aspect is the price that constantly shifts due to demand and affects the affordability of a house for the agent.

Prioritization of household agent desires arises from the unique beliefs that hold true at each turn for that household. Depending on which possible belief is true at each turn from the list below, a corresponding desire selection takes place, which leads to the appropriate intention/intentions selected and executed to bring about the original desire and change in the world/belief:

- Beliefs
  - Dwelling is suitable (number of rooms)
  - My needs are not met (number of rooms)
  - I can afford to live in this dwelling (mortgage)
  - I cannot afford to live in this dwelling (mortgage)
  - I live close to work

- I live far from work
- I have a child
- I am far from a school
- I am close to a school
- I am far from a park
- I am close to a park
- I am close to same demographic agents (income), neighbourhood is perceived as safe
- I am close to different demographic (income) agents, neighbourhood is perceived as not safe.

- Desires
    - Meet my needs (number of rooms)
    - Live closer to school
    - Live further from school
    - Live closer to work
    - Live closer to park
    - Live in an affordable home (mortgage)
    - Move close to neighbourhood with same average income as mine
    - Move away from neighbourhood with an average income outside my range

- Intentions
  - Remain in current dwelling
  - Enter market for a new dwelling
  - Search market for property
  - Find a list of suitable dwelling / pick one
  - Buy suitable dwelling / move (based on desire)
  - Put spare dwelling on the market

A unique variable to this BDI agent comes from the choice of theory for agent decision-making, the Theory of Planned behaviour. Each agent has three unique variables to himself that hold either True or False. These variables are the behavioural attitude, social norm and perceived behavioural control. According to the theory, the more of these variables that hold true for the action, in this case moving house to better suit the agent needs, the more likely the agent is to actually act upon it. As in the theory so in the model, when a desire is chosen, depending on the agent and their three decision-making variables, it influences whether the agent carries the desire to fruition by selecting the appropriate intentions. In some cases, there is no follow through of the chosen desire due to the unique complex background of the agents. This allows for a more complex agent decision-making process that goes further than traditional utility functions in representing their real-world alternatives by including social and cultural values unique to the individual. Furthermore, it constitutes the inclusion of uncertainty for the agents but not in a traditional sense. It does not form an uncertainty in a value calculation but rather an uncertainty in the sense of hesitation due to surrounding factors that have a chance to affect the agent's actions. More specifically, the information on price that the agent initially uses to register an interest for a house relies on past turns emergent demand outcome. The agent does not know if the price needed to purchase the house will change before they register interest. As such, this decision has an inherent uncertainty that the BDI agent has to deal with.

4.5.3 Sensing, interaction, learning, heterogeneity, observations and individual predictions

The underlining decision theory explained above provides the framework for the decision-making mechanisms. In the case of BDI architecture, at any given moment an agent may have a specific set of desires. Each desire / selection of desires has the capacity to trigger an intention, which is essentially the action to bring about that desire. The advantage of a BDI architecture is that it allows for desires / actions to be prioritised and executed in a logical sequence. For example, an active desire may be to stay close to the park that has as an intention to maintain household position while a different active desire of move closer to work may have a conflicting intention to enter the market and move house. Which intention should the agent implement first or at all? This is based on a logical prioritization sequence for the desire. Here is where the theory of planned behaviour comes in. Each agent, depending on their individual behavioural attitudes, social norms and perceived behavioural controls towards an action will assign specific weights to each desire. The weighting of the desires will allow for two distinct influences. The first is an influence on whether that desire is chosen to begin with and the second is whether the desire chosen is acted upon at all. Both of these steps are individual to each agent forming a subjective view on all choices made at an individual level.

This constant battle between desire prioritization only considers beliefs formed in the present moment. Therefore, in this model the architecture does not allow the agents to store experiences and change their decision-making because of them. Learning aspects from experiences are not included within this model at either an individual or a collective level.

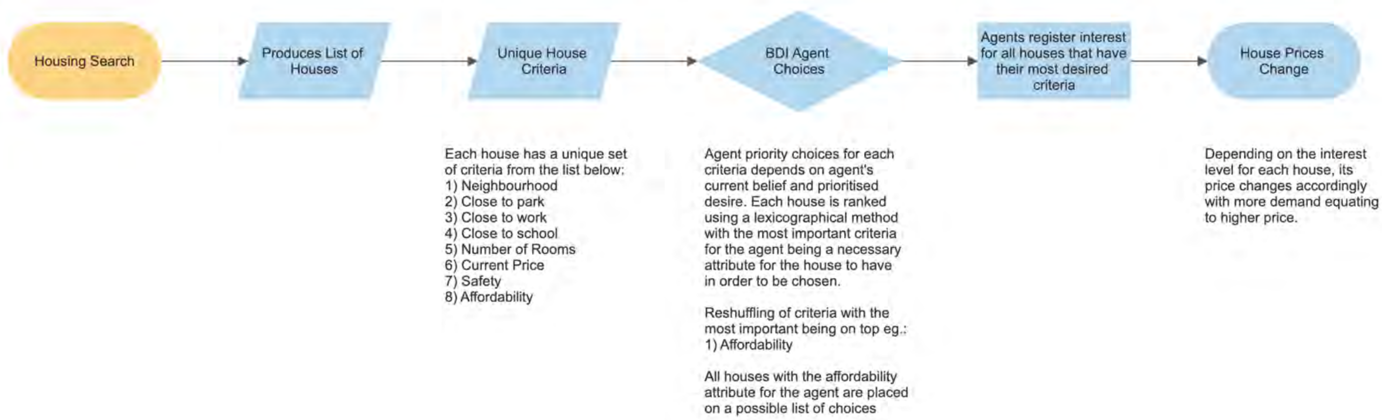


Figure 18: Overview of BDI architecture agents decision-making process for housing selection.

To elaborate on the individual sensing, the way choices made in the housing market for BDI agents in the model proves helpful. BDI agents have, as stated above, a number of competing desires that shift in priority based on the agent's unique belief or worldview at the start of every turn. This is an important aspect because it dictates how the agent will act in the housing market. Once a prioritized desire is set, the agent begins the search for suitable houses that, with the purchase of that house, fulfils set desire. The agent looks through the list of houses to find all houses that would achieve such a feat. Here lies a possibility, during the application of such agent architectures in real world settings, to limit the list of houses searched by the agent in line with the theory of bounded rationality that acknowledges consumers not having perfect knowledge. In this case, given that this is a test on the agent architecture and underlining decision theory, it deemed unnecessary to add. Therefore, in this and the other two models, the agents look at all houses available to them. Each house has a set of criteria or attributes. These include current price, safety, affordability, number of rooms, proximity to park, work and school and neighbourhood. In the BDI architecture, the agent priority housing choices are dependent on the agent's prioritized desire. This is individual to each agent and dependent on their own unique circumstances and attributes including income, family situation and current house. These form the variables that make agents heterogeneous and impacts uniquely in their decision-making. Each house is ranked using a lexicographical method with the most important criteria for the agent ranked at the top. Every house with that exact criterion is instantly placed on a shortlist. The agent proceeds to register an interest for all houses that have the criteria that fulfils their desire for that turn. Depending on the accumulated interest of all agents, house prices change with more demand equating to an increase in price while a decrease in overall demand for that round resulting in a decrease in price. The BDI agents then proceed to shuffle through the list of houses using a lexicographical method again. The shuffle the criteria with the most important for the agent on top followed by the second most important and so on. The order of the criteria depends on the agents own sorted list of desires with the most important criteria relating to the prioritized desire, the second most important house criteria relating to the agent's second desire and so on. The choice of a single house follows this method by eliminating all houses on the list that do not meet the first criteria and then all houses that don't meet the second and so on until there is only one choice left which best suits the agents unique desire prioritization for that turn. An important note added here is the fact that agents make their choices on safety and affordability, the two temporal aspects, on information available to them from the previous run. They do not possess the capacity to predict future state of such aspects.

Following the narrowing down of house choices to one, the BDI agent has a unique step before purchasing. Depending on the price change from the overall demand shifts of that round and the agent's own unique attributes of behavioural attitude, social norm and perceived behavioural control. The more of these attributes the agent has as positive and the more "attractive" the price in the form of change from last turn, the more likely the agent is to purchase set property. If a successful purchase manifests for the agent, the next step involves updating existing beliefs, which then causes the lists of available desires to shift and reprioritize. Depending on the new prioritized desire, if it requires the agent to join the market for a new house, the cycle begins anew in the next turn. It constitutes the means by which the agent deals with the initial uncertainty on house price change at the start of the round.

Interactions between agents exist indirectly as the effect of emergent patterns within the model. These include firstly the demand for housing by individual agents affecting house prices and therefore the affordability of that house to other agents. Secondly, the neighbourhood perception of safety that is the relation of the individual's income to the aggregation of the average income of all agents living within the neighbourhood. No communication or coordination networks exist within the model.

4.5.4 Collectives formed/Observations.

Observations within the model exist as the emergent properties of agent actions. Emergent properties of individual behaviours act as the feedback loop, influencing future decisions and maintaining the simulated urban world in constant flux. Three emergent patterns arise in this BDI architecture, average market price for dwellings (based on demand), detractors for individuals (based on income level of residents in the neighbourhood) and attractors for individuals again associated with average income levels of residents in a given neighbourhood. This attractor/detractor variable embedded in neighbourhoods average income originates from the literature (Jjumba & Dragićević, 2012) in other urban simulative models. For the purpose of this research, the concept will carry through in the BDI architecture model as another emergent pattern on top of average price. The reason for the choice is the possibility of conflicting desires allowing the architecture to further display its potential. At the same time, the neighbouring element of agents forms a collective that affect each other in either a positive or a negative manner. If agents of similar income exist as a collective in a neighbourhood, they form a bond that allows them to gain a sense of safety for their chosen household location.

The outputs generated by the model consists of the changes in house prices over time as well as a track of every individual's decisions, desires and house changes. The only one of interest for analysis in this research is the market price change for each house over the span of the model runs. This is due to the nature of this research essentially testing different agent architectures for real estate demand models and using this emergent pattern of price changes to identify patterns in decision-making for different models given the same variables.

4.5.5 Stochasticity

This BDI urban simulative model created as part of this research, does not rely on any empirical dataset from the real world. This is due to the model being representative of the capacity of such an architecture and conceptual in nature as opposed to applied. In this regard, the generation of satisfaction of the computerised agents from a space's qualitative aspects is not random but the agents introduced have randomly generated attributes. This means that the agent will have randomly generated true or false values for the behavioural attitude, social norm and perceived behavioural control decision-making variables. These variables influence the follow through of decision into intentions as a percentage of likelihood. This essentially forms the only core stochastic element in the simulation apart from the starting agent attributes which is constant in all models/simulations.

4.6 Overview of Model 2

Cognitive agent architectures, at their core, allow agents to have memory storage and representation. Within this research context, the memory stored by the agents is comprised of the satisfaction gained from the qualitative/quantitative aspects of the choices they made based on the agent's own perception. In this case, the choice is between different dwellings of unique collection of both quantitative and qualitative aspects. As the model runs, the agents perceive satisfaction from their dwellings, particularly those distinct features that make them up. Every time an agent tries to choose a new dwelling to move into, their experience, in the form of satisfaction for particular qualitative variables, changes some of the decision weightings. In that form, it allows agents to make decisions under uncertainty when they cannot know what all the qualitative variables may entail for their future success. Therefore, a successful agent action means the dwelling would have satisfy the agent's needs as much as possible. Dwelling prices are determined on the amount of excess demand present for the dwelling at the end of each turn and that derives from other agents' perception of the value of the qualitative and quantitative aspects of that particular dwelling. This shifts affordability factors which make up one of the agent's needs, to live in an affordable dwelling, and thus negates a single choice being the best at all times.

4.6.1 Theoretical and Empirical Background

The second model to be conceptualised, attempts to make use of cognitive agent architecture from the computer science domain as a means of including memory storage and representation in the decision-making process of agents demanding space. To achieve this, the agent's creation draws from cognitive theories that include Case-Based Decision theory and consumer behaviour theory in an attempt to deal with decision-making under uncertainty and cognitive decision-making on subjective qualities of space.

Creating a cognitive agent as a decision-maker in the real estate market requires a new set of theoretical frameworks. These frameworks need to allow for decision-making under uncertainty when a person has incomplete knowledge of all variables involved in the decision process. As such, the conceptual underpinning of the cognitive agent architecture model will include a mixture of Case-Based Decision Theory and Consumer Behaviour Theory.

Case-Based Decision Theory revolves around the idea of people choosing courses of action based on their performance in similar past situations (Gilboa & Schmeidler, 1995). In case-based decision theory, what actually exists in the memory of a coded agent is only past results that actually happened. Each result has information only on the action chosen and the subsequent outcome. This serves as a more realistic way of coding decisions in urban simulation models as the notion of bounded rationality (Simon, 1959) stands true in such a theory. Knowledge is not perceived to be perfect, as the information that make up the process of judgement is found lacking and allows for more conflicting and complex decisions to be taken.

4.6.2 Individual Decision-Making

Cognitive Agent Architectures require two unique attributes of its agents, memory storage and memory representation. Many cognitive agent architecture frameworks exist in the literature such as ACT-R, SOAR, Sigma, Google DeepMind and Genie. Though each cognitive architecture has its advantages, they seem inappropriate as frameworks for urban simulative models. Google DeepMind is intended as a learning algorithm for playing games, SOAR uses a mixture of procedural memory and working memory to identify the action to take given the current context (Lehman et al., 1996), ACT-R accomplishes tasks by coordinating cognition, perception and motor actions focused mostly in production (Stewart & West, 2006). The PECS framework might be the only one that tries to capture the emotional, social and inner drives of the agent as forces impacting behaviour (Schmidt, 2002). However, this model deals heavily with emotional intelligence and is more oriented in psychology studies rather than urban science although the study of this framework has provided some insight in potential modelling of a cognitive architecture for simulative urban models. Therefore, the choice made was for the research to create its own framework for cognitive agents. In this research, the conceptual model looked into consumer behaviour in an attempt to analyse what aspects of behaviour would be included in the memory of agents. Below is a breakdown of the included aspects:

- Agent Memory
    - Experience in the market acting as a stored case / experience. This includes an internal ranking of the value of each attribute associated to dwellings chosen.

- Family Situation. This includes the agent's family size, income and activity patterns/preferences.

- Memory Representation
    - Needs & Wants. The needs include all the requirements an agent has from the dwelling and wants are what the dwelling alternatives offer.
- Consumer Experience
    - Listing of potential alternatives (lexicographically)
    - Determinants of Demand:
        - Internal:
            - Motivation for purchase
            - Needs & wants
            - Personality Traits (is the agent physically active etc)
        - External:
            - Social Class (based on income)
            - Family

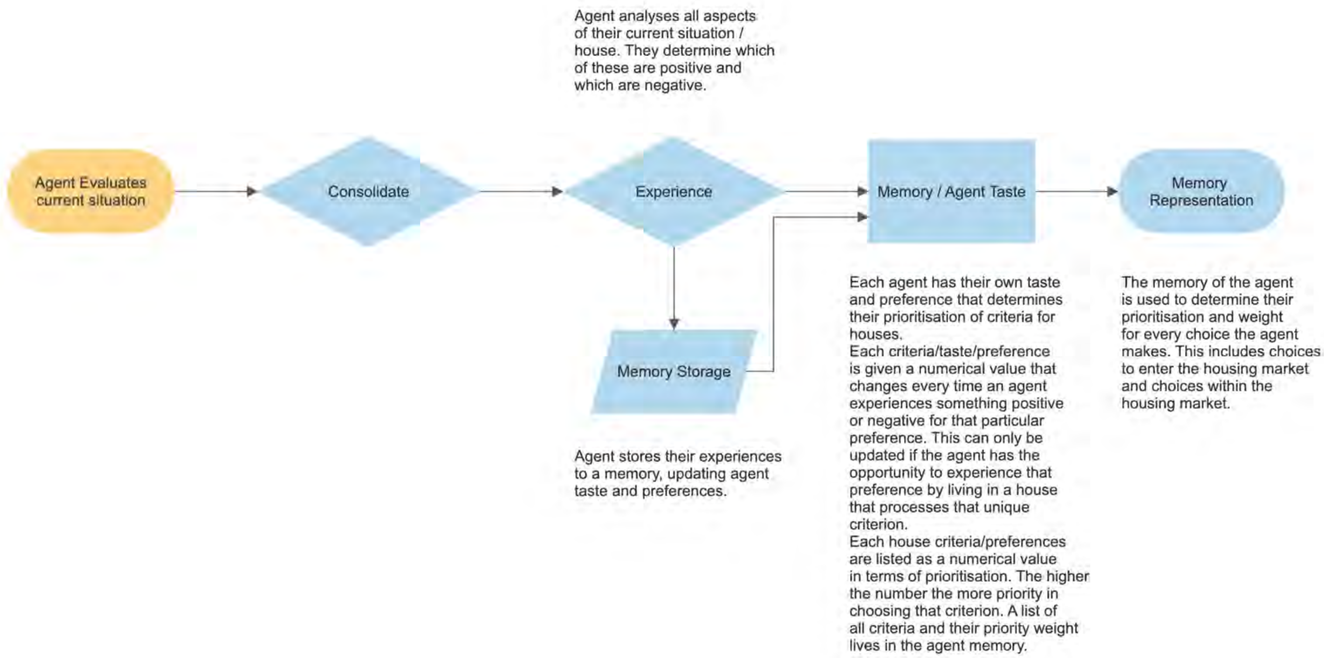


Figure 19: Cognitive agents overview of inputs to and from memory through experience.

The diagram above seeks to elaborate on how all the aspects of the created cognitive architecture function together. To form a start, the diagram describes what happens after the agent completes an action in the housing market, meaning the agent has purchased a house. After settling in set house, the agent begins to evaluate the current situation. The code below facilitates this process by allowing the agent, depending on their own attributes, whether they find aspects of the experience positive or negative.:

```
for house in houses:
  if ((agent.cd != "content") and (agent.h == house.id)):
    if house.n == "a":
```

```
if agent.a == True:
    agent.epark = agent.epark + 20
elif agent.a == False:
    agent.epark = agent.epark - 20
```

In the sample code above, the agent first evaluates if they are content or not and whether they even have a home at the time by searching if the attribute of home for the agent matches any house id in the list of houses. Afterwards, the code proceeds to determine the location of the agent's house, in this case the neighbourhood. This is an important step as it creates the context for the house, meaning if the neighbourhood is located near a park, a school or work. Once this is established, the agents own attributes come into play as judging the context positively or negatively depends on the agent's own perceptions. In this case, if an agent maintains an active lifestyle of physical exercise (agent.a == True) (jogging, hiking, walking etc) and the neighbourhood can facilitate for that to happen, the agent views that as a positive experience (agent.epark which is the experience of the agent with parks is positively reinforced). If the opposite stands true, meaning we have a non-physically active agent living in a neighbourhood with a park, the agent may view that experience as negative. He may perceive that they gain no benefits from the park and may view negative aspects such as noisy children playing in the park or potential spots for inappropriate dealings as a deterrent (agent.epark which is the experience of the agent with parks is negatively reinforced). At the very least, the agent recognizes that living next to a part does not mean a lot to them and therefore it goes lower on their priority list.

This process continues as the agent analyses all aspects of their current residence and determines based on their own attributes, if these are positive or negative. Effectively, they experience their surrounding allowing them to discover their own desires better. An important point to make is that an agent may only change/reinforce their taste or priorities for different house aspects through experiencing them. This is what makes cognitive architecture different from BDI or logic-based and why Case-Based decision Theory forms the basis of it as all attributes of a house get judged and only judged based on experiences drawn from previous cases.). If the opposite is true and we have a physically active agent living in a neighbourhood that inhibits his desire for physical exercise, the agent does not have the capacity to view living next to a park as positive due to not having experienced it for themselves.

An example of Case-Based Decision Theory utility calculation sees each case consisting of (q,a,r), where q is a problem, a is an act and r is a result. M is the memory that includes sets of such cases. The agent's decision is a utility function u, assigning a numerical value to results and a similarity function s which assigns a non-negative value to pairs of problems. Given a new problem p, the agent acts a in an attempt to maximize (Itzhak Gilboa and David Schmeidler, 1995):

$$U(a) = U_{p,M}(a) = \sum_{(q,a,r)\in M} s(p,q)u(r),$$

“In case-based decision theory the memory contains only those cases that actually happened. Each case provides information only about the act that was chosen in it, and the evaluation of this act is based on the actual outcome that resulted in this case”(Gilboa & Schmeidler, 1995).

In the cognitive architecture model, experience results in a utility number that gets added or subtracted from the memory’s numerical representation of utility for any given attribute thus making all decisions based only on previous decision outcomes. Therefore, memory storage forms the most important aspect of this architecture. Agent’s memories consist of utility values for every house attribute and are stored as agent attributes. They get altered by the experiences of the agent at each turn, effectively updating the agent’s taste and preferences. These utility representations include:

1. self.esuit = esuitable : Agent’s utility function for suitability
2. self.eaffo = eaffortable : 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

In these utility functions, the agent’s unique taste and preferences are represented, formed and updated. Each agent has his or her own taste and preferences that determine their prioritization of criteria for houses. These utility functions forming taste/preference maintain a numerical value that changes every time an agent experience something positive or negative for that particular preference. Updating the utility function values happens only if the agent has the opportunity to experience that preference by living in a house that possesses that unique attribute that corresponds to that preference. This means that ranking of housing attributes directly responds to these utility functions. The highest of which is given priority when making a choice and these priority weights for each housing attribute lie solely in the agent's memory. Thus, their experiences and their unique perspective drive every choice an agent makes, including if they wish to enter the housing market or choices made within the housing market. This process in the architecture is called memory representation and forms the second most important aspect of a cognitive agent, their ability to use stored memory to influence future decision-making.

4.6.3 Sensing, interaction, learning, heterogeneity, observations and individual predictions

Cognitive architecture's main advantage is the ability of agents to store experiences and draw from past ones to infer on current decision-making processes. Thus, the underlining adaptive behaviour for this cognitive model is the learning from experience and updating their decision-making mechanisms. Specifically, having a level of experience with the aspects of a dwelling they have previously owned / rented and using that level of experience to increase their affinity to future choices with attributes the computerised agent perceives as very satisfying. Through more experiences, an agent gains the capacity and understanding of their individual needs and what dwelling attributes they perceive as most important for them.

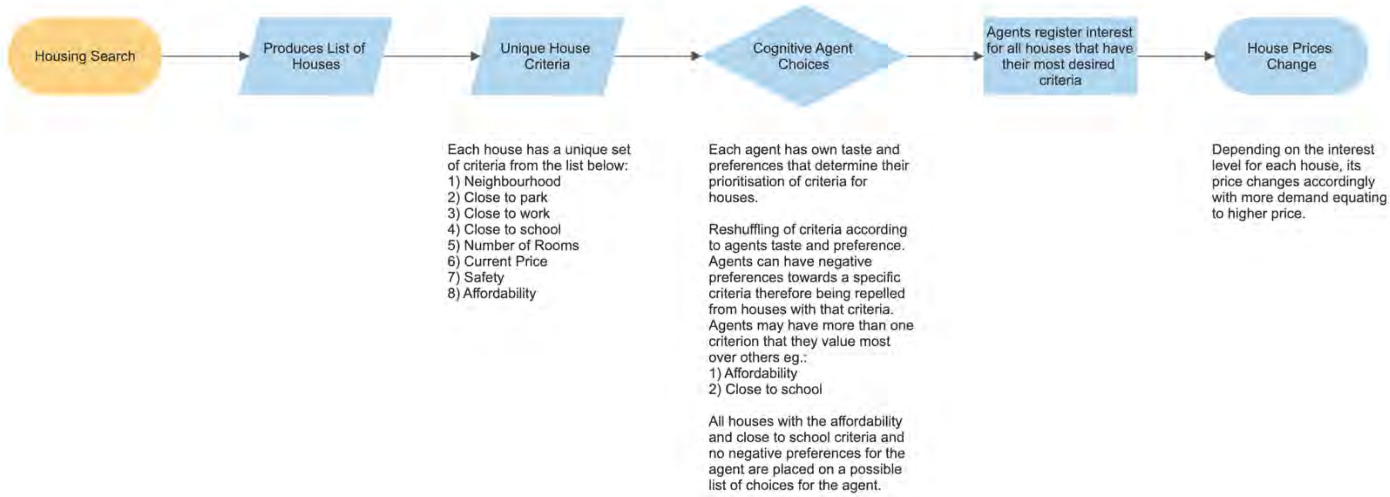


Figure 20: Diagram outlining the housing choice sequence for cognitive agents.

This adaptive behaviour is mostly prominent in the housing market where the agent uses their memory to infer on their decisions in the market. Elaborating on the individual sensing, it is important to understand the way cognitive agents make decisions in the housing market. The diagram above displays the steps taken by the agent to produce a list of houses that they are interested in for that turn and the effect of the list on the housing market itself and thus other agent choices. Once an agent chooses to enter the housing market, due to their desire to improve specific aspects of their living situation, the first step is for the agent to survey the market and determine all houses that may be an interest to them. On this step, as mentioned in the BDI agent (section 4.5.3), agents have perfect knowledge of the market and all alternatives.

Following the production of a list of all houses, the agent begins to research through the list for all houses that initially prove to fit the agent's most important preference for that turn. For cognitive agents, this is determined through what they perceive to be lacking at the start of that turn. That determines their initial desire to enter the market, as an attempt to improve on that.

Interactions between agents exist indirectly as the effect of emergent patterns within the model. These include firstly the demand for housing by individual agents affecting house prices and therefore the affordability of that house to other agents. Secondly, the neighbourhood perception of safety that is the relation of the individual's income to the aggregation of the average income of all agents living within the neighbourhood. No communication or coordination networks exist within the model.

4.6.4 Collectives formed/Observations.

Similar to BDI agents (section 4.6.4), observations within the model exist as the emergent properties of agent actions. The same three emergent patterns arise in this cognitive architecture, average market price for dwellings (based on demand), detractors for individuals (based on income level of residents in the neighbourhood) and attractors for individuals again associated with average income levels of residents in a given neighbourhood (see section 4.6.4 for more details).

The outputs generated by the model consists of the changes in house prices over time as well as a track of every individual's decisions, desires and house changes. The only one of interest for analysis in this research is the market price change for each house over the span of the model runs. This is due to the nature of this research essentially testing different agent architectures for real estate demand models and using this emergent pattern of price changes to identify patterns in decision-making for different models given the same variables.

It is worth noting that through the course of the simulation, some housing attributes end up being more valued by an agent than others are. These aspects have the potential to transcend traditional quantitative measures such as number of bedrooms for a dwelling, price and floor space size. Though such qualitative aspects do not feature in this simulation, it is the ambition of this research to allow them to be included in future simulations of this type through this architecture and theoretical basis. These qualitative aspects are important considerations as they affect demand for these spatial commodities that in turn changes the emerging patterns of prices (based on excess demand for the particular space). The cognitive agent architecture, therefore, is build with the explicit intention to allow agents to store their experiences with both quantitative and qualitative aspects in memory and use that memory to make future decisions. This will allow emergent patterns to arise from subjective rational behaviours valuing and demanding real estate differently based on the individual computerised agent's perspective.

4.6.5 Stochasticity

Similar to BDI agents (section 4.5.5) cognitive agents introduced have some randomly generated attributes, namely which house they were assigned at the start of the simulation (Please see section 4.5.5 for more details). This means that, even though all agents start with the same affinity for all experience aspects, there will be an initial effect on those variables by the starting conditions randomly assigned to agents at the start of the simulation. This is only an initial effect on the individual's experience level with the specific housing attributes they experience in round 1. As the agents learn from what they experience and through the course of the simulation, the agents will have the capacity to refine their taste negating much of the effect from the starting point circumstances.

4.7 Overview of Model 3

Model three features simple utility maximisation agents with logic-based architecture. For this specific simulation, similar to the previous two models, the agent is primarily focused on choosing a dwelling, moving to it and selling their previous dwelling. In this case, there are no real-world representations of agents that traditional urban simulative models seek to draw and calibrate the numerical values of their utilities from. Therefore the utility function needs to switch to ordinal utility that does not require specific values for utility, rather which alternative is perceived as most preferable (Batley, 2008). Hence, each housing attribute is assigned a preference in terms of the goals or desires that it achieves. For example, suitability goal/desire is determined by the house's number of rooms attribute. Choosing between conflicting desires to action becomes an interesting dilemma. This is where the theory of ordinal utility comes in.

Using this theory, each desire has a preference not in terms of numerical value but in terms of which alternative desires it is more preferable to. The agent choice aims to achieve the most preferable desire that is not currently satisfied by their unique situation in this round.

4.7.1 Theoretical and Empirical Background

The last model to be conceptualised, attempts to make use of logic-based agent architecture from the computer science domain as a means of determining decisions of agents demanding space. Normally, in the more common iterations of such household location modules within urban simulative models, agents would use a utility maximization equation to determine the best alternative. In this case, due to these models being conceptual and therefore lacking in empirical data by which to derive the utility values, a preference list of utility featuring each housing attribute is created. This essentially utilizes ordinal utility (Hicks & Allen, 1934) to enable agents to make logic-inferred decisions under certainty. Ordinal utility function ensures that the U value of a preferable alternative (Un) is greater than that of an alternative (Um) as seen in the equation below (Batley, 2008, p. 7).

$$\hat{U}_n \geq \hat{U}_m \text{ iff } \mathbf{x}_n \succeq \mathbf{x}_m$$

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

Similar to utility maximization, the theory ensures the individual acts so as to maximise utility by preferring alternatives (in this case housing attributes and the resulting goals/desires they achieve) with greater utility to those with less utility.

This research adopts the theory ordinal utility for its agents as a means of allowing individual objective choices on desires. The list of preferable desires/goals 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) is as follows:

1) Live in a house
2) Live in a suitable house (enough rooms to house the household)
3) Live in an affordable house
4) Live in a safe neighbourhood
5) Live near work
6) Live near a school
7) Live near a park

As this is a conceptual model, the basis for the model data does not lie in the real world. The agent data, which includes all house, neighbourhood and agent attributes, are artificially constructed to represent the effects of changes in the agent architecture and subsequently the decision-making mechanisms on emergent patterns/model outcomes. Therefore, this order of desires and the utility attached to them is artificial, though by existing in all three models, it allows for a fair comparison of results.

4.7.2 Individual Decision-Making

The model features a logic-based agent architecture, with agent decision making driven by a set of logic statements. As mentioned in the previous chapter, the agent seeks to constantly maximise their utility by trying to obtain their most preferred utility/desire from a list of desires they have yet to achieve. This aspect is ever-changing as it gets influenced by future decisions made by other agents, interpreted as feedback loops through the generation of the emergent patterns listed below:

1)Market Price changes for dwellings (average or individual)

2)Detractors emerge through the state of neighbourhood (income level of residents)

3)Attractors emerge from high average income neighbourhoods and same demographic agents

A previously mentioned for both BDI and Cognitive agent models, attractors and detractors are a product of the notion of relative poverty being a major determinant of crimes in accordance to studies made with the use of the GINI coefficient (Tsai, 2005). Inequality being the cause of crime and detractor. This means that the average income of an area in relation to the agent's own income is directly proportionate to the attractiveness of set area to the individual agent. This emergent pattern forms the agent's understanding of safety of a location and is one of the spatial aspects that play a role in the decision process alongside dwelling's proximity to work, school and park. Out of the four spatial aspects, safety is also one of two temporal aspect that exists in this model as it shifts in accordance with what agents move into which neighbourhood and what their individual financial circumstances are. The second temporal aspect is the price that constantly shifts due to demand and affects the affordability of a house for the agent. Both of these changing aspects, being affected by other agent decision-making, allows even these logic-based agents to adapt their housing choice as the price and safety attribute of an individual house attributes changes in value.

Prioritization of household agent desires is set by the researcher in a series of logic-based statements. In accordance with ordinal utility, the value of the utility is irrelevant, what matters is the preference order of set utilities. A mentioned in the previous section, due to these models being conceptual, no empirical data exists by which to calibrate the models and determine utility values. Therefore, the research adopts a consistent prioritization of utilities that is common in all three models. The preference list of utilities/desires is explained in the previous section, though it is important to note that logic-based agent architecture, unlike BDI and cognitive architecture, does not have any unique features that allow the agents to change the prioritization of their preference lists. They have a constant set of utilities that they seek to maximise by choosing from the most preferred utility/desire at every round.

Though ordinal utility use is for decisions made under certainty, the model, constitutes the inclusion of uncertainty for the agents but not in a traditional sense. It does not form an uncertainty in a value calculation but rather an uncertainty in the sense of not knowing other agent's decisions that may affect how they value their current housing choice. Though this is a form of uncertainty, there are no provisions for this agent to understand it as such and therefore does not impact of their decision-making. For all intents and purposes, the agent's decision is under certainty and following a pre-set utility preference order.

4.7.3 Sensing, interaction, learning, heterogeneity, observations and individual predictions

The underlining ordinal utility decision theory explained above provides the framework for the decision-making mechanisms. In the case of logic-based architecture, at any given moment an agent may have a specific set of desires/preferences satisfied. From the desires that are not satisfied, the agent refers to their preference order to prioritise the next preferred housing attribute that will help them further maximise their utility. The advantage of this is the simplicity of it. Agents have no capacity to learn, with the underlying expectations that all agents are rational and constantly seeking to maximise their utility.

This constant attempt to prioritise the most preferred utility from a list does not allow for any type of future predicting or consideration of future conditions. Furthermore, the agent has no capacity to learn both at an individual level or as a collective. Therefore, in this model the architecture does not allow the agents to store experiences and change their decision-making because of them.

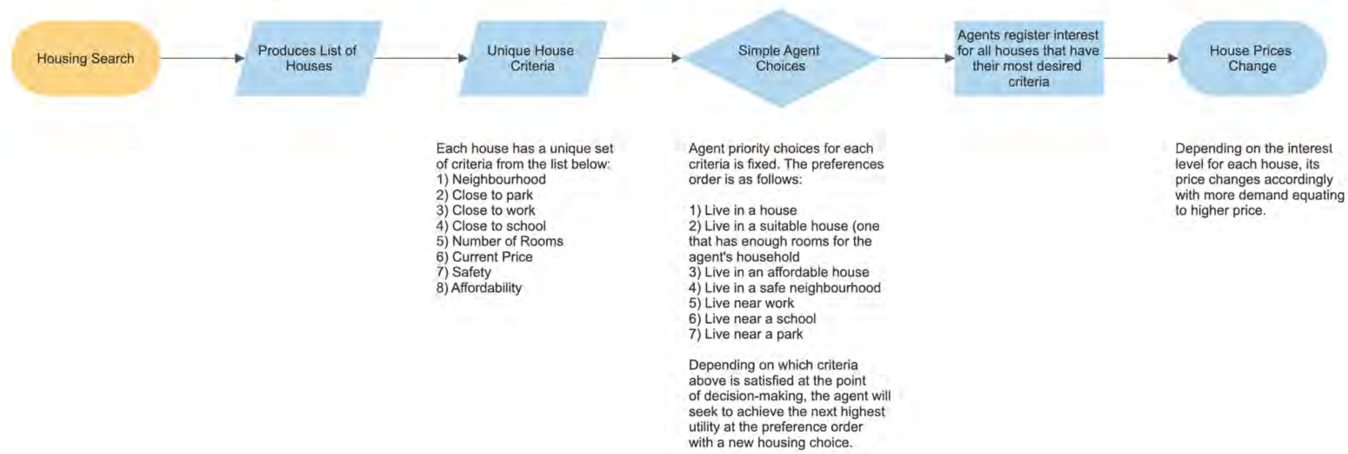


Figure 21: Diagram outlining the decision-making process for simple agents (ordinance utility)

The diagram above helps explain individual sensing, the way choices made in the housing market for simple agents in the model. Simple agents have, as stated above, a number of desires/utilities that have a set priority or preference order based on the agent's pre-set coded logic. At the start of every turn the agent evaluates what utilities it has achieved and then bases their housing decision on trying to achieve the most preferred utility that it is currently lacking from the preference order list. This is an important aspect because it dictates how the agent will act in the housing market. Once a prioritized desire is set, the agent begins the search for suitable houses that, with the purchase of that house, fulfils set preferred utility. The agent looks through the list of houses to find all houses that would achieve such a feat. Agents are assumed to have perfect knowledge in the market, other than the eventual outcome of temporal aspects that are dictated by the collective decision making of all agents. Therefore, in this and the other two models, the agents look at all houses available to them. Each house has a set of criteria or attributes. These include current price, safety, affordability, number of rooms, proximity to park, work and school and neighbourhood. The choice of housing is individual to each agent and dependent on their own unique circumstances and attributes including income, family situation and current house. These form the variables that make agents heterogeneous and impacts uniquely in their decision-making. Each house is ranked using a lexicographical method with the most preferred utility for the agent ranked at the top. Every house with that exact criterion is instantly placed on a shortlist. The agent proceeds to register an interest for all houses that have the criteria that fulfils their preferred utility for that turn in an attempt to maximise their utility. Depending on the accumulated interest of all agents, house prices change with more demand equating to an increase in price while a decrease in overall demand for that round resulting in a decrease in price. It's important to note the fact that agents make their choices on safety and affordability, the two temporal aspects, on information available to them from the previous run. They do not possess the capacity to predict future state of such aspects.

Interactions between agents exist indirectly (similar to BDI and cognitive models) as the effect of emergent patterns within the model through the affordability and safety criterion (see section 4.5.3 for more details).

4.7.4 Collectives formed/Observations.

Similar to BDI agents (section 4.6.4), observations within the model exist as the emergent properties of agent actions. The same three emergent patterns arise in this logic-based architecture, average market price for dwellings (based on demand), detractors for individuals (based on income level of residents in the neighbourhood) and attractors for individuals again associated with average income levels of residents in a given neighbourhood (see section 4.6.4 for more details). The outputs and observations generated by the model are the same as in BDI and cognitive agents (see section 4.6.4 from more details).

4.7.5 Stochasticity

Similar to BDI agents (section 4.5.5) logic-based agents have some randomly generated attributes, namely which house they were assigned at the start of the simulation (Please see section 4.5.5 for more details). The list of preferred order for desires/utility for the computerised agents, derived from housing attributes, is not random and set for the simulation as constant.

4.8 Implementation Platform & programming Language

The three models are coded using Python computing language without the use of any libraries/packages such as Mesa or Agentpy. This is due to the unique nature of these models, requiring innovative agent architecture that would be best coded from scratch rather than adopting a pre-existing framework. The simple agent's model could have been created using one of the two aforementioned packages though, for comparison reasons, the research elected to code it using the same basic self-created framework as the Cognitive and BDI complex agent models. All three models were coded on PyCharm, a coding integrated development environment (IDE) and run through the console within the program. All inputs for the models were inputted within the code, while all outputs generated by the code were exported to a series of csv files for future analysis.

There are several reasons culminating to the research's choice of Python over other coding languages. Firstly, Python is easy to learn and use due to its simple syntax that is closer to natural language than machine language. This would enable beginners and amateur professionals alike to both read and adopt the modelling frameworks created by this research at greater ease. This reason combined with the fact that Python has become a fundamental part of curriculums at all levels of education starting from primary school, would result in the research being more accessible for other researchers in the field. Python has a multitude of libraries and frameworks that deal extensively with both web development and data science, both of which could be utilized by both this researcher and other researchers in the field, for future expansion and repurposing of the code created by this research. This makes the practical application of the research easily implementable. The last reason for the choice of Python language is the flexibility it provides as it is not a language optimized for one aspect of computational processes or applications. This flexibility, could aid in future development of the research, enabling the addition of other, bolstering frameworks such as machine learning and application development without the need to translate the code to another language that better suits a particular computational technology.

4.9 Model Input Data

All three models have been created with the purpose to test the performance of different theoretical basis and agent architectures. They exist as conceptual models and thus will not be applied in a real-world scenario as part of this research. Furthermore, all three models feature the same artificial environment, made up of three neighbourhoods each with four houses (total of 12 houses), in which 24 agents, representing individual households, strive to choose a house that would best satisfy their unique needs. Given the conceptual and artificial nature of these models, no real-world data is required nor useful as input into them. The attributes of all three classes (neighbourhood, house, agent) are determined by the artificial and controlled nature of the interactions geared towards examining agent decision-making. All household agents and houses have their initial attribute data determined, finalized and inputted as part of calibration and parameter sweeping experiments described in the next chapter. This ensures that the models perform and output data that allows for a useful comparison between them.

Limitations of using simulation (lack of real-world data).

4.10 Chapter Summary

The chapter outlines the creation of three computational models that feature a series of agents interacting and making household location choices in an artificial environment made up of three neighbourhoods and twelve houses. The chapter first explains the theoretical basis for the models as well as the agent architectures needed to implement them. It establishes the ODD+D protocol for ABMs as the framework by which to describe the models. It then proceeds to overview the overarching elements of all three models followed by the detailing out the unique features of each of the three complex agent models. Finally, the chapter concludes with an explanation for the choice of programming language and model input data origin. The exact model input data as well as the resulting outputs for the three models will be explored in the next chapter.

CHAPTER FIVE: MODEL CALIBRATION EXPERIMENTS AND SIMULATION RESULTS

5.1 Introduction

Chapter five follows on the design and development of the three computational models outlined in chapter four. Within this chapter, the parameter values required for the models to run are set using a combination of sensitivity analysis and parameter sweeping experiments.

This is followed by running the three models with set parameters, recording, analysing and comparing the results obtained.

Firstly, all parameters present within the models are identified and investigated to understand their value's resulting effect on simulation outcome. This includes both BDI and Cognitive agent specific parameters. Cognitive Agent Architectures require two unique aspects to be included for its agents, memory storage and memory representation. BDI agent-based computational model included three unique, to this architecture, variables that hold either True or False. These variables are the behavioural attitude, social norm and perceived behavioural control. Following this, the research will then establish the range of values for all parameters given the underlining equations, ensuring that agents can achieve satisfaction in some attributes but not all with any given choice. Essentially, based on the equations, the research will argue on the combination of the attribute values chosen.

Following the assignment of values to parameters, the chapter describes the calibration of these values. As these models do not seek to replicate a real world set of outputs, there is no dataset that the models need to be calibrated for that consists of a given input and achievable output. Thus, calibration in these three ABMs seeks to ensure that agents constantly seek to improve their situation and that few truly satisfying options exist at limited intervals thanks to agent-influenced housing attributes such as safety and affordability. Therefore, the thesis runs a series of parameter sweeping experiments to ensure agent's endless pursuit of happiness.

The chapter then carries out the fourth activity outlines in the design science research methodology, demonstrations. The thesis runs the three created models' simulations in an attempt to showcase their ability to use different complex computational agents to make location choice decisions. This step aims to demonstrate not only the ability of the artifacts created to fill the role of a real-estate demand model but to also showcase differences in results between the three computational models created. The results will then be outlined and compared against each model to determine the effect a change in theoretical basis and agent architecture can have on resulting housing demand patterns. This will be achieved by monitoring price fluctuations of all houses within the simulation which is directly determined by level of demand at each turn.

5.2 Model parameters

5.2.1 Setting initial parameter values and determining minimum model simulation repetitions.

Setting up initial parameter values requires first an understanding of what are all the parameters present in the model and their value's effect on the resulting outcome. This is also referred to as sensitivity analysis (SA) (Norton, 2015). SA usage includes understanding the robustness of the model and its results, especially for agent-based simulation models (Macal & North, 2006).

In the three complex agent models, created for this research, agent decision-making is the important aspect in question. Here, factor screening and optimization become the major concerns in setting up parameter values as given the target value for a particular response, what is the appropriate input values that achieve it (Kleijnen, 1998)? Factor screening simply involves the selection of all input parameters. An analysis of existing models of household location choice (done in chapter 3) provided a list of parameters as well the relationships of common utility maximization principles that forms agent decision-making. Choices on these factors (factors are a general term used to describe inputs as they range from parameters to variables etc) primarily satisfies a respectable number of variables for agents to consider when making a house choices. These models' aim is not to be exhaustive in their variables but simple tests for different agent theories and architectures. In this case, the following three entities selection ensued:

1) Neighbourhood: The neighbourhood includes wider variables of amenity proximity within them as well as four houses each. Three neighbourhoods exist in total within each simulation.
2) House: Four houses exist within each neighbourhood totalling twelve house entities within the simulation. Each house has a separate combination of attributes.
3) Agent: An agent makes up the decision-making entity within the model, representing households. Each agent has a unique combination of attributes that influence house choice. There are twenty-four agents in total.

Each of these entities include a series of attributes as seen in the tables below. A neighbourhood has a unique ID (a, b or c), a list of houses included within its borders and whether it has a park, work or school amenity within it. A house has its own ID (a, b, c, d, e, f, g, h, I, j, k, l), neighbourhood (a, b or c), initial price (set at £100k for each), number of bedrooms, owner (the agent that owns the house at that specific simulation turn) and current price (the price determined by agent demand on that specific simulation turn). Agents have an ID (A, B, C,

D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U, V, W, X), unique income per year, number of children and currently owned home (specific to that simulation turn)

Neighbourhoods	ID	Houses	Park	Work	School

Table 7: Table outlining neighbourhood attributes for all simulations.

Houses	ID	Neighbourhood	Price Initial	Number of Rooms	Owner	Price Current

Table 8: Table outlining housing attributes for all simulations.

Agent	ID	Income (per year)	Children	Home	Current Desire

Table 9: Table outlining Agent attributes for simple agent simulation.

Agent	ID	Income (per year)	Children	Home	Behavioural Attitude	Social Norm	Perceived Behavioural Control	Current Desire

Table 10: Table outlining Agent attributes for BDI agent simulations.

Agent	ID	Income (per year)	Children	Home	esuitable	eaffortable	esafe	ework	eschool	epark	active

Table 11: Table outlining Agent attributes for cognitive agent simulations.

In addition to these core attributes, BDI agents also have four additional attributes specific to the agent architecture that are behavioural attitude, social norm, perceived behavioural control and current desire. The last one is unique to the architecture as BDI agents by nature prioritise desires. In this case, this attribute states the current desire priority by the agent for this turn. Cognitive agents also have a further seven attributes unique their agent architecture. The first six are the agent's experience/tastes and relate to the agent's memory on suitability, affordability, safety, proximity to work, proximity to school and proximity to park. The last additional attribute for cognitive architecture is the active trait. This dictates if the agent has an affinity for physical exercise that may dictate their experiences. The logic-based architecture agents of the third control model have one additional attribute that is similar to the BDI architecture in that it is the utility the wish to improve for that round in the form of current desire. Given that these agents are utility maximisers, they constantly seek to improve their lowest performing utility and therefore set themselves that goal at each round.

Determining the range of all attributes for the three entities, requires a sensitivity analysis. Two facts need consideration in a SA. The first is the simulation model's credibility depending on the knowledge of each parameter's importance, which without a SA it lacks predictive capacity (Norton, 2015). As the models of this research do not feature a predictive element of aim, rather an exploration on the merits of the decision-making theory and agent architecture used to prescribe it; a SA provides no input in the selection of parameters. The second and more important fact, SA highlights where the model needs improvement by understanding the relationship between parameter values and outputs. This allows for the calibration of inputs in order to achieve the desired range of outputs. Due to the simple nature of relationships within this model (excluding the emergent patterns), an analysis of the model's equations is sufficient in carrying out a SA (Norton, 2015). Therefore, to determine the range of values for all entity variables, the equations that drive agent decision-making needs investigating and analysis.

Before looking into the equations, some model assumptions need noting. Firstly, all houses have an initial price of £100k. This, regardless of attributes, remains the same. It allows demand to dictate price formation from the same starting point. It therefore enables a much better comparison of price changes in the market acting as the emergent pattern of agent interactions without an initial influence of housing price bias. In order to achieve this emerging pattern, the equations need to allow price-related decisions to exist given this initial price. Secondly, agents must not have the capacity to be fully satisfied. Whether no perfect house exists, or agents lack fundamental attributes to satisfy all their needs, this requirement ensures that agents will constantly seek to improve their situation rather than settle. This ensures that all agents are constantly influencing emergent patterns of price formation. In turn, it helps with the study of decision-making capacities, as agents must constantly choose their primary aim for that round. This is of course influenced by the type of agent architecture and the model's theoretical basis.

5.2.2 Analysis of equations:

In the section, the research will establish the range of values for all attributes of all entities given the underlining equations, ensuring that agents can achieve satisfaction in some attributes but not all with any given choice. Essentially, based on the equations, the research will argue on the combination of the attribute values chosen.

In the previous section, the research established that there are 12 houses, 3 neighbourhoods, 24 agents, all houses have a starting value of 100k, and no agent should be fully satisfied by any choice of housing though, as much as possible, there should be choices available for satisfying all individual agent desires. These statements form the basis for forming the values of all attributes for all entities. In addition to those statements, when determining the range and combination of values of attributes, the satisfaction criteria for each desire warrants consideration. Listed below are the satisfaction criteria for all 7 agent desires in all three computational models, regardless of architecture and agent theory.

1) Live in a house: If the agent owns a house, consider this criterion fulfilled.

2) Suitability: If the agent owns a house that has an amount of bedrooms equal or more to the amount of his children + one, then consider this criterion fulfilled.

3) Affordability: If the current price of the agent's owned house is less than three and a half times his income, then consider this criterion fulfilled.

4) Safety: If the average income of agents (including your agent) in your agent's owned house's neighbourhood is within + or – £10000, then consider this criterion fulfilled.

5) Live Close to Work: If your agent's owned house has an attribute close to Work as True, then consider this criterion fulfilled.

6) Live Close to a School: If your agent's owned house has an attribute close to a School as True and your agent has at least one child, then consider this criterion fulfilled.

7) Live Close to a Park: If your agent's owned house has an attribute close to a Park as True, then consider this criterion fulfilled.

The satisfaction of each criterion and the associated agent desire, hinders on the satisfaction of an equation. Therefore, carrying out SA for these models requires an analysis of the equations. Starting with the first criterion, live in a house, a simple Boolean operation determines the validity of this statement.

```
if agent.h == False:
    desire = "get_a_house"
```

If the agent attribute of Home (agent.h) is set to True, then the agent satisfies the criterion. There are 24 agents and only 12 houses, this ensures that half of the agents are always seeking to satisfy this criterion at any given turn which reduces the likelihood that any house will remain vacant even if it does not satisfy all of the agent's desires. The market assumptions include a perfectly inelastic supply as each house consists of unique attributes which extends to no change in quantity provided when price changes. Therefore, shifts in demand and competition for the limited supply have a more direct effect on price. Though land markets are relatively inelastic in supply by nature, this is an exaggerated case to observe the effects of agent decision-making more easily on housing prices.

The second criterion, suitability of space, sees the agent assess the viability of living arrangements based on their number of children. The equation below dictates suitability satisfaction where house.r is the number of rooms in the house and self.ch is the number of children the agent has.

```
if house.r >= (self.ch + 1):
    suitability = True
else:
    suitability = False
```

To ensure this criterion can be achieved by all agents with at least one housing choice, the max number of the rooms attribute given to the 12 houses is 1 more than max number of children attribute given to the 24 agents. This guarantees that agents with the maximum attribute number of children will have at least 1 house that satisfies the suitability criterion.

The third criterion, affordability, deals with the economic ability of the agent to afford a mortgage on the house. The logic statement/equation code for affordability (below) dictates that ability with house.pc being the house's current price (following market manipulation in the previous turn) and self.i is the agent's income.

```
if house.pc / 3.5 <= self.i:
```

```
        affortability = True
    else:
        affortability = False
```

The house's current price is dictated by agent demand/interest for that turn. Depending on the decision-making criteria (this changes depending on the model/theory/agent architecture), each agent has the ability to place an interest for a range of houses. The current price for a house is stated by the equation below where marketmulti is the multiplication variable determined by the number of interests by agents for that house (interest().count(house)) multiplied by 0.05 (5% increase per agent interest), house.pc is the current price of the house and house.pi is the initial price set at 100k.

```
marketmulti = interest().count(house)*0.05
house.pc = house.pi * (1+marketmulti)
```

This means that the current price of a house can only achieve a maximum of 210k. With a 5% multiplier, this is achieved when 23 out of the 24 agents have placed an interest on that house. The remaining agent is the owner of the house and not able to place an interest for it on that turn. Given the 210k maximum price and a satisfaction criterion of less than or equal to 3.5 times the income of the agent, a maximum income attribute of 60k ensures that all houses will be affordable for at least one agent on any given turn. At the same time, agent income attributes should be set at a 10k interval allowing for clear distinction between affordable housing brackets, 35k difference between each bracket given the affordability criterion, with a minimum of 10k income.

The fourth criterion of safety is determined at a neighbourhood scale. The 12 houses are equally distributed in 3 neighbourhoods. This enables a comparable calculation of safety. If the average income of agents (including the agent inquiring on safety) in the agent's owned house's neighbourhood is within + or – £10000, then the safety criterion is satisfied. In Appendix (Equation 1) is the definition of safety for the neighbourhood class where avg is the average income in the neighbourhood, h is homes, self.hs is list of homes in the neighbourhood, agents is the list of all agents, agent.h is the agent's home in this turn, h.id is the homes identity code, agent.i is the agent's income attribute, safety is a list containing True or False values relevant to each agent's income against the neighbourhood average and safetyrating is the neighbourhood's safety criterion fulfilment.

The code sets a 10k average income range for safety rating. With a 60k maximum agent income and 10k minimum agent income (defined above), results to 5 safety brackets (10k each starting from 10k up to 60k). Depending on the distribution of income attributes for the agents (extremes vs average), the safety criterion at each turn can drastically change allowing agents to constantly pursue this shifting goal.

The last three criterion of school, park and work are a direct Boolean check if the agent's house's neighbourhood is close to work, to a park or to a school. The three definitions in the

Appendix (Equation 2) describe the Boolean operation for checking if the agent's house is close to the three amenities with workprox, schoolprox and parkprox are the Boolean checks returned by the operation, self.h and house.id is the agent's house ID, house.n is the house's neighbourhood, neighbourhooda.w or neighbourhoodb.w or neighbourhoodc.w is the neighbourhood's Boolean attribute for proximity to work, neighbourhooda.sc or neighbourhoodb.sc or neighbourhoodc.sc is the neighbourhood's Boolean attribute for proximity to school, neighbourhooda.p or neighbourhoodb.p or neighbourhoodc.p is the neighbourhood's Boolean attribute for proximity to park.

Neighbourhood attributes for the simulations are outlined in the table below. The simulation ensures that not all 3 (park, work, school) attributes are true for a single neighbourhood to avoid issues of the perfect choice and ensure that agents constantly strive to improve their situation. Furthermore, the housing attributes within neighbourhoods have been determined with the amenity proximities in mind. For example, neighbourhood b with no school, has houses with many bedrooms so that people with no children are not without competition when choosing to move into that neighbourhood.

Neighbourhoods	ID	Houses	Park	Work	School
1	a	a, b, c, d	True	False	True
2	b	e, f, g, h	True	True	False
3	c	i, j, k, l	False	False	True

Table 12: Table outlining neighbourhood attribute values for all simulations.

It is worth noting that the school attribute and associated criterion does not matter if the agent has no children as they do not require or have use for such an amenity. For these agents, if they are homeowners that round, the school criterion is always satisfied.

These criteria, in all three models, change in terms of priority for each turn based on what the agent is lacking on that turn. This means that it is individual to each agent and dependent on their own unique circumstances and attributes including income, family situation and current house. This, in combination to the agents' heterogeneous nature ensures that different housing aspects are in more or less demand each turn which then uniquely impacts on demand. The equation that controls the ranking of houses, that narrows down the choice for the agent, is based on a lexicographical method with the most important criteria for the agent ranked at the top. The choice of a single house follows this method by eliminating all houses on the list that do not meet the first criterion and then all houses that don't meet the second most important criterion and so on until there is only one choice left which best suits the agents unique desire prioritization for that turn. An important note added here is the fact that agents make their choices on safety and affordability, the two temporal aspects, on information available to them from the previous run. They do not possess the capacity to predict future state of such aspects.

Additional Equations for BDI agent simulation:

In chapter 4, the research outlined that the BDI agent-based computational model included additional elements from the ones described in the previous section. Though these aspects are explained, in terms of their theoretical link in the methodology chapter, in this section the research will outline the equations that these unique variables make up.

Each agent has three unique, to this architecture, variables that hold either True or False. These variables are the behavioural attitude, social norm and perceived behavioural control.

Agent ID	Behavioural Attitude	Social Norm	Perceived Behavioural Control
A	True	True	False
B	True	False	True
C	False	True	False
D	True	True	True
E	False	True	False
F	False	False	True
G	True	True	True
H	False	True	False
I	True	False	True
J	True	True	False
K	True	False	False
L	False	False	True

M	True	True	True
N	True	True	False
O	True	False	True
P	False	True	True
Q	True	True	False
R	False	True	True
S	True	True	False
T	True	False	False
U	True	True	True
V	False	True	False
W	True	False	True
X	False	True	True

Table 13: Table outlines BDI agent specific attributes and their values

The more of these variables that hold true for the agent regarding this action, in this case moving house to better suit the agent needs, the more likely the agent is to actually act upon it. It constitutes the inclusion of uncertainty for the agents but not in a traditional sense. It does not form an uncertainty in a value calculation but rather an uncertainty in the sense of hesitation due to surrounding factors that have a chance to affect the agent's actions.

The logic statements stated in the Appendix (Equation 3) control the first instance of follow-through by the agent for selecting a particular desire to pursue. Depending on how many of those three variables, self.ba (behavioural attitude), self.sn (social norms) and self.pbc (perceived behavioural control), hold true for the agent, there is a greater chance (by 25% less for each False attribute) for the agent to follow through with their selected desire (represented here by true_desire).

In this model, price of the house forms the second time these variables determine follow through by the agents. House prices fluctuate depending on other agent's demand. The more of these attributes the agent has as positive and the more "attractive" the price in the form of change from last turn, the more likely the agent is to purchase set property. The logic statements in the appendix (Equation 4) control this function with housea.pc being the house current price for that round following the demand change, housea.pi is the initial price of a house (always set at £100k), agent.cd is agent current desire to pursue this round, desire_in_question is the original desire selected this turn, housechance is a random generated number from 1 to 100, "not willing to pay" is the new desire that signals the agent to not follow through with their original desire.

These variables influence the follow through of decision into intentions as a percentage of likelihood. This essentially forms the only core stochastic element in the simulation apart from the starting agent attributes which is constant in all models/simulations.

Additional Equations for Cognitive agent simulation:

Cognitive Agent Architectures require two unique aspects to be included for its agents, memory storage and memory representation. Memory storage sees the cognitive agents having six additional attributes in the form of agent experience. All desires, apart from having a home, that includes suitability, affordability, safety, proximity to work, proximity to school and proximity to a park, are expressed as an attribute for the agent with an initial value of 50. This represents the experience of the agent with that desire and, depending on the experience of the agent during the simulation, these values change. Higher value for these attributes represents what is most valuable for the agent, what they believe they should prioritise as aspects for a housing choice.

These agent experiences going through the housing market during the course of the simulation, their effect on the value of these attributes, depends entirely on the agent's own perceptions and characteristics. This leads to the seventh and final additional agent attribute, called active. It represents, as a Boolean value of True or False, whether the agent enjoys an active lifestyle of exercising/jogging. All extra attributes for the cognitive agents are listed below.

self.esuit = esuitable

self.eaffo = eaffortable

self.esafe = esafe

self.ework = ework

self.escho = eschool

self.epark = epark

self.a = active

At the end of each round, assuming the agent is a homeowner that round, the agent begins to evaluate the current situation. The code/equation below facilitates part of this process by allowing the agent, depending on their own characteristics, whether they find aspects of the experience positive or negative.

```
for house in houses:
    if ((agent.cd != "content") and (agent.h == house.id)):
        if house.n == "a":
            if agent.a == True:
                agent.epark = agent.epark + 20
            elif agent.a == False:
                agent.epark = agent.epark - 20
```

In the sample code above, the agent first evaluates if they are content or not and whether they even have a home at the time by searching if the attribute of home for the agent matches any house id in the list of houses. Afterwards, the code proceeds to determine the location of the agent's house, in this case the neighbourhood. This is an important step as it creates the context for the house, meaning if the neighbourhood is located near a park, a school or work. Once this is established, the agents own attributes come into play as judging the context positively or negatively depends on the agent's own perceptions. In this case, if an agent maintains an active lifestyle of physical exercise (agent.a == True) (jogging, hiking, walking etc) and the neighbourhood can facilitate for that to happen (by having a good proximity to a park), the agent views that as a positive experience (agent.epark which is the experience of the agent with parks is positively reinforced). If the opposite stands true, meaning we have a non-physically active agent living in a neighbourhood with a park, the agent may view that experience as negative. They may perceive that they gain no benefits from the park and may view negative aspects such as noisy children playing in the park or potential spots for inappropriate dealings as a deterrent (agent.epark which is the experience of the agent with parks is negatively reinforced). At the very least, the agent recognizes that living next to a park does not mean a lot to them and therefore it goes lower on their priority list. Worth noting, all experience values for all six of the experience attributes of the agent, increase or decrease based on the agent's evaluation at that round by + or – 20 each time.

In the cognitive architecture model, experience results in a utility number that gets added or subtracted from the memory's numerical representation of utility for any given attribute thus making all decisions based only on previous decision outcomes. Therefore, memory storage forms the most important aspect of this architecture. Agent's memories consist of utility values for every house attribute and are stored as agent attributes. They get altered by the experiences of the agent at each turn, effectively updating the agent's taste and preferences. These utility representations include:

7. self.esuit = esuitable : Agent's utility function for suitability
8. self.eaffo = eaffortable : Agent's utility function for affortability

9. self.esafe = esafe : Agent’s utility function for safety
10. self.ework = ework : Agent’s utility function for living close to work
11. self.escho = eschool : Agent’s utility function for living close to school
12. self.epark = epark : Agent’s utility function for living close to parks

In these utility functions, the agent’s unique taste and preferences are represented, formed and updated. Each agent has his or her own taste and preferences that determine their prioritization of criteria for houses. These utility functions forming taste/preference maintain a numerical value that changes every time an agent experience something positive or negative for that particular preference. Updating the utility function values happens only if the agent has the opportunity to experience that preference by living in a house that possesses that unique attribute that corresponds to that preference. This means that ranking of housing attributes directly responds to these utility functions. The highest of which is given priority when making a choice and these priority weights for each housing attribute lie solely in the agent’s memory. Thus, their experiences and their unique perspective drive every choice an agent makes, including if they wish to enter the housing market or choices made within the housing market. This process in the architecture is called memory representation and forms the second most important aspect of a cognitive agent, their ability to use stored memory to influence future decision-making.

The sample code in the Appendix (Equation 5) expresses how a cognitive agent within the simulation uses their stored memory, altered through their cognitive experience attributes, to make a house choice. Initially all experience values are set at the same amount at the start of the simulation for all agents allowing them to form their own experiences and tastes as they move from house to house and evaluate what they perceive to be good or bad.

5.2.3 Calibration method and parameter-sweeping experiments

In terms of calibration, the aim of it for this experiment takes an alternative form to traditional models within the housing location choice urban simulative modelling spectrum. As these models do not seek to replicate a real world set of outputs, there is no dataset that the models need to be calibrated for that consists of a given input and achievable output. Thus, calibration in these three ABMs seeks to ensure that agents constantly seek to improve their situation and that few truly satisfying options exist at limited intervals thanks to agent-influenced housing attributes such as safety and affordability. If agents are constantly unsatisfied with their choice, then they will participate more and more in the housing market and experience more and more housing options which both drives a healthy housing demand for comparison and allows the cognitive model's experience aspect to be utilized fully.

Parameter-sweeping experiments:

In order to determine a relatively balanced range of attributes for housing and agents, a series of parameter sweeping experiments was run. The parameters in this case consisted of the agent and housing attributes. The neighbourhood attributes were set with a range of parks, schools and work proximities and maintained with the explicit intent of one neighbourhood not having all 3 attributes at any given time to ensure agents can never have all desires fully satisfied. These were constant in all simulations and not part of the parameters changed during the parameter-sweeping experiments.

Housing parameter testing:

From the attributes of the house, the school, park and work parameters are set by the neighbourhood thus not altered. Each neighbourhood also has 4 houses in it therefore the houses are divided equally into these and not altered. Price initial is also fixed at £100k pounds for each house. The only variable forms part of the parameter sweeping experiments is the number of rooms.

Firstly, the range of this parameter needs determining. This becomes particularly tricky as it is intertwined with the agent attribute number of children. Therefore, this parameter's maximum range was set alongside the agent parameter max of number of children. For agents' maximum number of children attribute the value chosen was 4 and for housings' maximum number of rooms attribute was set at 5. This ensures that all agents can satisfy this parameter regardless of their children number. The lowest number parameter for housing rooms was set to 1 and for children 0 to again ensure the minimum can be satisfied by all housing choices.

Experiments were run to test the extreme case scenarios where housing room number was set to 1 for all houses and 5 for all houses. For all experiments, agent number of children was set to a relatively even distribution of 0 – 4 to ensure representation of all suitability scenarios. The results for attribute value 1 for all showcased that all agents, apart from agents without children, constantly tried to satisfy this criterion with no success and it caused them to place demand for housing independent of this variable. Within this range, cognitive agents did not have the ability to positively experience a suitability utility for any housing. This caused housing prices to be negatively determined independent of number of rooms which goes against the model aims and intends. The opposite was true for the run with number of rooms set to 5. All agents could satisfy that parameter given that choice and therefore never sought to satisfy it which affected the demand for housing and the price in a negative way. The third run consisted of all houses having 3 bedrooms each. This way a greater number of agents could be satisfied but this too caused an issue for agents with more than 2 children, being unable to satisfy that parameter regardless of choice. Therefore, the choice made was that of a mixture of values for this parameter. Further runs featuring this, revealed a greater competition for housing surrounding this parameter when all neighbourhoods had a) a good representation of all parameter ranges and b) a mixture of only high and low parameter values as opposed to medium. This ensures that competition is high and the likelihood of failure for the utility function of suitability, that is determined by this variable, exists in moderation. The parameter set below displayed one of the best performances in terms of demand and therefore competition of housing for the suitability desire and therefore forms the choice for this parameter.

Houses	Number of Rooms
House 1	4
House 2	2
House 3	1
House 4	5
House 5	5
House 6	4
House 7	4
House 8	2
House 9	1

House 10	5
House 11	5
House 12	4

Table 14: Table outlining number of rooms attribute of houses and their values.

Agent parameter testing:

Agents have two specific attributes to be considered in parameter sweeping experiments. These are number of children, which relates as previously mentioned to the number of bedrooms a house has available, and secondly income per year which relates mainly to affordability as well as neighbourhood safety. Agent home has proven irrelevant to start with, given the fact that the model parameter setting constantly ensures agents strive to improve their situation with no perfect solution, thus has no impact on the model outcomes after 30 turns.

For the number of children parameter, the previous section on house parameters already established the logic for maximum value of 4 and minimum value of 0. This serves to enable the possibility for all agents to satisfy the suitability desire. For the agent income parameter, the range depends on its ability to satisfy a) affordability and b) safety. Considering affordability, all houses have a starting value of 100k that can rise depending on demand. To make the least desirable house affordable for any agent, they need to have a minimum income of £28.6k. Assuming all agents desire the same house, the maximum price for a house can be as much as £220k which means the maximum income required to ensure satisfaction of the parameter in all circumstances is £62.9k. These will form the parameter values to be tested for agent income attribute.

The research run 2 experiments each featuring the minimum and maximum range of income for all agents respectively. The results showcased those agents reacting differently in each experiment yet had the same overall pattern in terms of results. For the experiment with all agents at £28.6k, agents seemed to be unable to afford all but the cheapest 2 houses (most undesirable) thus did not include it as part of their decision-making. Furthermore, safety desire also suffered as all agents had the same income thus rendering it unimportant. For the experiment with all agents at £62.9k, showcased that agents could afford all housing and therefore did not consider that aspect when choosing a house. Important to note here that safety desire was again rendered unimportant. Therefore, a range of values for this parameter needs to be considered. Experiments run with such values resulted in, for most rounds, all agents had a house that was affordable to them and thus not a major determinant of demand. Therefore, a decision was made to run the experiment with a lower maximum and minimum range to ensure that houses are unaffordable to some agents at all rounds and greater disparity in income meant safety became a much more major decision factor. The parameter sweeping experiments established that 25% of all agents needed to be below the £28.6k threshold with no agents fully reaching £62.9k in order to allow for a healthy competition for affordability at all price ranges of housing. Furthermore, in order to enable this, number of children had to be set at 0 or 1 to all agents that make up that 25% with income below £28.6k given the current housing room distribution and neighbourhood attributes. A relatively even distribution of children numbers at all other income ranges enables a variety of desired housing attributes again driving healthy competition in the market while ensuring that few houses can ever fully satisfy all agent desires with affordability and safety making sure that a housing choice can only ever do that temporarily. The final parameter distribution for number of children and income following the parameter sweeping experiments is as follows.

Agent	Income (per year)	Children
Agent 1	40k	2
Agent 2	50k	3
Agent 3	10k	1
Agent 4	50k	3
Agent 5	30k	2
Agent 6	50k	1
Agent 7	20k	0
Agent 8	60k	3
Agent 9	40k	3
Agent 10	50k	4
Agent 11	10k	0
Agent 12	50k	4
Agent 13	40k	2
Agent 14	50k	3
Agent 15	10k	1
Agent 16	50k	3
Agent 17	30k	2

Agent 18	50k	1
Agent 19	20k	0
Agent 20	60k	3
Agent 21	40k	3
Agent 22	50k	4
Agent 23	10k	0
Agent 24	50k	4

Table 15: Table outlining agent attributes and their values.

5.3 Final model simulation and analysis of results

Following the establishment of parameter values for the neighbourhoods, houses and agents following the parameter sweeping experiments, the research will run each computational model for 30 turns and record data on agent decision-making. This section explores the inputs of all parameters within the model and analyses the resulting outputs.

5.3.1 Background Characteristics of simulated household population

All three computational models consist of three classes that include neighbourhood, houses and agents (households). As established above, there are 3 instances of the neighbourhood class, 12 of the housing and 24 of the agents. Their final shared inputs for all three classes running on all three models are shown in the tables below. Both the BDI agent architecture model and the Cognitive agent architecture model has additional parameters that are outlined in the previous sections of this chapter. These did not feature in calibration as there are no real-world datasets to match with. In fact, these form the basis for the differences in both theoretical approach to decision-making and coding approach to modelling the framework for the decisions. Thus, these differences will be the fundamental aspects that are hypothesized to change the emergent patterns outputted by the models to a certain degree, testing viability and performance.

Neighbourhoods	ID	Houses	Park	Work	School
1	a	a, b, c, d	True	False	True
2	b	e, f, g, h	True	True	False
3	c	i, j, k, l	False	False	True

Table 16: Table outlines the value of neighbourhood attributes and their values.

Houses	ID	Neighbourhood	Near Park	Near Work	Near School	Price Initial	Number of Rooms
House 1	a	a	True	False	True	100k	4
House 2	b	a	True	False	True	100k	2
House 3	c	a	True	False	True	100k	1
House 4	d	a	True	False	True	100k	5
House 5	e	b	True	True	False	100k	5
House 6	f	b	True	True	False	100k	4
House 7	g	b	True	True	False	100k	4
House 8	h	b	True	True	False	100k	2
House 9	i	c	False	False	True	100k	1
House 10	j	c	False	False	True	100k	5
House 11	k	c	False	False	True	100k	5
House 12	l	c	False	False	True	100k	4

Table 17: Table outlines housing attributes and their values for all simulations

Agent	ID	Income (per year)	Children	Home
Agent 1	A	40k	2	A
Agent 2	B	50k	3	B
Agent 3	C	10k	1	C
Agent 4	D	50k	3	None
Agent 5	E	30k	2	D
Agent 6	F	50k	1	E
Agent 7	G	20k	0	F
Agent 8	H	60k	3	G
Agent 9	I	40k	3	H
Agent 10	J	50k	4	I
Agent 11	K	10k	0	J
Agent 12	L	50k	4	None
Agent 13	M	40k	2	K
Agent 14	N	50k	3	L
Agent 15	O	10k	1	None
Agent 16	P	50k	3	None
Agent 17	Q	30k	2	None
Agent 18	R	50k	1	None
Agent 19	S	20k	0	None

Agent 20	T	60k	3	None
Agent 21	U	40k	3	None
Agent 22	V	50k	4	None
Agent 23	W	10k	0	None
Agent 24	X	50k	4	None

Table 18: Table outlines agent attributes and their values for all simulations

5.3.2 Simulated residential location choices raw data.

For all three computational models, the outputs were written onto a csv file. These outputs included a list of house prices for that round, a list of priorities for the agents on that round, a list of owners at the start and end of the round for each house and list of Booleans confirming if houses are owned at the start and end of each round. The code in the appendix (Equation 6) outlines how the collection of outputs is transferred onto a csv file, arranged within columns.

The tables below feature a sample of the raw data. This data undergoes refinement before analysis to convey emergent demand patterns for the different model outcomes. The important outcome for analysis includes the decisions made by the individual agents at any given turn (Table 2), the current round data that forms the context for those decisions (Table 1) and the price change for houses over time (Table 3). The latter forms the emergent pattern of agent interactions and decision-making, helping understand the overall trends over time. The other two datasets complement the observations made by looking at the housing price changes over the course of the simulation and help explain the various trends that may arise.

	Round 1		
	Neighbourhood A	Neighbourhood B	Neighbourhood C
Avg Income	32500	42500	37500
		Current Price	
	House A	185000	
	House B	140000	
	House C	130000	
	House D	170000	
	House E	165000	
	House F	170000	
	House G	175000	
	House H	140000	
	House I	120000	
	House J	170000	
	House K	160000	
	House L	175000	

Table 19: Table of raw data at the end of each turn that showcases current price for each house and average income of all residents in a neighbourhood.

Round	1	2	3
Agent	Choice	Choice	Choice
1	FALSE	b	b
2	d	a	d
3	FALSE	i	i
4	k	d	d
5	FALSE	j	b
6	FALSE	a	b
7	i	h	h
8	a	a	l
9	k	a	g
10	e	e	e
11	h	h	i
12	d	e	d
13	d	d	g
14	e	f	b
15	FALSE	c	i
16	f	f	a
17	f	d	f
18	b	f	h

19	i	h	g
20	d	l	l
21	e	j	e
22	d	d	f
23	FALSE	c	h
24	k	d	e

Table 20: Table of raw data outlining choice of house for each agent for each round. False signifies agent not entering the market and the letter value corresponds to the house id.

is house owned at start	owner at start	house_price	is house owned at end	house owner at end
[True, True, True, True, True, True, True, True, True, True, True, True]	['b', 'p', 'a', 'w', 'l', 'o', 'd', 'q', 'r', 'v', 's', 'x']	[140000, 114999, 105000, 140000, 140000, 140000, 125000, 114999, 105000, 130000, 145000, 130000]	[True, True, True, True, True, True, True, True, True, True, True, True]	['b', 'p', 'a', 'w', 'l', 'q', 'd', 'r', 't', 'v', 's', 'x']
[True, True, True, True, True, True, True, True, True, True, True, True]	['b', 'p', 'a', 'w', 'l', 'q', 'd', 'r', 't', 'v', 's', 'x']	[140000, 114999, 110000, 135000, 140000, 125000, 125000, 114999, 110000, 145000, 130000, 125000]	[True, True, True, True, True, True, True, True, True, False, True, True]	['b', 'p', 'c', 'w', 'l', 'u', 'o', 'r', 't', 'none', 's', 'x']
[True, True, True, True, True, True, True, True, True, False, True, True]	['b', 'p', 'c', 'w', 'l', 'u', 'o', 'r', 't', 'none', 's', 'x']	[125000, 105000, 100000, 140000, 140000, 130000, 130000, 100000, 100000, 145000, 140000, 135000]	[True, True, True, True, True, True, True, True, False, True, True, False]	['d', 'q', 'c', 'w', 'p', 'v', 't', 'r', 'none', 'a', 's', 'none']
[True, True, True, True, True, True, True, True, False, True, True, False]	['d', 'q', 'c', 'w', 'p', 'v', 't', 'r', 'none', 'a', 's', 'none']	[125000, 114999, 105000, 140000, 155000, 130000, 130000, 114999, 105000, 125000, 140000, 130000]	[True, True, True, True, True, True, True, True, True, True, True, True]	['l', 'q', 'c', 'w', 'p', 'v', 't', 'r', 'b', 'o', 'u', 'x']

Table 21: Table with raw data showcasing housing ownership at start and end of a round as well as current price.

Recording agent choice in each round as well as which houses are currently occupied at the start and end of each round helps in understanding agent decision-making. However, the most important aspect to help judge the effectiveness of the different models in terms of their theoretical basis and agent architecture, is the price evolution of different houses over time. The models, as previously mentioned, feature a housing market that has perfectly inelastic supply. Therefore, demand levels for each house, driven by individual agent decision-making influenced by other agents' decision making, directly impacts the housing prices. This, plus the fact that the models are not replicating a real-world situation and thus not able to compare outputs with a real-world dataset, elevates the emergent patterns of price fluctuations as the performance matrix by which these models will be judged and compared by.

5.3.3 Price evolution in the property market

As established above, price evolution as an emergent pattern forms the dominant comparison method for the three models. In this section, the changes in prices for all 12 houses over a 30-turn run of a simulation will be analysed and plotted onto line graphs for all 3 models. The results are then compared between different models in relationship to their theory and architecture in an attempt to establish why there are differences in patterns observed as well as the magnitude of those differences.

Firstly, the base model featuring simple agents has its model outputs plotted onto a line graph (Figure (22) below). The x axis represents the turn number while the y axis represents the price. Each house instance features its own colour line on the graphed outlined in the key at the bottom of the figure. The analysis reveals that, for the simple agents with a utility maximization theoretical basis (using ordinal utility) and a logic-based architecture, four distinct price bands form that remain consistent (Observation 2) with slight fluctuations of no more than £35000 (Observation 4). It is evident that a there is a distinct separation between the two higher performing housing bands (in terms of price/demand) and the two lower performing ones. Furthermore, it is worth noting that at no point during the simulation are any houses at the base £100000 which indicates that even the worst performing house has some demand for it (Observation 5). On the other end of the price scale, omitting round 1 due to the initial manual inputs influencing the demand, the maximum house price for any house does not surpass £170000 achieved in round 3 or £165000 at any point after that (Observation 5). Prices were more in turmoil during the first few rounds until the effect of the initial starting inputs was smoothed out and negated in subsequent rounds (Observation 1). Therefore, the research concludes that the industry standard of utility maximization (represented here by ordinal utility theory) and logic-based architecture agents have a steady and predictable decision-making pattern (Observation 6) that does not deviate much between rounds regardless of agent context at the time.

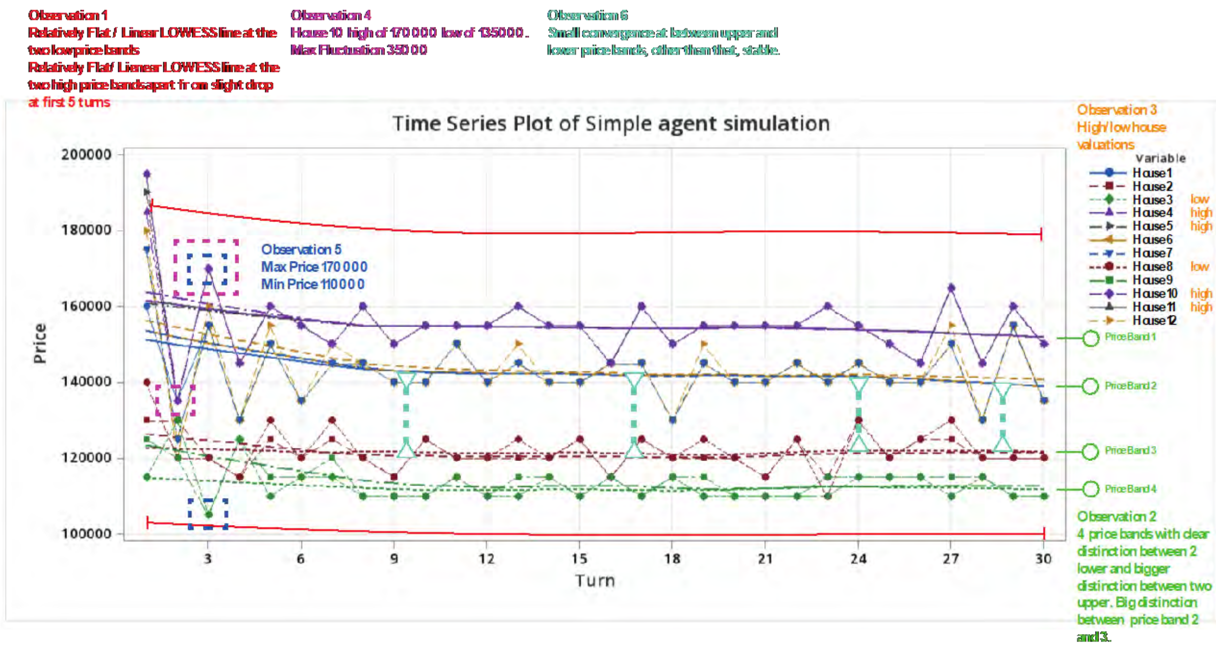


Figure 22: Graph of outcomes for simple agents showcasing change of price over 30 rounds for each house in the simulation.

The second model results to be analysed features a belief, desire, intention (BDI) agent architecture with a Theory of Planned Behaviour theoretical basis. The model outputs are plotted onto a line graph (Figure (23) below), similar to the previous simple agents. The x axis represents the turn number while the y axis represents the price. Each house instance features its own colour line on the graphed outlined in the key at the bottom of the figure. The analysis for BDI agents reveals that, like the previous simple agent model, there are four distinct price bands forming (observation 2) that remain relatively distinct (apart from the lower 2) throughout the simulation with major price fluctuations as high as £45000 (observation 4), more than that of the simple agents. It is worth noting that for both the BDI simulation and the simple agent simulation, the worst performing houses (in terms of price/demand) and highest performing houses are the same (observation 3). This indicates that agent values are consistent in both models. Within the four distinct price bands for housing, house prices do not follow a single trend of price fluctuation which is evident in the previous simple agent results. On the contrary, they exhibit a more chaotic pattern that sees the highest priced house for that price band in one round become the lowest prices one in the band a few rounds later (observation 6). This results in much more volatile market fluctuations at regular intervals throughout the 30 rounds simulation. This can be attributed to the random element within the BDI agent model, the willingness to buy aspect that stems from the theoretical basis, as well as the agent architecture itself. BDI architecture has a tendency to prioritise between desires based on what it lacks due to the changing belief system. This means a BDI agent will value a property differently at different points during the simulation depending on context rather than rate all properties in terms of what would be overall best. The theoretical basis for the BDI architecture itself deals in likelihoods and not in absolutes which translates to a more chaotic price evolution pattern. This features as the willingness to buy (seen as “not willing to change” in the BDI code) part of the code that sees the agent have a likelihood to follow through with their intention based on their behavioural attitude, social norms and perceived behavioural control attributes assigned to them. Furthermore, it is worth noting that again, unlike the simple agents, at some rounds during the simulation, there are houses at the base price of £100000 which indicates that the worst performing houses achieve zero demand at times (observation 5). On the other end of the price scale, omitting round 1 due to the initial manual inputs influencing the demand, the maximum house price for any house does not surpass £170000 achieved in round 10 and 17 by two different houses (observation 5). This is consistent with the simple agents’ model that achieves the same maximum price though the price evolution here sees them bounce much more in both frequency and size. Prices were in turmoil throughout the simulation which again, contrasts the simple agent model. However, during the first few rounds, until the effect of the initial starting inputs was smoothed out and negated in subsequent rounds, the price changes were more chaotic than in the latter stages of the simulation that sees them follow market peaks and dips every 3 rounds consistently (observation 1). These observations in the analysis concludes that BDI agent architecture allows for a much more volatile and unpredictable decision-making pattern that still follows an overall trend similar to simple agents in terms of which houses it values most and least throughout the simulation. Furthermore, there are more peaks and drops within the market as opposed to simple agents that is indicative of constant market corrections ensuring prices do not stay high for long.

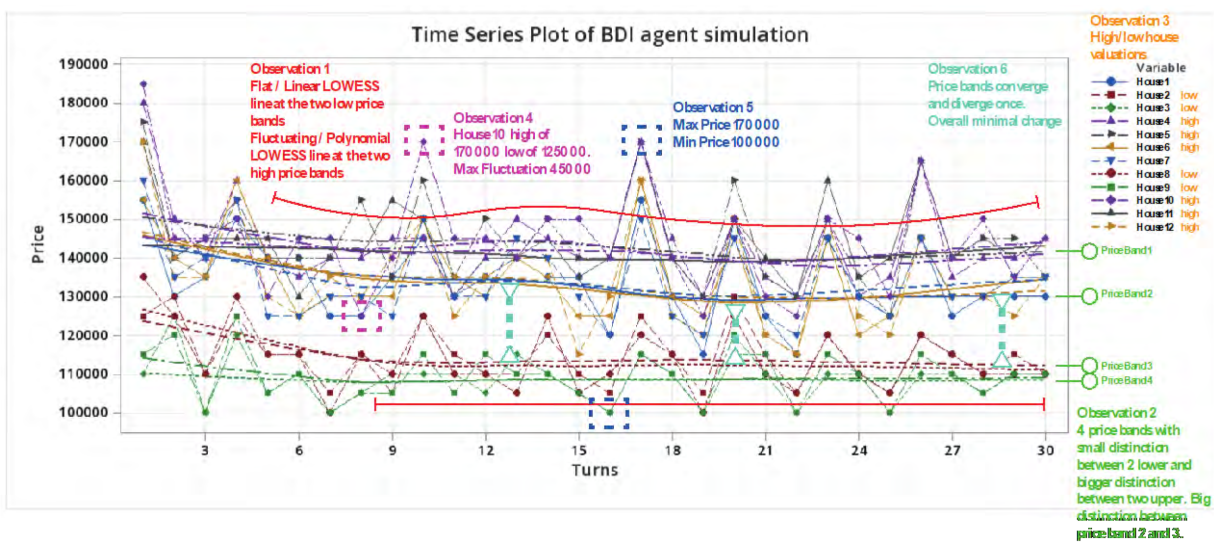


Figure 23: Graph of outcomes for BDI agents showcasing change of price over 30 rounds for each house in the simulation.

The last model to analyse is the Cognitive agent model, featuring cognitive agent architecture. The model outputs are plotted onto a line graph (Figure (24) below) similar to the previous two.

The x axis represents the turn number while the y axis represents the price. Each house instance features its own colour line on the graphed outlined in the key at the bottom of the figure. The analysis reveals that, similar to the simple agents, for the cognitive agents with a case-based decision theoretical basis and a cognitive architecture, four distinct price bands form that remain consistent throughout the simulation (observation 2). However, in contrast to the simple agents, there price bands change at time both a) the houses that feature in them and b) their position in terms of highest price band. Though only a few houses switch to the closest band for a limited time, it does showcase price fluctuation that match BDI agents of up to £50000 (observation 4). This is more in line with BDI agent rather than simple agent results. It is worth noting again that for all three model, the worst performing houses (in terms of price/demand) and highest performing houses are the mostly the same (observation 3). This indicates that agent values are consistent in all models thus ensuring that agents collectively are attracted to similar features albeit to a different degree. Within the four distinct price bands for housing, house prices do not follow a single trend of price fluctuation which is evident in the previous simple agent results (observation 6). On the contrary, they exhibit a slightly more chaotic pattern that sees the highest priced house for all price band in one round become the lowest prices one in the second band a few rounds later. Though the chaotic behaviour is not as pronounced as in the BDI architecture, it is still significantly greater than in the simple agents. This results a moderate volatile market fluctuations at regular intervals throughout the 30 rounds simulation, which again performs as the middle ground between BDI and simple agent results (observation 1). It is evident that a there is a distinct separation between the two higher performing housing bands (in terms of price/demand) and the two lower performing ones similar to the simple agents. However, in the cognitive architecture, this separation is far greater at times reaching a maximum of £50000 compared to the simple agent maximum of about £35000. This can be credited to the memory representation and experience attributes that is unique to cognitive agents. It enables them to change and reinforce what they perceive as important values or even the most important housing attribute as the simulation goes one. This in turn results in a much more definitive split between the highest and lowest performing houses in the price evolution emergent patterns. Furthermore, it is worth noting that at no point during the simulation are any houses at the base £100000, similar to simple agents and unlike BDI agents (observation 5). This indicates that even the worst performing house has some demand for it, in fact, the worst performing house during a round does at some point during the simulation, reach a price of £125000 compared to £110000 in the simple agents. It seems that cognitive agent's ability to reinforce how they value certain housing attribute, enables them to value even the worst overall house higher. On the other end of the price scale, omitting round 1 due to the initial manual inputs influencing the demand, the maximum house price for any house does not surpass £200000 achieved in round 12 and 24 which is far greater than in both BDI and simple agent simulations (observation 5). This further proves the effectiveness of both case-based decision theory and cognitive agent architecture's memory storage and representation's ability to reinforce what agents value as the simulation moves on. Given the performance of cognitive agents, the analysis concludes that this type of architecture, combined with a case-based decision theory basis, allows for higher levels of demand at both the top and bottom end of the housing market. At the same time, similar to BDI agents, the model features massive oscillations in price showcasing the ability of change to change their decision-making patterns considerably throughout the simulation. However, unlike BDI agents and much like simple agents, cognitive agents have a clear differentiation of four price bands, indicative of their ability to distinguish, to a better degree than BDI agents, overall value out of a series of housing attributes.

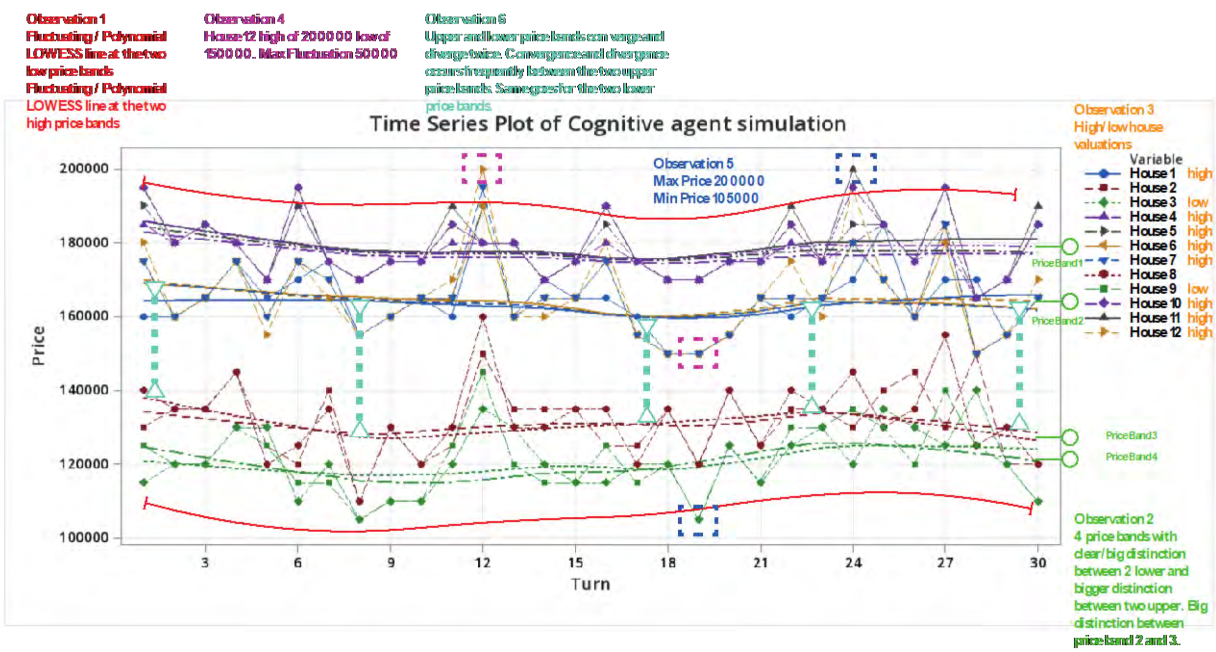


Figure 24: Graph of outcomes for cognitive agents showcasing change of price over 30 rounds for each house in the simulation.

5.4 Chapter Summary

This chapter sought to explain the choice of values for the different parameters featuring within all three complex agent models. Some of these parameters are unique to a single model and specific considerations were outlined in terms of how they feature in the code and how their values were set. Parameter sweeping experiments allowed for the setting of parameters that would yield appropriate results for analysis and comparison. After running all three agent models, the research has attained different outputs. The research analysed the results by plotting price evolution on line graphs for each model. The resulting analysis showcased differences in overall emergent patterns, though with various similarities between them. These similarities and differences were attributed to the theoretical basis and agent architecture used to create the models. Each model's performance varies, and the analysis allowed for a descriptive comparison between the three. However, understanding which of these models performs best in an applied scenario, requires some form of external validity.

CHAPTER SIX: MODEL VERIFICATION & VALIDATION

6.1 Introduction

This chapter undertakes the fifth activity within the design science research methodology, evaluation. The thesis will seek to evaluate and validate the results obtained in the demonstration by comparing the observed results of the three artifact demonstrations to a real-world equivalent. This includes relevant analysis and comparison techniques (active-role-playing simulation) that seek to measure the effectiveness of the results while considering the objectives set out in activity two.

This chapter provides the methodological reasoning, selection and set up for this research's Laboratory experiment (active role-playing simulation). The experiment aims to test the generalisations of applicability (external validity) of the three different simple and complex agents (logic-based, BDI and Cognitive) used in the computer simulations outlined in Chapter 4 & 5. This type of experiment tests the qualitative variant of external validity as an initial step towards fully validating the three complex agents. It falls under basic research, contributing to knowledge by examining the value of the three decision-making theories and agent architectures, which the three complex agent simulations are based on, as interpretations of household location choice phenomena.

The chapter sets out how (a) generalizability of operationalizations, and (b) generalizability of results is achieved through the experiment while distinguishing between different types of laboratory experiments and arguing for the choice of an active role-playing simulation as the basis for this research experiment. It then proceeds to determine participant pool selection as well as sample size, justifying the choice of 24 participants for the experiment and their demographic attributes. Following that, the chapter sets out material for the experiment that includes initial recruitment letter to potential participants, activity general information sheet and the participant's workshop consent form. The ethics application for the experiment, submitted through Ethos also features in this chapter, ensuring the active-role-playing simulation workshop is in accordance with MMU ethical regulations.

The chapter then details the set up for the laboratory environment. This consists of a virtual environment that mimics the one present in the three complex agent computer simulations outlined in Chapter (4). This includes three neighbourhoods and twelve houses alongside twenty-four agents competing to live within those houses. The neighbourhoods maintain their inclusion combinations of the three amenities of park, school and workspace while neighbourhood safety remains an emergent effect driven by and affecting participant decision-making. All houses' attributes remain consistent with the other three simulations with their current price remaining an emergent property driven by and affecting participant decision-making. Similar to the houses, agents also maintain their attributes while assigning participants a specific agent to roleplay as and make decisions for given the agent's context and unique situation.

The chapter then continues by outlining the experiment briefing for participants. In this part, references to the experiment change to a role-playing game to better illustrate to participants the competitive and objective driven aspects of their actions within the experiment. The explanation to participants includes the fact that the game consists of thirty turns with each turn having three phases. This once again mimics the process of the three computer simulations with the only difference being participants making decisions as opposed to the complex agents. Participants make a choice at each phase aimed at achieving the ultimate goal of the game, satisfying their agent needs. These needs are characterised by seven satisfaction criteria whose fulfilment is unique to each agent depending on their attributes.

The chapter ends with some thoughts and expectations on results and potential differences between complex agent decision-making and participant decision-making. Aspects such as strategy and collaboration could feature within the experiment, which differs from the three complex agent capacities. These comments are noted down prior to the experiment running and will be used to understand the shortcomings of the approach as well as complex agent capacity to imitate human decision-making.

6.2 Validating models/agent behaviour

6.2.1 Distinguishing validation type:

The stage at which the research investigation presides directly influences the validation adopted. These fall between two types, internal and external validation.

“Internal validity is the extent that inferences of causality could be made about the obtained relationship between the independent variable and the dependent variable. Confidence in causal inferences is enhanced when the treatment or manipulation is under the systematic control of the researcher. External validity is the extent of generalizability or certainty that results can be applied to other respondent groups, different settings, and different ways of operationalizing the conceptual variables." (Crano & Brewer, 2015, p. 27)

In experimental strategies, questions that deal with both the generalizability and validity of interpretations of relationships obtained in a specific study as well as their applicability beyond the specific study, fall in the realm of external validity. This research uses a laboratory experiment as a means to test the performance of different types of complex agent models with real human decisions made in a controlled environment. **The aim here is to test the generalisations of applicability of the different complex agent architectures/theories for residential location choice modelling in the context of urban simulative models.** As such, the type of validation concern in this research is external.

This choice warrants further explanation in more detail at a later section however, it is worth noting the overall method in order to frame the validation discussion. In social science, debates on laboratory research versus field research have existed for a long time. Field researchers generally argue that only in a real-world setting may discoveries of value occur as they view participant responses in laboratory environments as not valid representations of what would otherwise be normal, everyday behaviours (Crano & Brewer, 2015). In other words, the external validity of a laboratory experiments comes under question here. In the context of this research, field research would involve the investigation of household location choices in the real world through either data collection or a study of participants undergoing this decision. On the other hand, laboratory researchers argue that the multitude of external factors and events that occur in a natural environment led to constant uncertainty on the true relationships among variables. Again, if we situate this in the context of the current research, data on household location choice does not include all possible reasons that affected that decision as inferences made on a selection of variables have an inherent uncertainty on the effect of "invisible" variables that are not considered. Though some laboratory experiments contain questionable practical or scientific utility, not all are behaviourally, socially and psychologically "unreal" (Aronson & Mills, 1959; Aronson & Wilson, 1998). Therefore, one cannot outright deny that laboratory experiments have some external validity value. Both methods serve a purpose and could complement each other as findings from a laboratory experiment retested in the field serves as means to test if the relationships hold leading to significant contributions to knowledge. Vice-versa, observations in the field should withstand rigorous testing in a laboratory setting in order to prove their validity and value. The research here concentrates on the laboratory experiment as a means to test the qualitative variant of external validity. The research recognises that this is an initial step towards fully validating new complex agents and that further research beyond the scope of this one will require appropriate field-testing of agents to confirm any findings obtained by this one.

It is also worth establishing that laboratory testing in this research falls under basic research as the goal is to contribute to knowledge by examining the value of a range of decision-making theories and agent architectures as interpretations of household location choice phenomena. The work done here is fundamentally on the theoretical interpretations of household location choice in urban simulative models. Therefore, the concerns here constitute issues of external validity that require answering. These can be further divided into (a) generalizability of operationalizations, and (b) generalizability of results to other places and participant populations (Cook & Campbell, 1979).

Regarding the first point, validity of operations, this refers to the extent of the operations and measures used in the particular study reflect the theoretical concepts the study is based on to begin with (Crano & Brewer, 2015). Aronson et.al (Aronson & Wilson, 1998) regards the complex constructs of social research as having multiple meanings. Consequently, influences on participant decisions could be due to several factors beyond the conceptual variables of interest in the study. This reduces the confidence of relationships obtained in the experiment on the influence of a particular construct. A way to substantiate the relationship sees the experiment run as a series. Each experiment should have a different operation to represent the conceptual variable. If different techniques yield similar results, then the validation of the common conceptual variable's effect stands true. In this particular experiment, the theoretical concept under question comes in the form of the decision-making mechanisms of an individual for a household location choice scenario. Effectively, the measure of demand for a particular house should be representative of its unique variables and the variables of the households engaged in the market. The proposed variables for different houses and agents as well as their relationship is represented in different operation with different theoretical underpinnings on human decision-making as well as the agent architectures used to code them. The laboratory experiment acts as a means to validate the performance of each operation towards a better representation of the household decision-making mechanism. One can therefore argue that the conceptual variable for this operation is the decision-making algorithm itself. This is well represented by four different operations and therefore, subject to results, is in line to achieve validity of operation.

The second point, generalizability of results, refers to the conclusions of the study transcending its applicability to the particular people, time and setting. In this particular case, generalisability of results refers to the decision-making mechanisms for the model that proved to more closely resemble the results of the human laboratory experiment, having the ability to be used in other settings as part of other urban simulative models beyond the controlled environment of this study.

Two issues with this point need overcoming. The first is the sufficient representation of the human organism in the experiment. To elaborate, if the laboratory subjects are comprised of primarily one section of the population (i.e. university students), the results may come under scrutiny. This is primarily due to the over-representation of a specific demographic (intelligence, heath, socio-economic background) that may respond differently to specific variables than other demographics. However, even this population differences hypothesis is subject to the same rules of evidence as any other hypothesis (Sears, 1986) meaning that in this particular phenomenon (household location choice) it may not play such a massive role. Implementation of techniques such as random selection from the representative population still relies on chance to determine the participants. Random selection is a rarely realised ideal in social research due to the limitation in resources and participant availability. One way of overcoming the lack of generalizability is to repeat the experiment with other populations as they become available. This will enhance our understanding of the findings as even failure to replicate the original findings with the original population still contributes to our understanding of the phenomenon. In this research, even an over-representation of a specific population may yield sufficient results to warrant further investigation. This is due to the nature of the decision-making mechanisms present and the controlled environment in which they exist. Agents within the experiment have a fixed set of attributes that carries through in all models/experiments. Participants represent an agent and make decisions given the agent's unique attributes and not the participants. Though some variation may exist in the decision-making process of different populations, the external and the internal context in which those decisions are made is controlled and fixed minimising the effect of participant sampling.

The second point, beyond the generalizability of the sampled participants, is the reproducibility of the research findings. This may be limited to specific conditions present in the initial experiment. Here, two aspects come into question. The first is the internal conditions of the research participants across time and the second is the external physical and social environment in which the research is carried out (Crano & Brewer, 2015). In this research, the environment used for the study is controlled and artificial. The neighbourhoods, houses, and agents all have controlled attributes that exist in an artificial setting. This means that a repeat of the experiment should have no issue with the external aspects. The internal conditions of the research participants in some ways also from part of the controlled environment within the experiment. Agent attributes such as income, family situation and lifestyle come pre-set within the experiment with participants being assigned specific agents to represent and consider the choices made given those attributes. In essence they act as if they were those individuals with those attributes in that particular context. This allows for condition replicability.

In conclusion, the generalisability of results for this research can only be tentative. This is due to the complex nature of the phenomenon and the extent to which laboratory experiments can claim external validity. This would be true even if the alternative field research method were to be selected given that different case studies may yield different results due to underlining factors not considered. In essence, the external validation method of laboratory experiment used in this study forms an initial attempt at validating the different complex agents, but further study would be needed to fully explore their generalisability.

6.3 Setting-up the experiments

6.3.1 Type of experimental method used.

In social science, a classic experimental design follows a series of steps. These include (1) identifying and obtaining a number of participants, (2) pretesting participants on the dependent variable of interest, (3) dividing participants between the control and experimental groups, (4) controlling differences in the experiments between the two groups and lastly, (5) measuring again both groups on the dependent variable at some future point after the experimental manipulation.

Variations on this basic structure exist including the elimination of specific steps (such as pre-test) and the addition of others (Crano & Brewer, 2015). In this research's particular experiment, the testing variable is the decision-making made by the participants. In many ways, the variable in question forms a fundamental element of human thinking and therefore impossible to remove from subjects. This makes the control group attain a new meaning for this experiment. The control group in this situation consists of the three artificial agent models that run the same simulation in the digital world. In fact, the last step of measuring the differences between the control and the people subjected to the decisions makes up part of the validation of the different complex agent models. The research aims centres on the testing of different decision theories and agent architectures and their performance/similarity against a real world agent. An argument exists were the participants themselves form the control group for the artificial agents. In many social experiments, the aim centres on the fundamental pursuit of understanding the effects of one variable on a social phenomenon. In this experiment, the focus lies in discovering/testing the decision-making theories and the agent architectures that best describe real human decision-making within the household location choice market.

In classical social laboratory experiments, there are two important concepts that govern the manipulations used as well as the setting up of experiments. These are experimental realism and mundane realism (Aronson & Wilson, 1998). Experimental realism is the degree by which the experiment forces an unconscious, spontaneous and natural reaction/behaviour from the participants. If the experiment is set up correctly, the participants will be unable to intellectually reason before acting and respond to the experimental situation in a similar way to their behaviour outside the laboratory. Mundane realism focuses on the degree to which features of the experiment such as instructions or treatments, mirror real world events that participants may encounter. Depending on the participants' level of engagement (if they are bored of apathetic), responses to the manipulations deployed in the experiment may be varied and untrue to their real-world counterpart. This is why these two concepts are fundamental and crucial as they seek to engage participants and keep them interested. The concern here lies in maintaining the participators' interest and that the laboratory environment created is impactful even if it bears little resemblance to a non-laboratory encounter. This particular experiment does not share the above concerns. The laboratory study here has the explicit intention of emulating events occurring in the "real world". The major concern is the degree of correspondence between the household location market in the experiment and the real-life household location market.

Two particular types of laboratory experiments focus on achieving this, role-playing simulation and analogue experiment. Role-playing simulations "preserve many of the advantages of controlled laboratory experiments while approaching conditions that are more generalizable to the real world"(Crano & Brewer, 2015). It enables the isolation of the social phenomenon in question while maintaining the natural context through the participants actively imagining themselves in the situation thus manifesting all the natural relations existing within the particular real-life social situation. Participants get clear instructions, and they act out a role while imagining themselves in that situation. An analogue experiment on the other hand, gives no roles to participants to act out. Presented with a real situation, the participants respond naturally and directly. Though analogue experiments have advantages, for this particular validation process, the participants need to act out the roles of agents in the other simulations, taking on their current attributes such as family situation and income and make decisions on the housing market in an attempt to satisfy this role's imaginary needs. Therefore, the laboratory experiment choice for this research is a role-playing simulation.

The research considers two main types of role-playing simulation to determine the model by which to base the experiment on. Passive role-playing simulations offer a verbal or written description of the situation and the participant's role, prompting the participant to estimate or predict their behaviour in that situation. Active role-playing simulations allow the participants to naturally respond to experimental situations based on their individual interpretation of the assigned role given to them in the simulated social situation (Crano & Brewer, 2015). This type of method, also referred to as role-playing game, gives specific social roles to participants to play. Though the researchers control the parameters of the experiment and the system, the participants are free to make choices and decisions within this context appropriate to their own unique perceptions of the role given. In this way, the behaviour of the participants, their consequences, and influences on other participant choices forms the dependent variables in this type of experiment/research design. The length of participation varies however, it can last a considerable timeframe with role players maintaining high levels of involvement and motivation. Examples of this type of experiments range from management and production teams, business organizations, and market economies (Bousquet & Le Page, 2004), jury deliberations (E. R. Smith, 2000), to whole societies and intercultural relations (An, 2012). This method has been used in computational social science as a means to test precise social hypothesis (Janssen & Ostrom, 2006). Data from the experiments helped compare alternative models of human decision-making. Other examples of role-playing simulation experiments in land use decision-making include Evans, Sun and Kelley (2006) that help test the assumptions of basic theories of spatial decision-making scenarios. Others like Jager and Janssen (2002) have utilized experimental data as a means to calibrate/validate their model. Though non-spatial, it established the use of laboratory-based experiments in decision-making dynamics built into ABMs (Evans et al., 2006; Janssen & Ostrom, 2006).

Given the two options, the research choice for laboratory experiment method is the active role-playing simulation. Past examples of this method have established its usefulness in comparing the decision-making mechanisms of ABMs that this research seeks to achieve. The research will therefore utilise this method to create a highly controlled environment, mirroring the artificial environment used in the BDI, Cognitive agent and simple (rules of inference) agent models. Chosen participants will then act out and make the same decisions as the different agents, in the same environment with the same context. This means that the participants' roles are the agents themselves with the same motivations, background and criteria for satisfaction. This is in line with the research method as all active role-playing simulations include programmed relationships among variables set by the researcher and the un-programmed responses/activity of decision-making participants. Simulations that are more complex require the use of computers that record all inputs by participants and offer real-time consequences and recordings of data. This usually results in each simulation having a range of components that could lead to more planned and unplanned variations. In many experiments, using a simulation approach could entail the systematic varying of input or design parameters across a series of "runs" of the simulation. This means that, in many cases, multiple runs are required when testing a series of parameters, which may result in a costly and time-consuming method for doing experimental research. In this research, the input parameters are going to be set. The design of the experiment will not vary, as the dependent variable is the decisions made by individuals and their similarity with complex agents (both theory and architecture wise). As such, the research will not seek to run multiple sessions with changing variables as all variables are set in the three digital models and by effect the role-playing simulation as well. There is however a point to be made on the merit of running the simulation with different participants. This would ensure that the decision-making recorded by individuals playing the role of these artificial agents and the resulting emergent patterns on household demand/location choice does not change with different actors/participants.

6.3.2 Selecting Participant Pool

In many experiments, the initial arrangement of the pool of eligible participants is key. It dictates many aspects such as form of manipulation and types of measures. Researchers must define which participants are eligible to take part in the experiment. This may limit choices of the participants to those with specific characteristics, age range, religion, race and background/experiences. This type of control and selection comes at the cost of some external validity (Crano & Brewer, 2015). In this research experiment, as it features an active role-playing approach, participant selection has no limits or restrictions in regards of specific attributes. A broader range of characteristics may better serve towards amplifying the external validity of the process as it ensures decisions made are not restricted to a specific characteristic. This leads to the selection of a participant pool for this research to include people from different social and cultural backgrounds as it ensures no social or cultural norms influence the outcome of the experiment. The choice on eligible participants included graduating students from Manchester Metropolitan University that come from the UK, Europe and Asia. This allowed for willing subjects, interested in the research, capable of making informed decisions based on the variables presented to them, as they have proven with their ability to pass a university course. Their unique backgrounds coupled with their intellectual capacity allows for a varied array of test subjects that will add further external validity to the process. One issue with the selection needs mentioning, students tend to be of a specific age group. This issue is somewhat offset by the roles given to them as they represent agents in specific situation (specific income, family status etc.) and not age. This means that age does not represent a variable with direct link to the choices made and therefore should not be considered a major issue in the participant pool choice.

6.3.3 Deciding on Sample Size

Having decided on the pool of participants consisting of graduating students, the next decision to address is the number of participants. In laboratory experiments aiming to prove a relationship between one or more factors, this decision is one of statistical power. The aim is to ensure the experiment runs with enough participants to enable a high statistical inference in an attempt "to detect meaningful differences between experimental conditions above and beyond random variation" (Crano & Brewer, 2015). Cohen (1992) provides a table with rules of thumb for sample sizes based on the statistical tests for social sciences. This requires a power analysis prior to the experiment in order to use. Computer applications such as GPower enables this power analysis to be easily determined.

In the case of this experiment, the participant pool size takes a slightly different dimension. The role-playing nature of this experiment and its close mirroring of the complex agent simulates dictates that participant size is 24 in order to match the number of complex agents in each simulation. This however only proposes the number of participants needed to run the experiment once. The question of sample size in this case is purely in terms of how many times should this experiment run with 24 people? The experiment does not seek to prove a relationship between variables within it. This role-playing experiment merely seeks to record results in order to identify differences at a pattern level, on decisions made by the participants versus decisions made by three different sets of agents. There is no underlying hypothesis on the patterns generated by the participants and therefore statistical significance of results is not a major consideration in this research. The only consideration here is one of consistency in order to enable comparison of results between models of different agents with different theoretical basis. Therefore, the experiment requires more than one turn to ensure patterns generated remain consistent. The experiment will therefore run 30 turns similar to the complex agent models. The basis for this consists of a practical guide of computational simulation runs suggesting number of turns should be 10d, where d is the input dimension (Loeppky et al., 2009). In this case, the input dimensions are three, the decision-making of individuals, the houses, and neighbourhoods. This is in fact a computational simulation run, ran as a manual simulation with computational agents substituted with real world counterparts. Therefore, 30 turns will enable pattern generated to be comparable to those created in the complex agent models.

6.3.4 Preparing Materials / Experiment features.

Following the sample size selection, a range of materials and experiment features required preparation. These include instructions to participants outlining the experiment process, consent forms, and guidelines for measurements recorded during the experiment and debriefings. These are featured in the Appendix (Item 2) and have been used by the author to collect consent and invite the participants to join the role-playing simulation experiment.

6.3.5 Submit Plan for Ethical Approval

In accordance with MMU regulations, the active role-playing simulation workshops has undergone ethics approval with an ethics application submitted through Ethos. This included details on all aspects of the experiment including data security, identification of risks and overall study procedures. This has been approved by MMU ethics committee in April 2022 with the experiment taking place the following month.

6.4 Setting up Laboratory Environment

The aim of the laboratory experiment, as mentioned earlier in the chapter, is to validate the three ABMs that include BDI agent architecture, cognitive agent architecture and logic-based agent architecture. In order to achieve this, the laboratory experiment must mimic the processes in the other three models with one key difference, substituting decisions made by computational agents with the decisions made by experiment participants.

The laboratory environment set up mimics perfectly the other three model set-ups. The active role-playing simulation takes place in a virtual environment consisting of three neighbourhoods and twelve houses. The neighbourhoods maintain their inclusion combinations of the three amenities of park, school and workspace while neighbourhood safety remains an emergent effect driven by and affecting participant's decision-making.

Similar to the three computational simulations, the laboratory experiment will include the same 12 houses complete with identical attributes (attributes detailed in table 22 with all other choices detailed in chapter 4). All houses feature an initial price of 100k but agent decision-making, relating to choices of demand for specific houses, pushes the price up in the same way as previous experiments. This is to allow demand to dictate price formation from the same starting point. It enables a much better comparison of price changes in the market acting as the emergent pattern of the participant's interactions without an initial influence of housing price bias.

marketmulti = interest().count(house)*0.05

house.pc = house.pi * (1+marketmulti)

The equations above dictate the current price of a house (house.pc) at every turn. Marketmulti is the percentage increase of the house per turn over the initial 100k value, represented here by house.pi. Interest().count(house) is the number of participants that declare an interest for the house at that turn. This results in a system, driven by participant choices affecting further participant choices.

Houses	ID	Neighbourhood	Near Park	Near Work	Near School	Price Initial	Number of Rooms
House 1	a	A	True	False	True	100k	4
House 2	b	A	True	False	True	100k	2
House 3	c	A	True	False	True	100k	1
House 4	d	A	True	False	True	100k	5
House 5	e	B	True	True	False	100k	5
House 6	f	B	True	True	False	100k	4
House 7	g	B	True	True	False	100k	4
House 8	h	B	True	True	False	100k	2
House 9	i	C	False	False	True	100k	1
House 10	j	C	False	False	True	100k	5
House 11	k	C	False	False	True	100k	5
House 12	l	C	False	False	True	100k	4

Table 22: Table of attributes for houses for active role-play simulation.

The final aspect of the laboratory environment is that of the agents. In the three computational models, driven by artificial agent decision-making, each agent has a set of attributes that influences the context by which they make their decisions on house choice. These attributes are mimicked here for all 24 agents, with each participant being assigned a specific agent's attributes in order to role-play as them. This allows participants to make decisions on behalf of agents given the same context as them. The attributes of the agents are outlined in the table below while further reasoning for the attributes and their effect on satisfying agent needs is given in section 5.2.3.

Agent	ID	Income (per year)	Children	Home
Agent 1	A	40k	2	A
Agent 2	B	50k	3	B
Agent 3	C	10k	1	C
Agent 4	D	50k	3	None
Agent 5	E	30k	2	D
Agent 6	F	50k	1	E
Agent 7	G	20k	0	F
Agent 8	H	60k	3	G
Agent 9	I	40k	3	H
Agent 10	J	50k	4	I
Agent 11	K	10k	0	J
Agent 12	L	50k	4	None
Agent 13	M	40k	2	K

Agent 14	N	50k	3	L
Agent 15	O	10k	1	None
Agent 16	P	50k	3	None
Agent 17	Q	30k	2	None
Agent 18	R	50k	1	None
Agent 19	S	20k	0	None
Agent 20	T	60k	3	None
Agent 21	U	40k	3	None
Agent 22	V	50k	4	None
Agent 23	W	10k	0	None
Agent 24	X	50k	4	None

Table 23: Table of attributes for agents for active role-play simulation.

In order for participants to appreciate the extent of their choices, at the end of each turn, all results are categorised in individual graphical outputs that outline which of the agent's needs are met and which are not. The green highlight indicates that the criterion is satisfied while the red indicates that it fails to meet that criterion. This will help participants in making the choices for the next round; they will have knowledge on what aspects are lacking at the end of each of round, which will in turn influence their future house choices in an attempt to remedy that.

Live in a House	Suitability	Affordabilit y	Safety	Live Close to Work	Live Close to a School	Live Close to a Park

Table 24: Table of results presented to participants at the end of each round. Green signifies the participant has satisfied that criterion, red means they are currently failing at that criterion.

6.4.1 Experiment Briefing for Participants

The active role-playing simulation adopted by this research, features a thirty-turn event in which participants must make choices on behalf of agents that have unique attributes and objectives. In order for participants to engage adequately with this experiment, they require briefing in advance of the procedure and their roles. Therefore, participants have the following briefing on the experiment to aid them in understanding what choice will lead to their ultimate goal. The briefing below also outlines the procedure of the experiment that is referred to as a game due to the competitive nature of participants striving to satisfy their agent's needs.

Information on the Experiment:

> The experiment you are participating in, involves an active role-playing simulation game. You will be making decisions in an artificial environment with a given context, in an attempt to satisfy all of your agent's needs.
>
> Your Agent and their Aim/Objective:
>
> The agent you will be representing has a set of unique attributes that include annual income, number of children, and a home assigned to them. Some agents do not

have a house assigned to them at the start of the game and therefore must acquire one during the course of the game. Please refer at the table below during the experiment to see your agent's unique attributes.

Agent	ID	Income (per year)	Children	Home
Agent 1	A	40k	2	A

Table 25: Table of agent profile given to participant to role-play.

The agent also has a set of seven satisfaction criteria that govern their needs. Participant's aim/objective is to fulfil these criteria at the end of the game. Below is the list of seven criteria alongside their fulfilment conditions:

1) Live in a house: If the agent owns a house, consider this criterion fulfilled.

2) Suitability: If the agent owns a house that has an amount of bedrooms equal or more to the amount of his children + one, then consider this criterion fulfilled.

3) Affordability: If the current price of the agent's owned house is less than three and a half times his income, then consider this criterion fulfilled.

4) Safety: If the average income of agents (including your agent) in your agent's owned house's neighbourhood is within + or – £10000, then consider this criterion fulfilled.

5) Live Close to Work: If your agent's owned house has an attribute close to Work as True, then consider this criterion fulfilled.

6) Live Close to a School: If your agent's owned house has an attribute close to a School as True and your agent has at least one child, then consider this criterion fulfilled.

7) Live Close to a Park: If your agent's owned house has an attribute close to a Park as True, then consider this criterion fulfilled.

Playing the Game:

The game consists of thirty rounds, each with a set of three phases. At each phase, you must make a choice on behalf of your agent. Participant inputs of choices are noted down on a master spreadsheet that contains tables for each choice to be recorded on.

Phase 1: Here you will look at all houses (regardless if they are on the market or not at this moment). You will consolidate your agent's satisfaction criteria. Are all criteria fulfilled by your current housing state? Would some other house perhaps fulfil your criteria better? From the list of houses below you can choose which houses you believe will best satisfy your needs, given your knowledge of your agent's needs as well as your speculation one two emergent conditions:

1) Is the price of that house likely to remain stable or demand from other players will cause it to become unaffordable to you?
2) Will the average income of the house's neighbourhood change? Or will it remain stable to be considered safe for your agent?

Houses	ID	Neighbourhood	Near Park	Near Work	Near School	Price Initial	Number of Rooms
House 1	a	a	True	False	True	100k	4
House 2	b	a	True	False	True	100k	2
House 3	c	a	True	False	True	100k	1
House 4	d	a	True	False	True	100k	5
House 5	e	b	True	True	False	100k	5
House 6	f	b	True	True	False	100k	4
House 7	g	b	True	True	False	100k	4
House 8	h	b	True	True	False	100k	2
House 9	i	c	False	False	True	100k	1
House 10	j	c	False	False	True	100k	5
House 11	k	c	False	False	True	100k	5
House 12	l	c	False	False	True	100k	4

Table 26: Table of housing attributes and their values in active role-playing simulation.

Suggestion: Please study the housing table and your agent's attributes prior to the game starting and note down which houses would satisfy which of your agent's needs.

Having considered your potential house choices, it is time to issue your interest on as many houses as you wish. These interests indicate which houses you may wish to pursue/purchase in the future, given that they offer the possibility to satisfy criteria that, at present, are unfulfilled. To input your interests for the round, you will be using a spreadsheet with the same table below. In the area next to your agent's name/ID, fill in with a 0 if you don't have any interest in the house this round, or a 1 if you wish to place an interest in that house for this round. Remember, you may place an interest in a house even if you do not intent to move house this round.

Agent	housea	houseb	housec	housed	housee	housef	houseg	househ	housei	housej	housek	housel
agent1	0	0	0	0	0	0	0	0	1	1	1	0

Table 27: Table of response by the participants indicating housing interest for the round.

Phase 2: Following the submission of interest by all players, you will be given the emergent information for the round. This consists of the average income of each neighbourhood that will aid in evaluating safety, and the current price of each house that will aid in evaluating affordability. This information exists in the form of a spreadsheet that includes the table below.

	Neighbourhood A	Neighbourhood B	Neighbourhood C
Average Income	37500.0	40000.0	37500.0

	Current Price
House A	100000
House B	100000
House C	100000
House D	100000
House E	185000
House F	185000
House G	185000
House H	100000
House I	220000
House J	220000
House K	185000
House L	185000

Table 28: Table of results given to participants at the end of each round in order to consider before making decisions for the next round.

With this information in hand, you need to make a choice on whether to enter the market for a new house or not. You need to fill in the table below in the overall spreadsheet. Placing TRUE indicates that you wish to enter the market. This means that your agent's current house will become available for others to purchase while you are free to pursue the purchase of a different house. Placing FALSE on the table, indicates that you are not willing to sell or buy at this time and you are exempt from any further choices in this round.

Round	1	2	3
Agent	Sell/Buy	Sell/Buy	Sell/Buy
agent1	TRUE	TRUE	TRUE
agent2	FALSE	TRUE	TRUE
agent3	TRUE	TRUE	TRUE
agent4	TRUE	TRUE	TRUE
agent5	TRUE	FALSE	TRUE
agent6	TRUE	TRUE	TRUE
agent7	TRUE	TRUE	TRUE
agent8	TRUE	TRUE	TRUE
agent9	TRUE	TRUE	TRUE

Table 29: Table outlining participant decision to enter the real estate market at each round. True means they wish to enter, False means they do not.

Phase 3: This is your housing choice round. Following your interest in houses, your knowledge of their current prices, your indication that you wish to enter the market to buy a new home, you are now ready to narrow your choice to one house. In the table below, found in the master spreadsheet in the "Choice of House to Purchase" sheet, you will be required to place the house id that you wish to purchase (please refer to house attributes table for id number). If you have indicated in Phase 2 that you do not wish to enter the market, then you simply fill in FALSE.

Round	1	2	3	4	5
Agent	Choice	Choice	Choice	Choice	Choice
a	FALSE	a	a	c	g
b	B	j	b	b	f
c	I	c	c	l	c
d	D	d	k	d	d
e	H	e	g	e	e
f	F	f	f	f	f

Table 30: Table outlining participant choice for house to buy at each round.

Following the successful completion of the round, participants receive their own spreadsheet named "Turninfo agent" followed by their agent's number. Here, your agent's satisfaction criteria are displayed on a table, each with a value of either a GREEN highlight or a RED highlight. The GREEN highlight indicates that the criterion is satisfied while the RED indicates that it fails to meet that criterion. The table is indicative of how well you are performing in the game. This aims to guide your decision-making in the next round towards achieving as many satisfied criteria as possible.

Live in a House	Suitability	Affordability	Safety	Live Close to Work	Live Close to a School	Live Close to a Park

Table 31: Table of results given to participants at the end of each round.

6.5 Expectation prior to running the experiment:

All elements of the laboratory experiment have been set and explained above, though the research had some initial concerns regarding some aspects of it. Firstly, coordinating 24 participants over a long experiment could be problematic as participants may lose interest over the period of the experiment which may hinder their ability to make an informed decision at latter stages of the simulation. Furthermore, unlike computer agents, participants may oversee or forget about some houses that may also satisfy their needs. The notion of bounded rationality (H. A. Simon, 1982) may well exists, even in an experiment with only 12 alternatives from which the participant can choose. Though this may be a possibility, the experiment should still yield sufficient results to allow for the comparison and external validity of the three complex agent models.

Given these expectations, the research has taken extra steps in order to ensure as much as possible that a) participants are always aware of all choices and their attributes and b) to keep participants engaged and making informed decisions throughout the duration of the experiment. To achieve this, the experiment firstly planned for sufficient breaks and motivation to be provided throughout the experiment. Secondly, the design of the experiment placed all houses and their attributes on the board in the centre of the room, visible by all participants always.

6.6 Running Experiment:

The active role-playing simulation laboratory experiment was conducted on Friday the 13th of May 2022 in a controlled room in the University. All 24 participants have agreed and signed consent for the experiment prior to its start.

The room was organized with desks arranged along the three edges of the room, all facing towards the far edge that contained a board in the middle of the wall. The board displayed all relevant information to aid the participants in their choices. It contained all information for the current rounds (as described in a previous section of this chapter) as well as all houses and their attributes. At the same time, it provided instruction on what the participants had to do at that step and kept everyone informed of progress. Each participant had their own laptop with access to the specific files in which to input their choices and receive their end of round results/feedback.

Participants were allowed breaks in between the experiment to ensure their mental performance was high. There was a lunch break in the middle to allow participants the chance for an extended break. Overall, the experiment overrun by an hour and a half. The research attributes this to a slow start that saw participants take a long time to make decisions on both housing interests for the round and final housing choice. It was evident that participants required some time to familiarize themselves with the different choices available to them and make sense of how their choices and resulting various housing/neighbourhood attributes, corresponded to achieving goals and desires.

The first 10 rounds saw the biggest delay in decision-making. At that point, the participants began to find innovative ways by which to make decisions. This was observed as they were allowed to express their frustration or joy and discuss their end of round achievements with the researcher in between rounds. The researcher did not provide any feedback to them in any way that may influence their decision-making. The only questions asked by the researcher were 1) What choice have you made this round, and 2) Why have you chosen that over other alternatives. All three complex agent computational models had their choices coded by the researcher so the reasoning behind them is known. By having the researcher ask these questions to the participants, the research gains knowledge as to why certain decisions were made. It enables the research to not only view and compare results on emergent patterns but also agent logic and reasoning.

Having all 24 participants in one room created a competitive atmosphere with some housing choices seeing massive levels of competition. Participants quickly realized that, in order to satisfy even some goals and desires, they had to make housing choices that did not necessarily yield the highest utility but the next best alternative. This was an attempt to face less competition and thus better chances at getting a house at the end of the round. Some expressed their desire to only go for the best choice, offering the highest satisfaction rating, though that choice was different at different points in the experiment as the market prices and safety ratings fluctuated throughout the simulation.

The total run time for the experiment was three and a half hours which included half an hour for breaks. Initial rounds lasted up to 15 minutes each while later rounds lasted 3 minutes. The participants grew more confident in their decision-making as the simulation progressed and quickly developed a particular fixation on a select few choices, unique to each participant, that they cycled through during each round depending on their current round housing prices and neighbourhood average income.

6.7 Experiment Results:

As established in the previous chapter, price evolution as an emergent pattern forms the dominant comparison method for the three models. In this section, the changes in prices for all

12 houses over a 30-turn run of the active role-playing human simulation will be analysed and plotted onto a line graph. The results are then compared in the next section between the three complex agent models and discussed in relationship to their theory and architecture in an attempt to establish how closely the emergent patterns from human decision-making in the same situation, relate to emergent patterns stemming from the complex agent decision-making patterns.

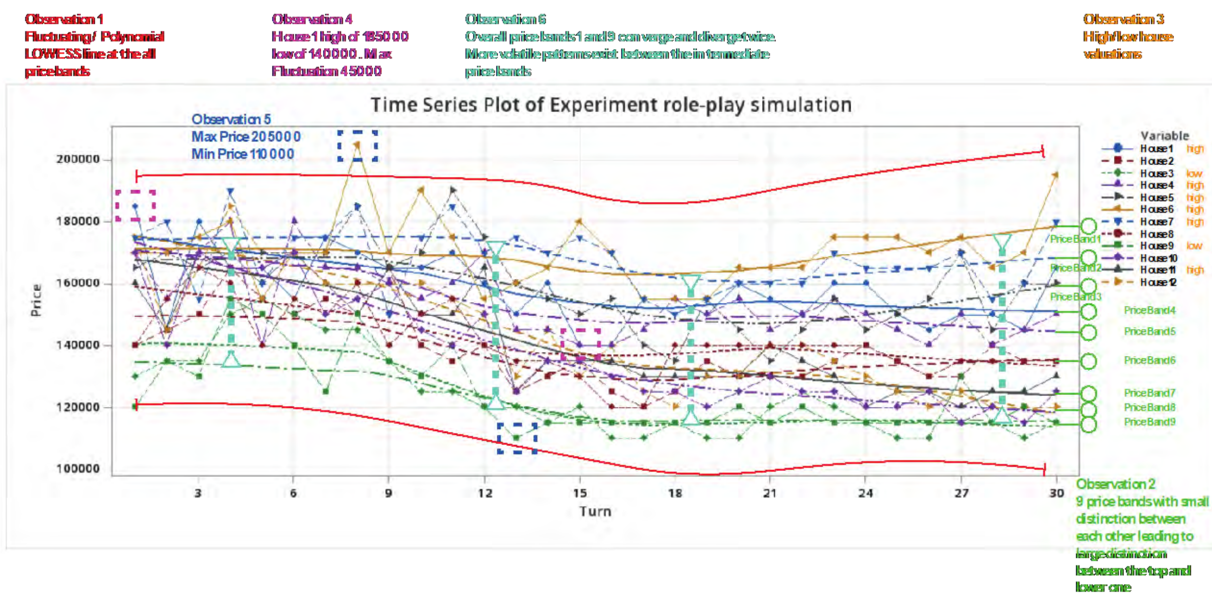


Figure 25: Graph showcasing the results of housing price evolution for active role-playing simulation.

The laboratory experiment featuring real people role-playing agents has its model outputs plotted onto a line graph (Figure 25 above). The x axis represents the turn number while the y axis represents the price. Each house instance features its own colour line on the graphed outlined in the key at the bottom of the figure.

A number of conclusions, derived from the price evolution patterns of the active role-playing simulation, hint towards a complex decision-making pattern. House prices follow a massive inflation pattern during the first 10 rounds with the highest price recorded hitting £205000 and the lowest price £110000 (excluding round 1) (observation 5). After round 10, the market begins to form 9 distinct price bands (observation 2) that remain relatively consistent with slight fluctuation of no more than £45000 (observation 4). It is evident that a there is a distinct separation between the higher performing housing bands (in terms of price/demand) and the lower performing ones. The lower performing houses have a much more stable price after round 10 while the higher performing houses much more volatile prices that have a general upwards trend as the simulation goes on (observation 6). It appears that the role-playing agents establish that the higher performing houses help them satisfy more of their needs and thus reinforce their desire for them, driving prices for those houses higher. Furthermore, there is a much greater separation between the price bands as the simulation moves to the last 10 rounds, further illustrating the point of role-playing agents reinforcing their decision-making patterns and thus distinguishing between houses more clearly. It is worth noting that at no point during the simulation are any houses at the base £100000 which indicates that even the worst performing house has some demand for it (observation 5).

On the other end of the price scale, omitting round 1 due to the initial manual inputs influencing the demand, the maximum house price for any house does not surpass £205000 achieved in round 8 with maximum prices falling steadily until round 17 and then picking up steadily until the end, achieving a maximum price of £195000 at round 30. Prices were more in turmoil during the first few rounds until the effect of the initial starting inputs and bounded rationality was smoothed out and negated in subsequent rounds (observation 1). Therefore, the research concludes that real world people, role-playing agents in this virtual environment, have an initial chaotic decision-making pattern, until they establish and reinforce connections between house choices and resulting goal/desire achievements. Later rounds prove this as agents begin to establish a much more stable demand pattern, with clear housing price bands and a general push to further differentiate between them as the higher band houses steadily increase in value until the end.

6.8 Comparison of computer agent results vs human simulation using a series of further statistical analysis of the four simulation results

The active role-playing simulation results, as described in the previous section, provides some form of external validity for the three, computer ABMs. This section focuses on comparing the results from the three different models, against the results of the laboratory experiment in order to determine their performance. The research, on top of the initial time-series graph analysis performed for the four simulation results, uses a series of other statistical analysis to determine the performance of each computational agent. Each statistical method and conclusion derived from it is explained in the following sub-section. The sub-sections have an introduction that defines the analysis, the terms within the analysis and the various patterns or observations that the analysis may yield as well as what those patterns observed would mean in the context of this thesis. The research then proceeds to identify the observed patterns in each statistical analysis for each computational agent simulation and compare it to the real-world experiment simulation results. In section 6.8.7, all observations are collated into a table to visually represent the performance of each computational agent simulation and the observations likeness to real-world experiment role-playing simulation. This essentially attempt to reveal which agent theory and architecture created as part of this research has the capacity to exhibit subjective rational behaviours similar to those exhibited by their real-world counterparts within this virtual environment.

6.8.1 Cross Correlation analysis to determine price similarity between computational simulations results and experiment results (Price cross-correlation for high value and low value house)

Cross-correlation function analysis is a measurement that tracks the movements of two or more sets of time series data relative to one another (Derrick R. & Thomas M., 2004). It allows for the comparison of multiple time series towards objectively determining how well they relate/match with each other at every point within the timeline. The research run a cross correlation function analysis pitting each computational agent simulation result for individual low and high value house prices over the period of 30 turns, against those produced by the role-playing agent simulation. This attempts to identify how the price, and by association, the demand patterns produced by the computational agents at every turn in the simulation for an individual house, match up or best mimic those obtained during the laboratory experiment. The smaller the value of the degree of cross-correlation is on the y-axis, the more similar the demand for that house was, on that turn, by both the computational agents' model in question and their real-world agents' counterparts.

This type of analysis reveals two important conclusions. Firstly, the degree of similarity at each point alludes to the ability of the computational agents to mimic the decisions of real-world agents. Secondly, if sudden changes to similarity over a 30-turn period exist, it may reveal how real-world agents are evolving their decision-making while the particular computational agent fails to do so. This is an important observation as it means that those particular computational agents may not be able to maintain performance as real-world agents gain experience which diminishes their fitness in the real-world application of these models. On the other hand, a lack of sudden changes, may be indicative of the computational agents' ability to maintain similar decision patterns to real world agents and thus indicative of a measure of subjectivity in their rationality.

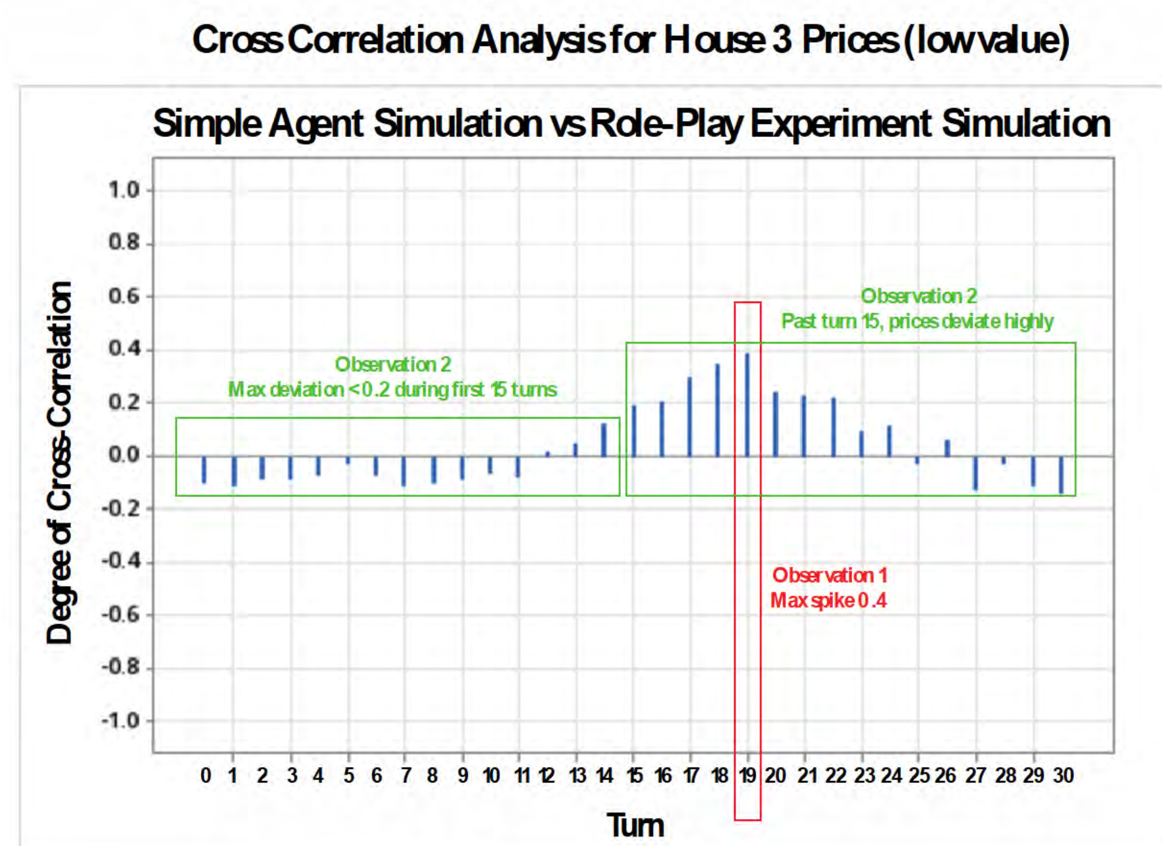


Figure 26:The figure showcases a cross correlation analysis for the relationship of House 3's price between simple and role-play agents over 30 turns.

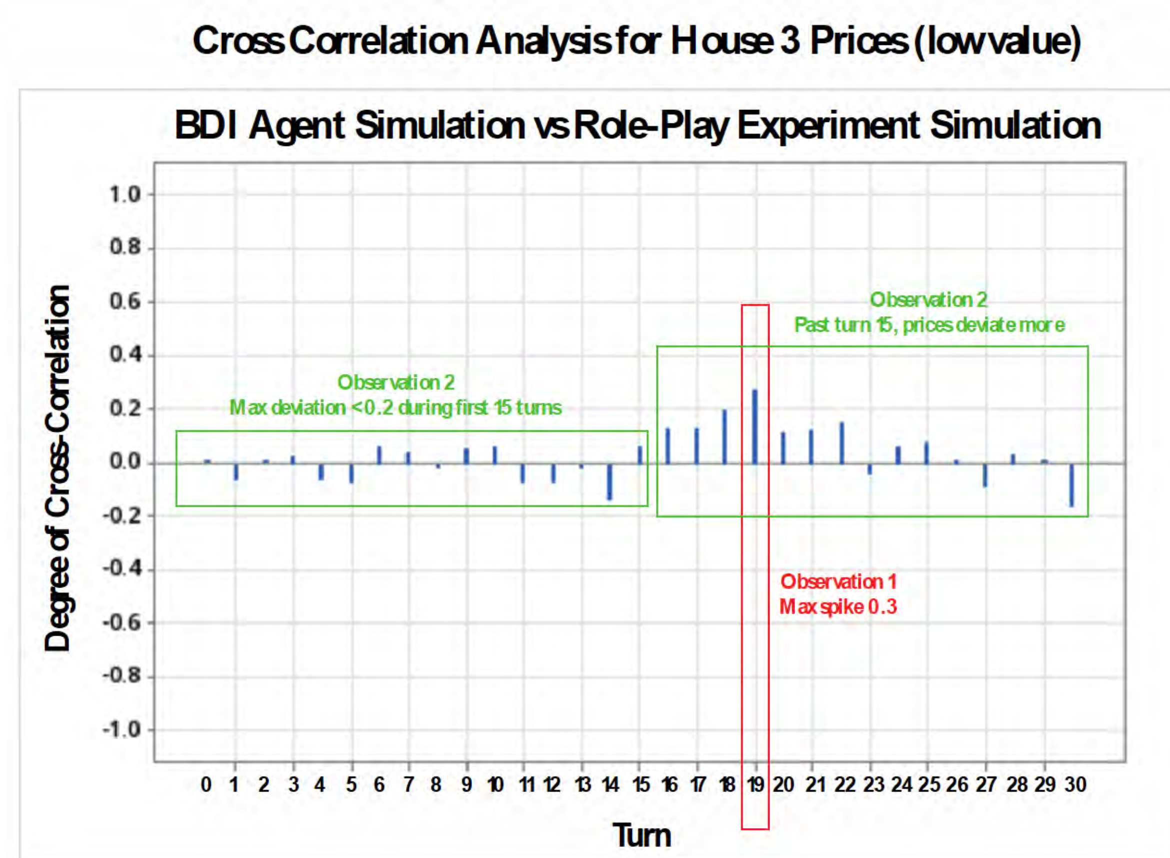


Figure 27: The figure showcases a cross correlation analysis for the relationship of House 3's price between BDI and role-play agents over 30 turns.

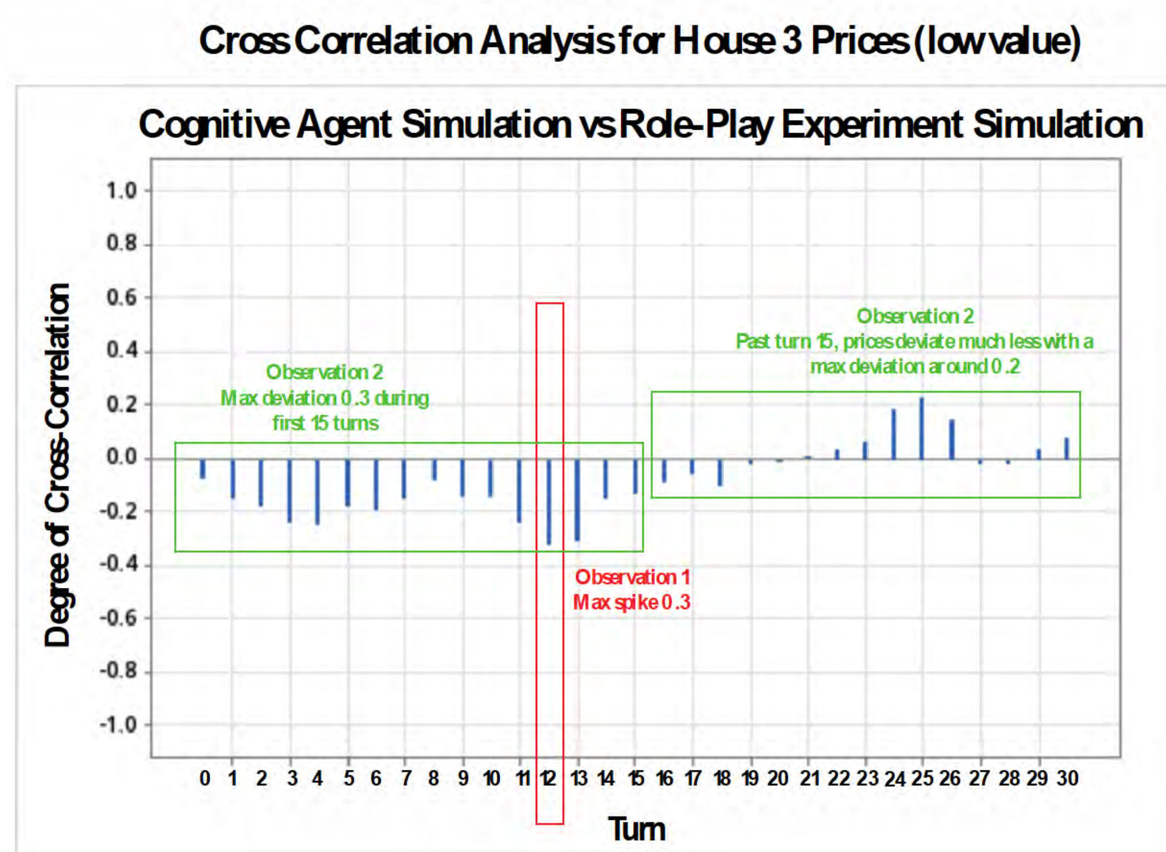


Figure 28: The figure showcases a cross correlation analysis for the relationship of House 3's price between cognitive and role-play agents over 30 turns.

Observation 1 & 2: Price cross-correlation for low value House (number 3) for both the first 15 turns and the last 15 turns in the simulation

The comparison of the multiple time series price data for House 3 for each computational simulations against the experiment results, aims to objectively determining how well they relate/match with each other at every point within the 30 turn timeline. Looking at the cross-correlation function graph for low value House 3, it is evident that the simple agent's simulation (Figure 26, observation 1) achieves the highest deviation from the experiment role-playing agents (turn 19) while both BDI (Figure 27, observation 1) and cognitive (Figure 28, observation 1) have a maximum deviation of around 0.3 when compared to the role-playing agents. As seen from the graphs, simple agents during the first 15 turns appear to have only a slight correlational difference of maximum -0.1 which then begins to differ significantly during the second half of the simulation past turn 15 (Figure 26, observation 2). BDI agents' simulation on the other hand have a much closer alignment at the lower range housing values with a similarly short spike at turn 19 as simple agents simulation but with a smaller amplitude and a much smaller overall correlational difference between the House 3 values (Figure 27, observation 2). Cognitive agents have a bit of an anomaly as they perform the worse during the first 15 turns but then the best during the last 15 turns (Figure 28, observation 2). It appears that as the real-world agents begin to gain knowledge of the alternatives and what satisfies their own goals and criteria, they begin to mimic the demand patterns of cognitive agents much closer. Thus, both simple and BDI agent simulations are unable to mimic changing or reinforcing demand patterns to the degree of cognitive agent simulation, revealing a greater degree of subjective rationality in the cognitive agents' decision-making mechanisms.

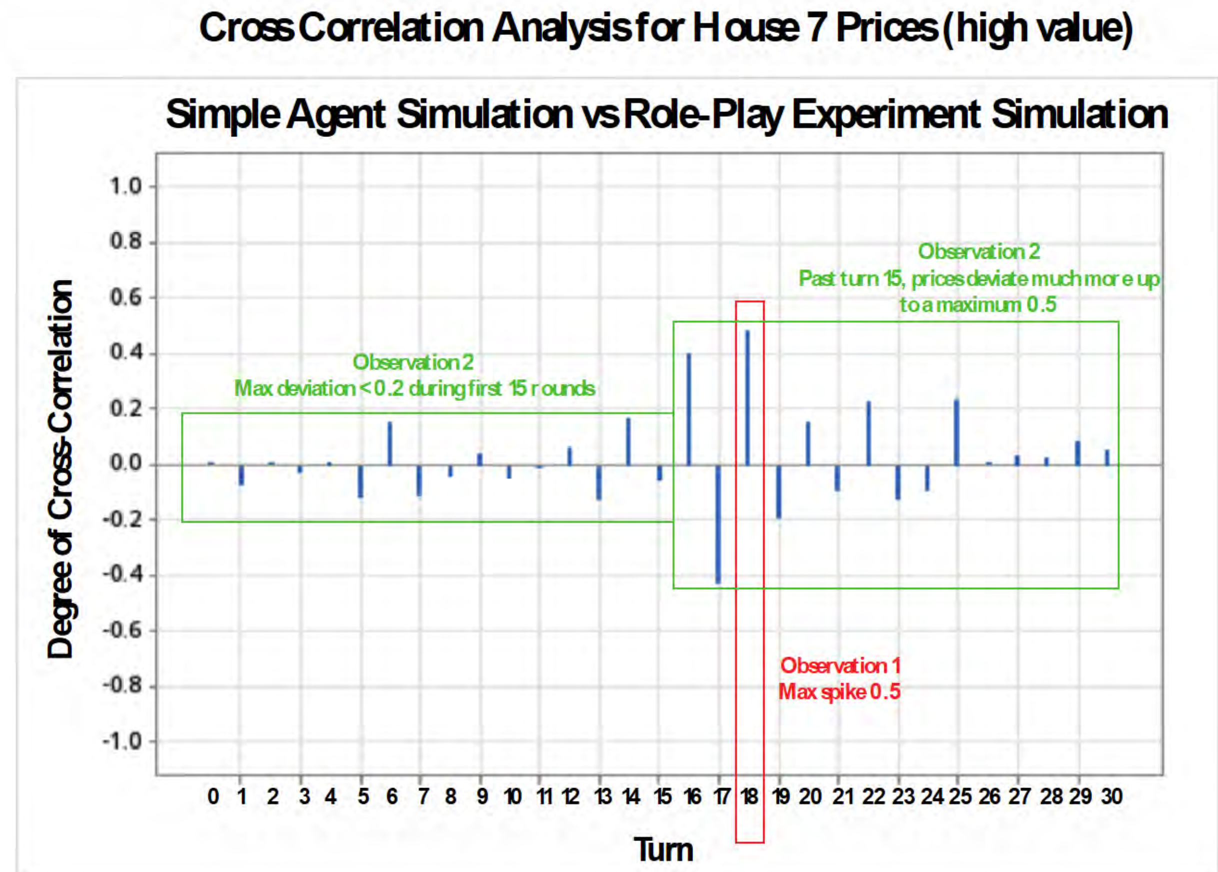


Figure 29: The figure showcases a cross correlation analysis for the relationship of House 7's price between simple and role-play agents over 30 turns.

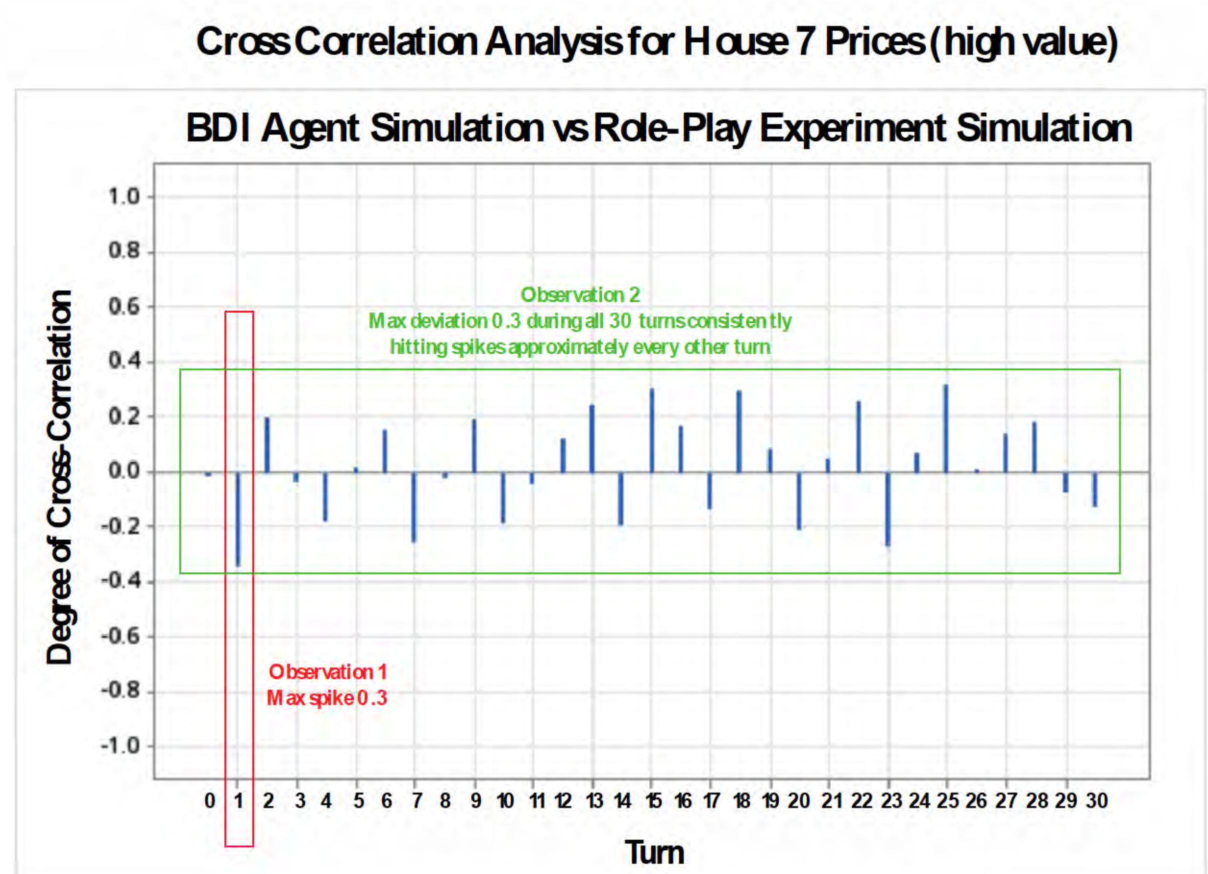


Figure 30: The figure showcases a cross correlation analysis for the relationship of House 7's price between BDI and role-play agents over 30 turns.

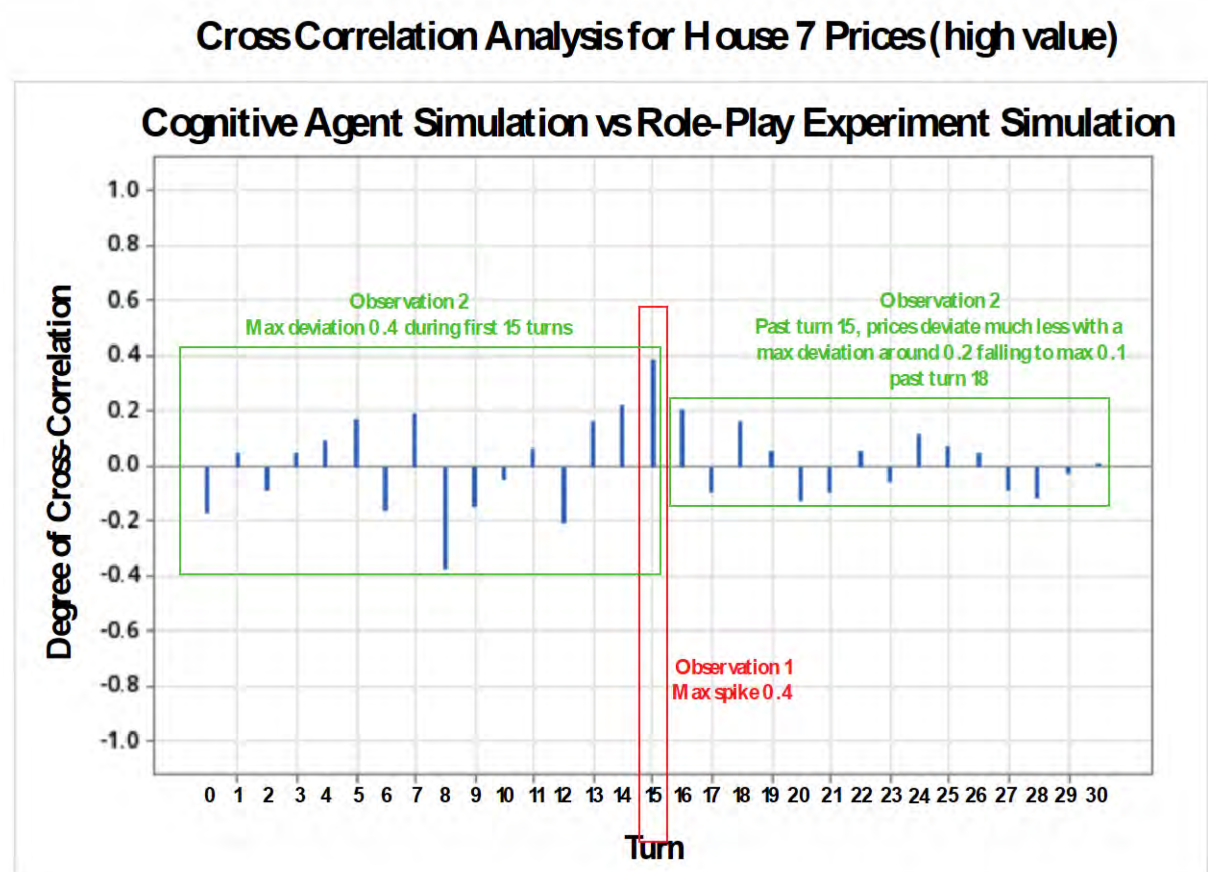


Figure 31: The figure showcases a cross correlation analysis for the relationship of House 7's price between cognitive and role-play agents over 30 turns.

Observation 1 & 2: Price cross-correlation for high value House (number 7) for both the first 15 turns and the last 15 turns in the simulation

Similar patterns and conclusions can be observed when cross correlating a high value house, House 7. As before, the simple agent simulation for the first 15 turns seems to match more closely the demand and value patterns generated by role-playing agents during the laboratory experiment (Figure 29, observation 2). However, after that point, the simple agent simulation results showcase a spike in deviation (Figure 29, observation 1) that signifies their decision-making pattern vary significantly, up to 0.5, from their real-world counterparts. BDI agent simulation seems to have a steady pattern of almost deviating by an average of 0.2 every other turn from the demand patterns set by real-world agent experiment (Figure 30, observation 1, 2). This deviation fluctuates from positive to negative meaning that at times, BDI agent simulation overestimates values or underestimates values for high value homes when compared to the laboratory experiment results. However, the relative consistency of this patterns is indicative of BDI agents' ability to showcase some measure of subjectivity in their decision-making patterns. Cognitive agent simulation, similar to low level houses, fairs the worst during the first 15 turns with positive to negative fluctuations of up to 0.4 (Figure 31, observation 1). However, it seems to match the demand patterns set by the role-playing agents better than the other computational agent simulations during the latter stages of the simulation, past turn 15 (Figure 31, observation 2). This signifies again, that even at this range of demand and house pricing, real-world agent decisions evolve to be more closely affiliated or matched by cognitive agents. Given that cognitive agents use experience and memory representation, it seems their changing patterns eventually begin to match their real-world counterparts. This once again indicates how cognitive agents evolve their decision-making patterns to match the subjective rationality of the real-world agents.

6.8.2 Decomposition analysis to determine overall demand patterns for each simulation over 30 turns (trend, seasonal fit, frequency, amplitude, MAD, for high value and low value homes)

A method of analysis of time series data involves the decomposition of it to various sub-components to determine how these components affect the data in the series (Prema & Rao, 2015). The data is mainly composed of seasonal and trend patterns. There are two different decomposition models, additive and multiplicative. Additive is effective when peak values do not vary much and multiplicative is most effective when values change over time (Prema & Rao, 2015). The two main results from the analysis are a trend that is increasing or decreasing in value in the series and a seasonal fit that is a repeating short-term cycle in the series.

The research run a multiplicative time series decomposition analysis with a seasonal period of 5 turns in order to identify both trends and fluctuation fits for individual houses from both a low value and high value spectrum. This method also identified the mean absolute deviation (MAD) which measures the dispersion in a set of data. In this case, the dispersion refers to the range of demand, and therefore price, for a given house in a particular simulation. Low MAD means that demand for that house does not fluctuate heavily while a high MAD portrays the opposite.

This type of analysis reveals three conclusions. Firstly, a high fluctuation of demand indicated both in a high MAD value and in the seasonal fit – either through a lack of defined cyclical shape (wave like) or number of differently valued peaks within a seasonal cycle – is indicative of changing or evolving decision patterns and thus a measure of subjectivity in the rationality as a changing context, experience or personal perspective of agents forces a change in demand patterns over time for that house. Secondly, the overall trend is indicative of how the 30-turn pattern of demand for each computational agent simulation relates to the 30-turn pattern of the experiment agents in both direction and steepness. The importance of that is again to see how overall demand patterns match between computational simulations and experiment simulation thus determining the ability of computational agents to follow the real-world agent trends over time. Lastly, this analysis uses the actual pattern of price changes over time for that individual house in each simulation to comment on the amplitude and frequency of fluctuations in price. When these two elements are irregular, similarly to the first point, indicate a measure of subjectivity in decision-making as agents showcase development and strengthening of their decision-making patterns over time as a response to other agent decisions and thus breaking otherwise predictable patterns.

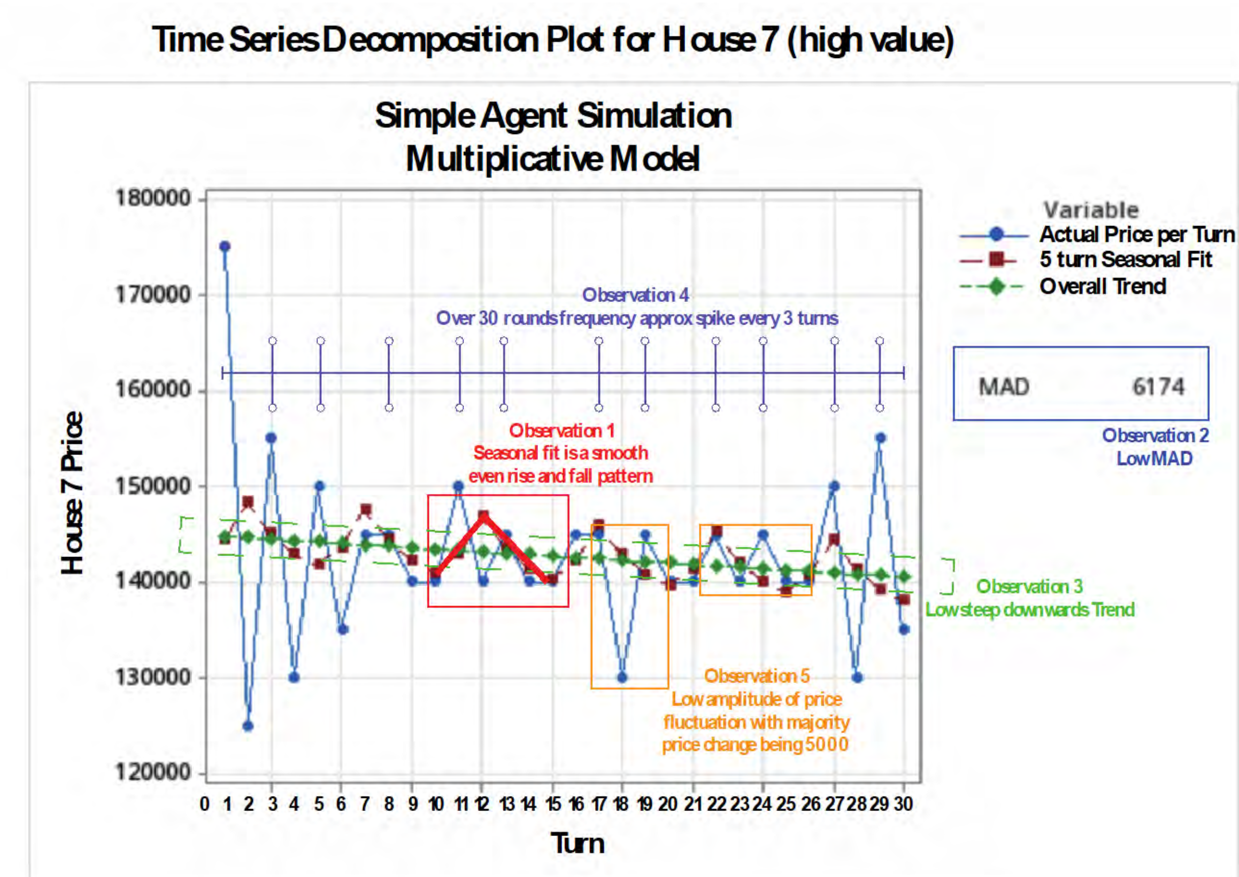


Figure 32: The graph showcases the results of a decomposition analysis for the results of price changes to House 7 in simple agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

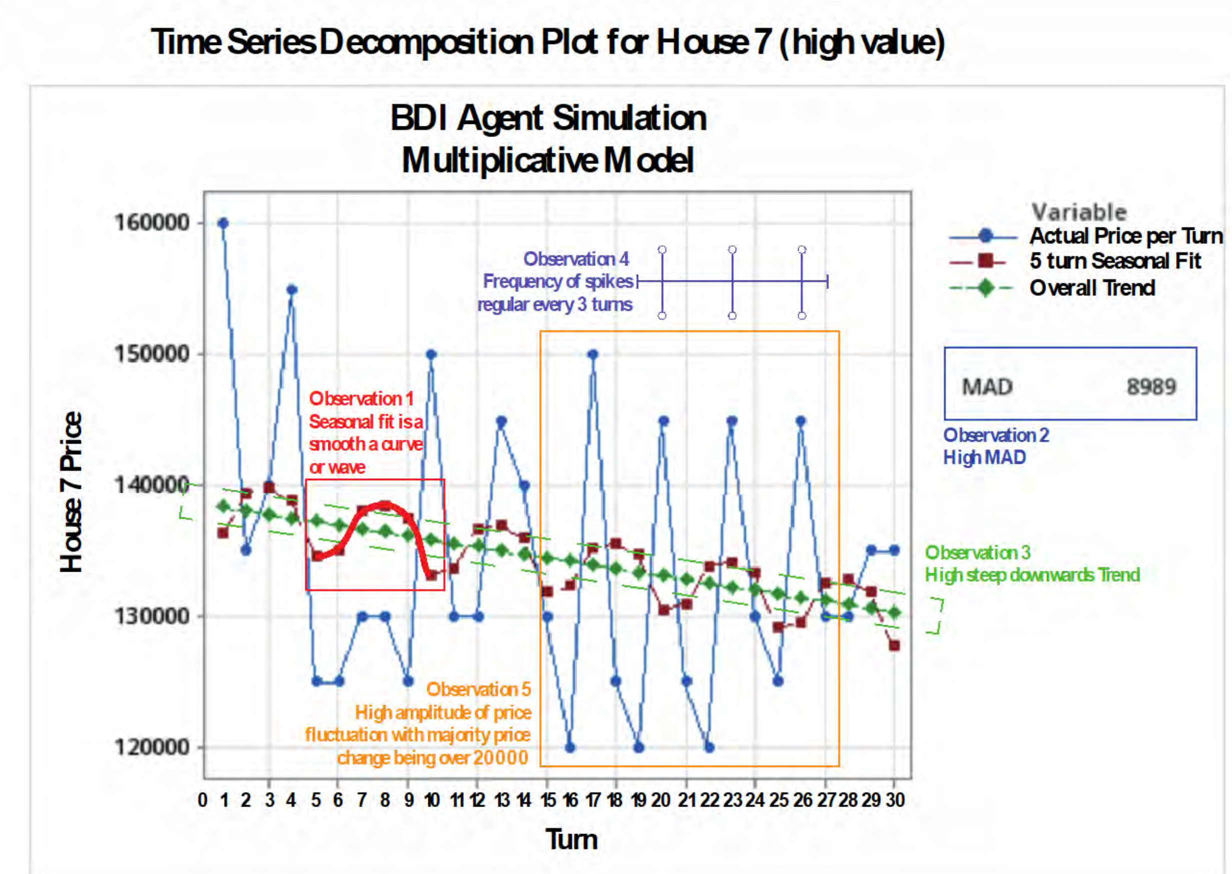


Figure 33: The graph showcases the results of a decomposition analysis for the results of price changes to House 7 in BDI agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

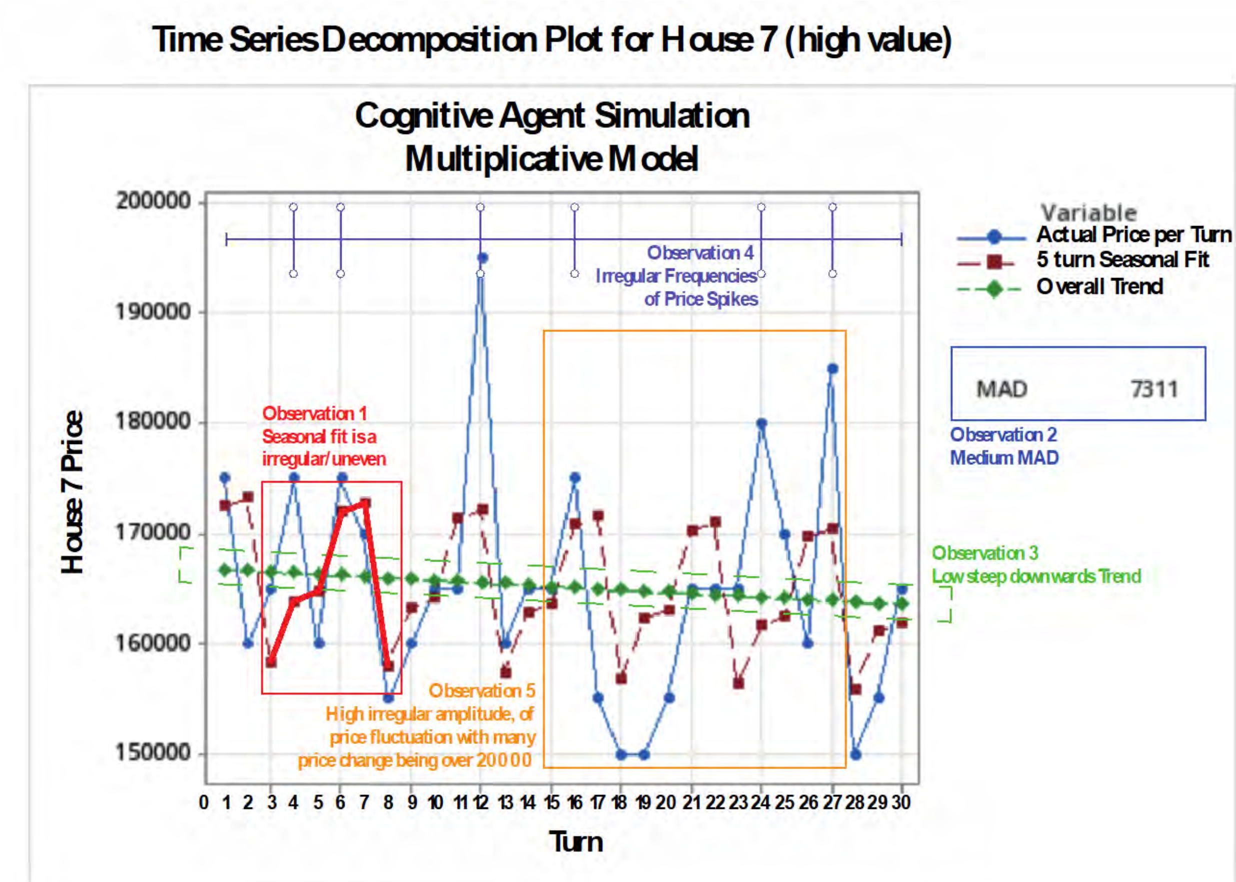


Figure 34: The graph showcases the results of a decomposition analysis for the results of price changes to House 7 in cognitive agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

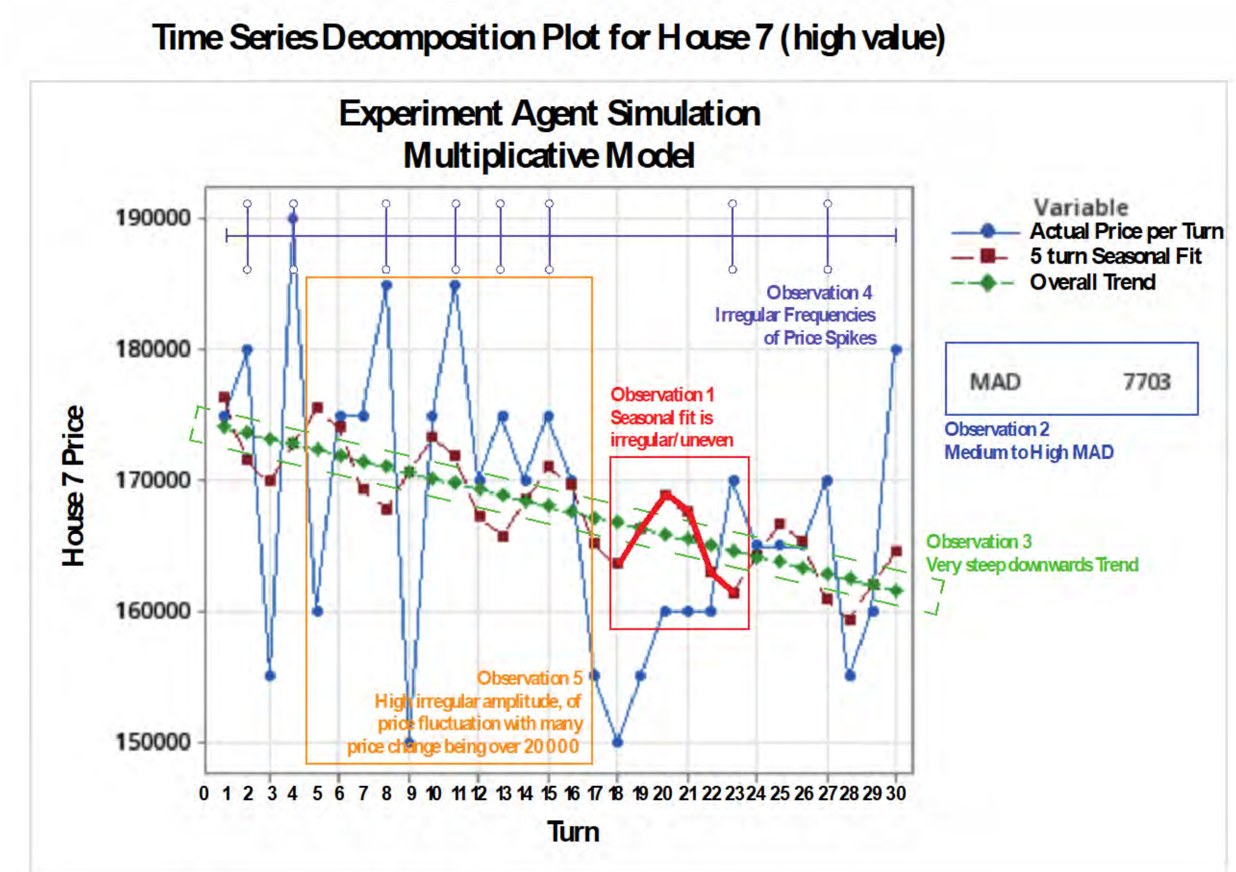


Figure 35: The graph showcases the results of a decomposition analysis for the results of price changes to House 7 in experiment role-playing agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

Observation 1: Decomposition seasonal fit for high value House (number 7)

The research initially used house 7, a relatively high value house, to run a time series decomposition on for each of the simulations. Initially the seasonal fit pattern was observed in each simulation to determine the evolutionary pattern of demand and subjectivity of decision-making. Cognitive agent simulation achieves a seasonal fit that is somewhat irregular/uneven in shape due to the relative unpredictability of fluctuation amplitude (Figure 34, observation 1). The seasonal fit undergoes an uneven stepped rise in price to the peak followed by a smooth fall. This is similar to experiment agents (Figure 35, observation 1) that has a smooth rise to the peak followed by an uneven stepped fall. These results are indicative of changing or evolving decision patterns and thus a measure of subjectivity in the rationality of cognitive and real-world agents. Opposing the seasonal pattern of these two simulations, simple agent simulation achieves the smoothest seasonal fit pattern with a relatively even rise and fall pattern (Figure 32, observation 1). BDI agent simulation has a predictable rise and fall pattern too through it is not an even rise with the trend resembling a curve or a wave (Figure 33, observation 1). This is indicative of a steady yet volatile pattern of demand which does not exist in simple agent simulation.

Observation 2: Mean absolute deviation (MAD) for high value House (number 7)

Simple agent simulation achieves an MAD of 6174 (Figure 32, observation 2) which is lower than both the other computational agent simulations and the experiment results. This is not unexpected as both the decision-making theory of utility maximisation and the logic architecture that transcribes it within the model are geared towards stability of results and objectivity in decision-making. In contrast, BDI agent simulation (Figure 33, observation 2) achieves the highest MAD of 8989 possibly due to the random element of decision-making by the BDI agents. Cognitive agent simulation (Figure 34, observation 2) achieves a MAD of 7311 that is closer to the experiment's real world agent simulation MAD of 7703 (Figure 35, observation 2). Similarly to the seasonal fit, the results of the MAD for all simulations apart from simple agents showcase some measure of subjective rationality in their decision-making.

Observation 3: Overall trend for high value House (number 7)

All four simulations have an overall trend that has a downwards direction. Simple agent simulation (Figure 32, observation 3) has a low steep trend downwards, BDI simulation achieves a much steeper trend downwards (Figure 33, observation 3) than both simple agents and cognitive agents, with only experiment agents (Figure 35, observation 3) having a steeper one. The trend in cognitive agent simulation is the middle child, not as steep as the BDI agent simulation nor the experiment agent simulation but steeper than the simple agent simulation. However, BDI agents seem to match the trend of experiment agents better than the rest of the computational agents. This showcases the ability of the BDI agent architecture and theoretical basis to mimic shifting trends at a 30-turn interval for high value homes. To that degree, on average, they behave the most similar over time to their real-world counterparts.

Observation 4 & 5: Amplitude and frequency of price fluctuations for high value House (number 7)

Simple agent simulation (Figure 32, observation 4 & 5)) managed a low amplitude of price fluctuation when compared to the other simulations with a relatively stable frequency of 1 peak within a 3-turn period. Again, this is not unexpected as both the decision-making theory of utility maximisation and the logic architecture that transcribes it within the model are geared towards stability of results and objectivity in decision-making. BDI agent simulation (Figure 33, observation 4 & 5) achieves visibly greater and more regular fluctuations in price. Though the BDI agent simulation also achieve one peak in price over a 3-turn period, they more or less are consistently hitting that peak every 3 turns which is not always the case with simple agent simulation. The regularity of the fluctuations as well as the high amplitude of them stems from their use of the Theory of Planned Behaviour that only prescribes a higher or lower probability of undertaking a decision/action. This results in a predictable frequency but chaotic amplitude. Cognitive agent simulation (Figure 34, observation 4 & 5) has demand patterns fluctuate at more irregular amplitudes and frequencies throughout the simulation when compared to the other two computational agents. This irregularity in both amplitude and frequency appears on the experiment agent simulation's time series decomposition (Figure 35, observation 4 & 5) as well as cognitive agents signifying the development and strengthening of the decision-making patterns based on the experience of previous rounds which is achieved through the use of case-based utility theory and the cognitive agent architecture. As previously mentioned, the experiment role-playing agents achieve a highly irregular frequency and amplitude of price fluctuations for house 7. The pattern appears to change after turn 15 significantly as real-world agents gain experience in the effects of their choices. This irregularity is mostly similar to the cognitive agent simulation which indicates a measure of subjectivity in decision-making for cognitive agents as it showcases both them and real-world agents making decisions in a manner that breaks otherwise predictable patterns.

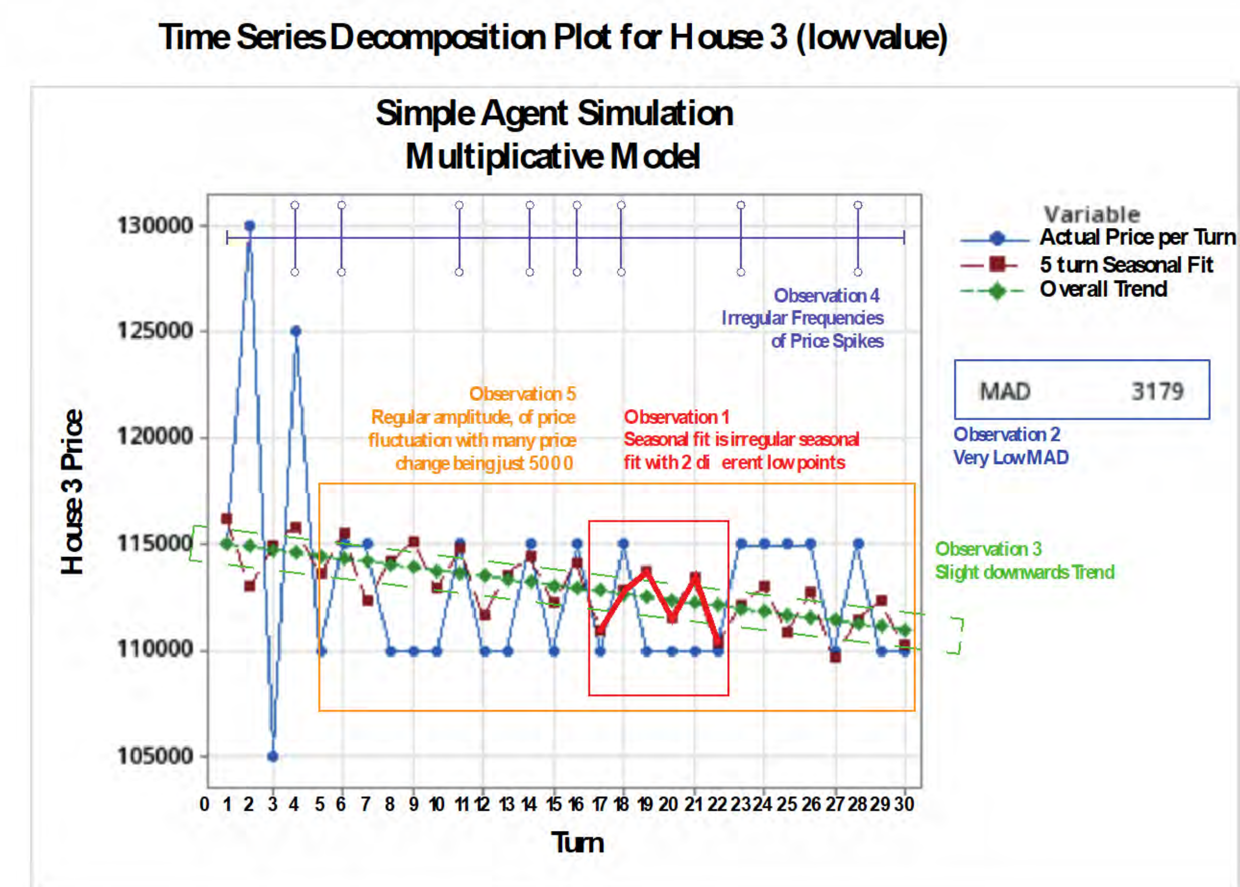


Figure 36: The graph showcases the results of a decomposition analysis for the results of price changes to House 3 in simple agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

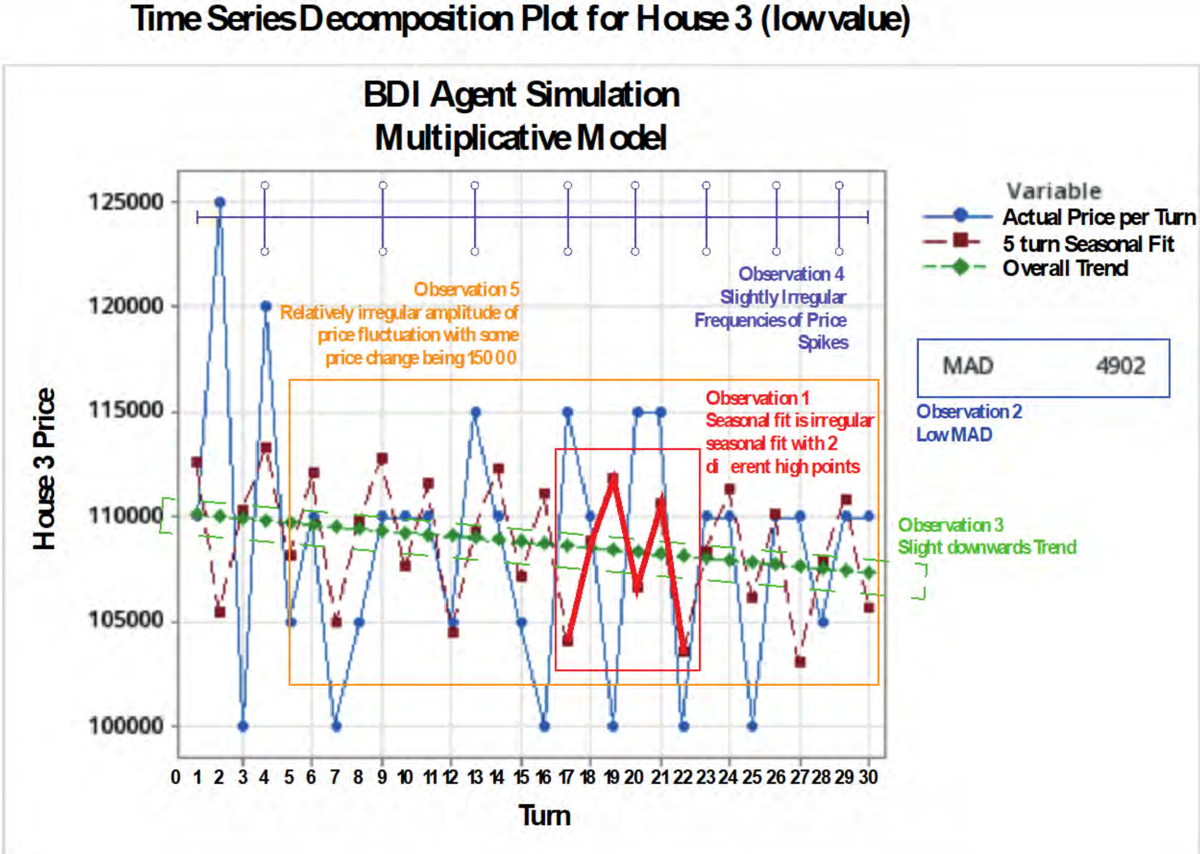


Figure 37: The graph showcases the results of a decomposition analysis for the results of price changes to House 3 in BDI agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

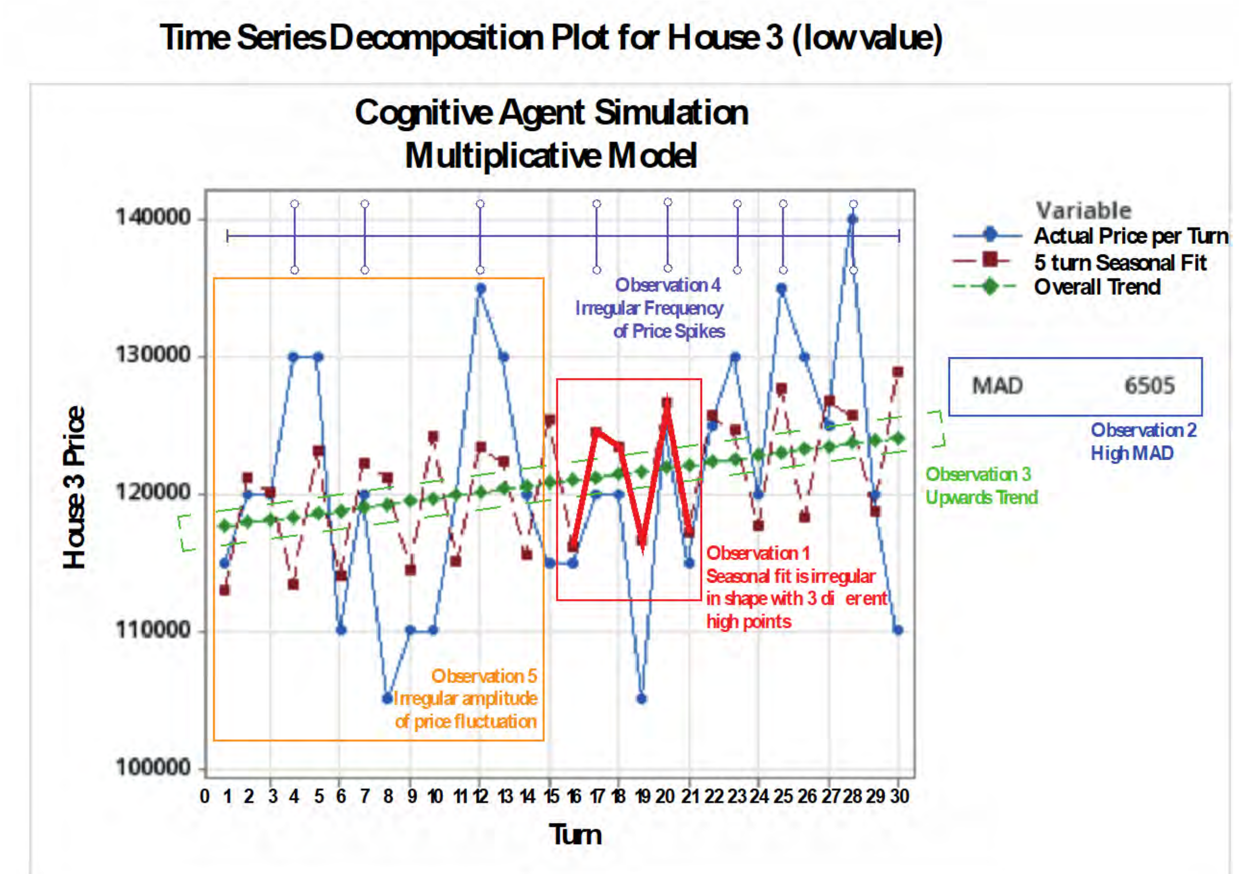


Figure 38: The graph showcases the results of a decomposition analysis for the results of price changes to House 3 in cognitive agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

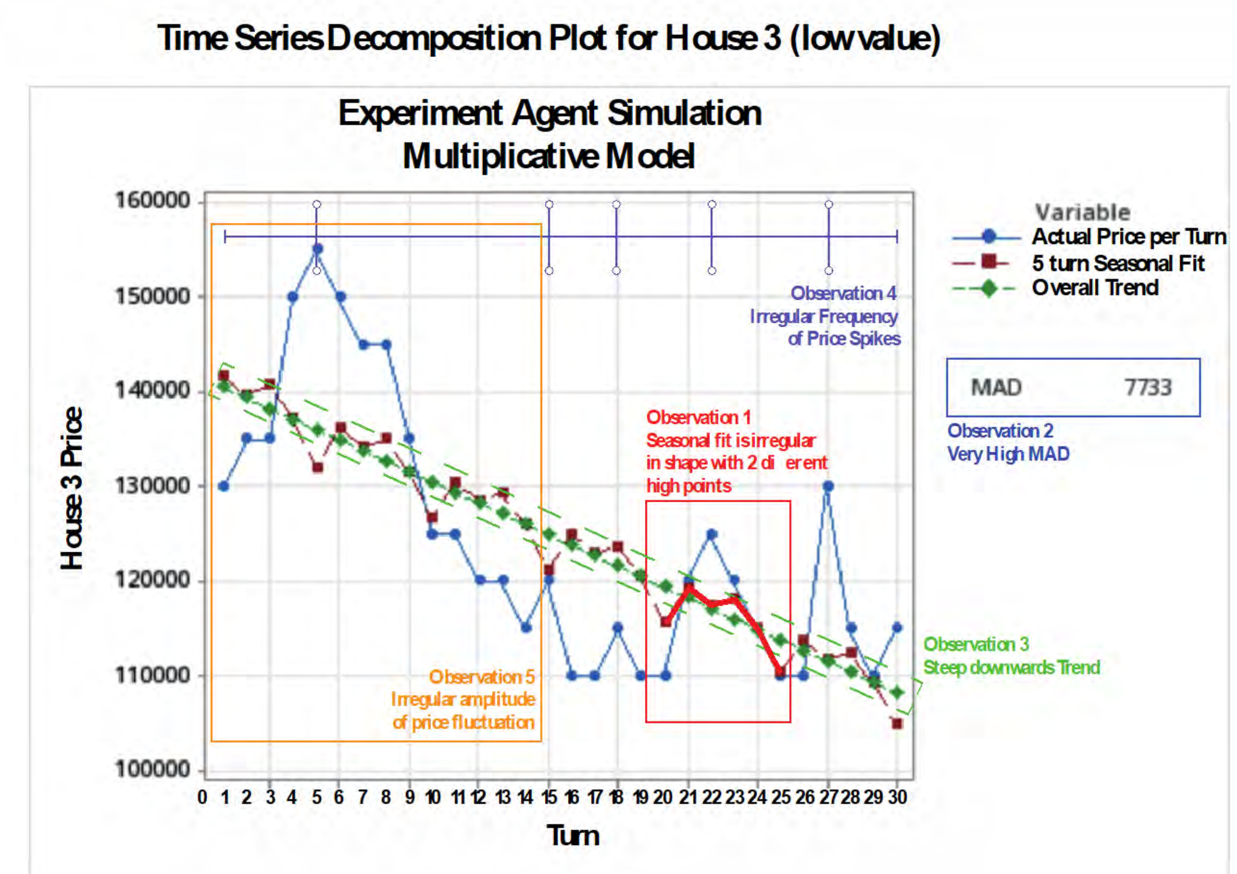


Figure 39: The graph showcases the results of a decomposition analysis for the results of price changes to House 3 in experiment role-playing agent simulation. The blue dots/line are indicative of the actual values over the course of 30 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

Observation 1: Decomposition seasonal fit for low value House (number 3)

The research proceeded to use house 3, a low value house, to run a time series decomposition on for each of the simulations. Initially the seasonal fit pattern was observed in each simulation to determine the evolutionary pattern of demand and subjectivity of decision-making. Cognitive agent simulation achieves a seasonal fit that is somewhat irregular/uneven in shape with 3 different high points per 5 turn seasonal period (Figure 38, observation 1). The seasonal fit undergoes an even rise in price to the peak followed by a smooth fall and a second rise to a new second peak followed by an uneven stepped fall within a 5 turn seasonal cycle. This is not unique to them as for low range housing, all computational agents and the role-playing agents of the experiment (Figure 39, observation 1) achieve uneven seasonal fits with multiple high and low points. However, the two low points achieved in a seasonal cycle in the cognitive agent simulation are at a similar value. This pattern is somewhat unique to the cognitive agent simulation as the simple agent simulation has an irregular seasonal fit with 2 different low points (Figure 36, observation 1). Both the BDI agent simulation (Figure 37, observation 1) and the experiment simulation also achieve 2 different low points. This irregularity in seasonal fit pattern may be attributed to the relatively high impact of a single agent's decision in this range causing a much more irregular frequency of seasonal patterns for all of the simulations. These results are indicative of changing or evolving decision patterns and thus a measure of subjectivity in the rationality of all agents.

Observation 2: Mean absolute deviation (MAD) for low value House (number 3)

Simple agent simulation achieves a MAD of just 3179 which is significantly lower than both the other computational agent simulations and the experiment results (Figure 36, observation 2). As evidenced in the high value house, this result can be attributed to objective nature of the decision-making theory of utility maximisation and the logic architecture that transcribes it within the model. Similarly, BDI agent simulation (Figure 37, observation 2) achieves a MAD of 4902 which is surprisingly not the highest amongst computational agents, a trend that is dissimilar to the high value homes. Cognitive agent simulation (Figure 38, observation 2) a MAD of 6505 that is the closest to the experiment's real world agents MAD of 7733 (Figure 35, observation 2). In observation 2 we see a dichotomy to the trend viewed in observation 1 with all simulations having a similarly irregular seasonal trend. Unlike in high value homes, only the cognitive and the experiment agent simulations maintain high levels of MAD and thus indicative of drastically changing demand and pricing patterns which reveals a notion of subjective rational decision-making behaviour.

Observation 3: Overall trend for low value House (number 3)

All four simulations have an overall trend that has a downwards direction apart from cognitive agents. Simple agent simulation (Figure 36, observation 3) managed a steep trend downwards though that might have been skewed from the initial high fluctuation in price in the first 5 turns. BDI simulation achieves a the least steep trend downwards when compared to simple agents and experiment agents (Figure 37, observation 3). The trend in cognitive agent simulation, unlike all other simulations over 30 rounds, has a low steepness trending upwards (Figure 38, observation 3). This is unique and points to the agents realising the value of maintaining a house even if it does not satisfy all their needs, thus through the build-up of experience, sees them demand lower range houses at a greater degree. As previously mentioned, the experiment role-playing agent simulation (Figure 39, observation 3) has the steepest downwards trend that seems to persist in both high and low range houses with the pattern once again changing drastically after turn 15. The research removed and rerun a decomposition analysis for experiment role-playing agent simulation for values after turn 15 (Figure 39, observation 3) yielding a similar upwards trend to cognitive agent simulation. It appears that the real-world agents begin to value more, the basic criteria of having a house past turn 15 after they have come to grips with the effects of their decisions in previous rounds, an observation similar to that witnessed only in the cognitive agents.

Observation 4 & 5: Amplitude and frequency of price fluctuations for low value House (number 3)

Simple agents' simulation (Figure 36, observation 4 & 5) achieved a constant low amplitude of price fluctuation with a slightly irregular frequency of fluctuation, significantly lower than both the other computational agent simulations and the experiment results. In fact, demand for this house fluctuated between 2 values, £5000 apart for 25 rounds. As evidenced in the high value house, this result can be attributed to objective nature of the decision-making theory of utility maximisation and the logic architecture that transcribes it within the model. The relative irregularity of the fluctuation causes an irregular seasonal fit with 2 different low points for simple agents. BDI agent simulation (Figure 37, observation 4 & 5) maintains visibly greater amplitude and more regular frequency of fluctuations in price than the other computational and real-world agent simulations, however, the unpredictable nature of the price fluctuation in this low value range is comparable to the simple agent simulation that alongside the BDI agent simulation, were the only ones that had a stable frequency at higher value homes but visibly slightly more irregular at lower value ones. It appears that even though the architecture and theoretical basis of BDI agents adds a random element of decision-making, the relative regularity of the fluctuations as well as the high and irregular amplitude of them, over time creates a relatively predictable pattern at lower ranges. Cognitive agent simulation (Figure 38, observation 4 & 5) evidently has demand patterns fluctuate at more irregular amplitudes throughout the simulation when compared to the other two computational agents. This irregularity in both amplitude and frequency also appears on the experiment agents' time series decomposition, albeit in a much less volatile degree between rounds (Figure 39, observation 4 & 5). This suggest that, similarly to high value homes, both sets of agents either through the use of case-based utility theory and the cognitive agent architecture or the real-world person's ability to learn from experience, have their demand patterns evolve over time.

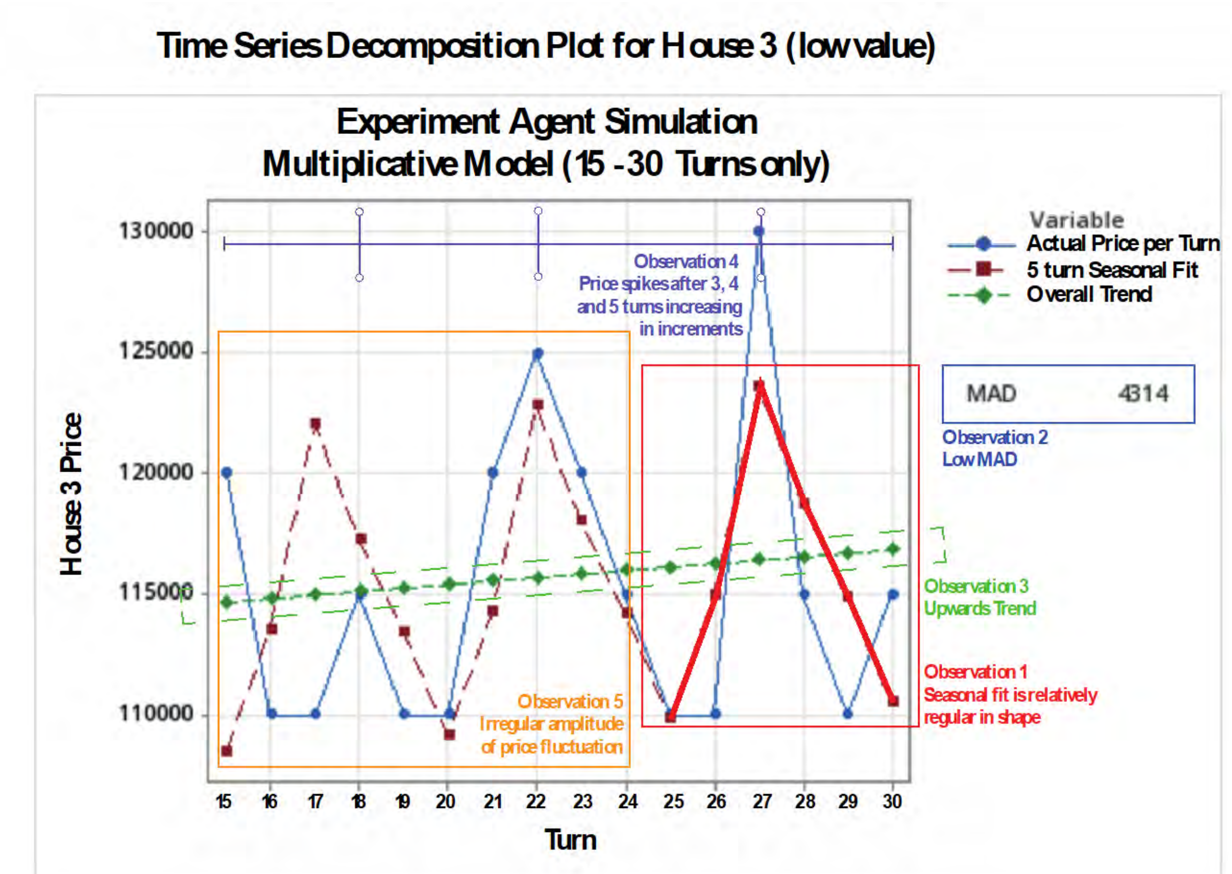


Figure 40: The graph showcases the results of a decomposition analysis for the results of price changes to House 3 in experiment role-playing agent simulation. The blue dots/line are indicative of the actual values over the course of the last 15 turns, the red line/square indicates a 5 turn seasonal fit analysis of the patterns and the green line is indicative of the overall trend analysis.

As previously mentioned, the irregularity of amplitude and frequency of the experiment's simulation results is mostly similar to cognitive agent simulation. The research removed and rerun a decomposition analysis for experiment role-playing agents for values after turn 15 (Figure 40, observation 4 & 5) yielding an irregularity in amplitude of price fluctuations though at a more regular frequency with peaks appearing after 3 turns, then 4 turns, and then 5 turns signifying a steady incremental decrease in frequency of occurrence. This stability in frequency is mirrored in the seasonal trend for the post 15 turn decomposition that sees it achieve a relatively smooth pattern of peaks and troughs. It appears that real-world agents begin to value more, the basic criteria of having a house past turn 15 after they have come to grips with the effects of their decisions in previous rounds, an observation similar to that witnessed in the cognitive agents.

6.8.3 Descriptive statistics analysing possible subjective rationality patterns in each of the simulation results (mean, stDev, Q1, Q3 (difference), Max, Min)

The research analysed the results of all computational and experiment simulations using descriptive statistics. This revealed underlying similarities and differences at an aggregate level with a look into Standard Deviation (StDev), Mean, 25% and 75% Quartile (Q1 & Q3), interquartile range (IQR) and minimum and maximum value per house.

Descriptive Statistics for simple agent simulation

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum	IQR
House 1	30	0	142500	1329	7281	130000	140000	140000	145000	160000	**5000**
House 2	30	0	121500	801	4385	114999	120000	120000	125000	130000	**5000**
House 3	30	0	113000	884	4842	105000	110000	110000	114999	130000	**5000**
House 4	30	0	155000	1626	8906	135000	150000	155000	160000	185000	**10000**
House 5	30	0	155167	1737	9513	135000	150000	155000	160000	190000	**10000**
House 6	30	0	142667	1708	9353	125000	140000	140000	145000	175000	**5000**
House 7	30	0	142667	1708	9353	125000	140000	140000	145000	175000	**5000**
House 8	30	0	122167	1090	5972	110000	120000	120000	125000	140000	**5000**
House 9	30	0	113666	828	4536	105000	110000	114999	114999	125000	**5000**
House 10	30	0	155333	1856	10165	135000	150000	155000	160000	195000	**10000**
House 11	30	0	155333	1856	10165	135000	150000	155000	160000	195000	**10000**
House 12	30	0	143667	2019	11059	120000	140000	140000	150000	180000	**10000**

Observation 3
Majority of Mean values around 145000 with a 155333 high

Observation 2
StDev Low 4385, high 11059

Observation 4
Max value 195000

Observation 1
Max IQR 10000

Table 32: The table showcases the descriptive statistics results for the simple agent simulation.

A Standard Deviation is the measure of dispersion for the data in relation to the mean value. A high StDev portrays the data values as spread out while a low StDev indicates a clustering of values around the mean. The mean is the average value of the house and is calculated by adding up the price of each house at the end of every turn and then dividing it by 30. A quartile splits the data into quarters so that 25% of the data values are less than the lower quartile (Q1) while the upper quartile (Q3) is the value that 75% of data values are less than. The interquartile range (IQR) consists of the difference between Q3 and Q1. IQR is the best measure of variability for skewed distributions or data sets with outliers.

The minimum is simply the lowest value in a set of values, while the maximum is the highest. In this case, these values signify the highest and the lowest price recorded for each house.

The research can draw 4 conclusions from this analysis of simulation results. Firstly, a high StDev indicates that there is a high level of price fluctuation for each house, meaning agents tend to alter their demand for that house widely across the 30 turns. It could indicate that they do not have a fixed or reinforced value for that property, or that their patterns have changes over time, reinforcing or reducing demand as the simulation goes on. The latter is an indication of subjective rationality as it conveys a temporal change in personal perspective for the agent as the house attributes remain mostly the same apart from price and safety rating. Secondly, high mean values across the 12 houses indicates that agents are interested in a larger number of houses each round than if the mean values were low across the range. A larger distribution of interest to more houses per turn is indicative of a decision-making pattern that values more than just the optimal solution at this moment/context but rather casts a wider net for houses that can help the agent achieve the majority of their criteria. This too showcases subjectivity in decision-making as a wider interest in houses outside the optimal range is indicative of taste and preference unique to that agent's perspective. Thirdly, the IQR, much like the StDev reveals the extend of price fluctuation per house while eliminating the outliers from the equation. In essence, it allows for a truer representation of the extend of price fluctuation for the majority of rounds which similar to StDev is an indication of subjective rationality as it conveys a temporal change in personal perspective for the agent. Lastly, the value of the minimum and maximum price achieved by each simulation for a house is indicative of how high and low demand managed to reach for a single house in a simulation. A high maximum value indicates that agents have reinforced demand patterns, highly valuing a particular alternative. A minimum value above £100000 indicates that at all times, demand exists for all houses within the simulation.

Descriptive Statistics for BDI agent simulation

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum	IQR
House 1	30	0	134167	1949	10674	114999	125000	132500	141250	155000	16250
House 2	30	0	114666	1396	7649	105000	110000	114999	120000	130000	10000
House 3	30	0	108667	1123	6149	100000	105000	110000	110000	125000	5000
House 4	30	0	144000	2163	11847	130000	135000	140000	150000	180000	15000
House 5	30	0	144833	2203	12069	125000	135000	140000	151250	175000	16250
House 6	30	0	134833	2083	11408	114999	125000	132500	141250	160000	16250
House 7	30	0	134333	1973	10807	120000	125000	130000	145000	160000	20000
House 8	30	0	114000	1579	8650	100000	110000	110000	120000	135000	10000
House 9	30	0	109166	1224	6706	100000	105000	110000	114999	125000	10000
House 10	30	0	145000	2514	13772	125000	138750	145000	150000	185000	11250
House 11	30	0	144000	1968	10780	130000	140000	140000	146250	170000	6250
House 12	30	0	134667	2444	13386	114999	125000	132500	141250	170000	16250

Observation 3
Majority of Mean values around 140000 with a 145000 high

Observation 2
StDev Low 6149, high 13772

Observation 4
Max value 185000

Observation 1
Max IQR 20000

Table 33: The table showcases the descriptive statistics results for the BDI agent simulation.

Descriptive Statistics for cognitive agent simulation

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum	IQR
House 1	30	0	164667	1625	8899	150000	160000	165000	170000	190000	10000
House 2	30	0	131500	1764	9662	110000	125000	132500	136250	150000	11250
House 3	30	0	120833	1645	9010	105000	114999	120000	130000	140000	15000
House 4	30	0	177000	1061	5813	165000	173750	175000	180000	190000	6250
House 5	30	0	178000	1236	6772	165000	173750	175000	185000	190000	11250
House 6	30	0	164833	1770	9692	150000	158750	165000	171250	190000	12500
House 7	30	0	165167	1910	10462	150000	158750	165000	171250	195000	12500
House 8	30	0	132333	1944	10646	110000	125000	132500	136250	160000	11250
House 9	30	0	121333	1744	9553	105000	114999	120000	126250	145000	11250
House 10	30	0	179167	1574	8619	165000	173750	175000	185000	195000	11250
House 11	30	0	179833	1720	9421	165000	173750	175000	190000	200000	16250
House 12	30	0	166167	2308	12641	150000	155000	165000	175000	200000	20000

Observation 3
Majority of Mean values around 160000 with a 179833 high

Observation 2
StDev Low 5813, high 12641

Observation 4
Max value 200000

Observation 1
Max IQR 20000

Table 34: The table showcases the descriptive statistics results for the cognitive agent simulation.

Descriptive Statistics for experiment simulation

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum	IQR
House 1	30	0	158000	2043	11188	140000	150000	157500	165000	185000	15000
House 2	30	0	138500	2092	11458	120000	130000	135000	146250	165000	16250
House 3	30	0	124333	2511	13755	110000	113749	120000	135000	155000	21250
House 4	30	0	153833	2140	11721	140000	145000	150000	161250	180000	16250
House 5	30	0	159333	2488	13629	135000	148750	160000	170000	190000	21250
House 6	30	0	170667	2127	11651	155000	165000	170000	175000	204999	10000
House 7	30	0	167833	1958	10722	150000	160000	170000	175000	190000	15000
House 8	30	0	141167	1987	10882	120000	135000	140000	150000	165000	15000
House 9	30	0	123666	2286	12522	110000	114999	117500	131250	155000	16250
House 10	30	0	137333	3302	18087	114999	125000	130000	151250	170000	26250
House 11	30	0	141333	3041	16657	120000	128750	135000	160000	170000	31250
House 12	30	0	142667	3497	19152	120000	125000	140000	160000	185000	35000
			Observation 3 Majority of Mean values around 150000 with a 170667 high		Observation 2 StDev Low 10722, high 19152					Observation 4 Max value 205000	Observation 1 Max IQR 35000

Table 35: The table showcases the descriptive statistics results for the experiment role-play agent simulation.

Observation 1: Comparing Quartile and Interquartile results for each simulation.

Comparing the difference between Q1 and Q3 numbers for all simulations, also known as the IQR, it is evident that simple agent simulation (Table 32, observation 1) has the least difference up to a maximum of £10000 difference, with cognitive (Table 34, observation 1) and BDI (Table 33, observation 1) agent simulations achieving a maximum of £20000 while the experiment simulation (Table 35, observation 1) has a difference of up to £35000. This is indicative of the extent of price deviations present in the simulations as simple agents with their use of ordinal utility maintain a much steadier housing value and demand fluctuation. Real-world agents appear to drastically change their demand patterns as the simulation goes on. This aspect is better represented in both BDI and cognitive agent simulations with a Q1-Q3 difference closer to the real-world agents. This is an indication of these two computational agents' ability to convey notions of subjective rationality as their high IQR results expresses a temporal change in personal perspective for the agent.

Observation 2: Comparing StDev results for each simulation.

The IQR pattern is also observed when analysing the StDev of the different simulation models. Simple agent simulation has the least values of StDev (Table 32, observation 2) on average followed by cognitive agent simulation (Table 34, observation 2), then BDI agent simulation (Table 33, observation 2), and lastly experiment real-world agent simulation (Table 35, observation 2) that has the highest StDev values. Cognitive agent and BDI agent StDev simulation results indicate that they do not have a fixed or reinforced value for that property or that their demand patterns alter over time, reinforcing or reducing demand as the simulation goes on. The latter is an indication of subjective rationality as it conveys a temporal change in personal perspective for the agent as the house attributes remain mostly the same apart from price and safety rating.

Observation 3 & 4: Comparing mean and maximum price results for each simulation.

Demand pattern differences between the simulations can be observed through both the mean and maximum price points showcased in the descriptive statistics tables. Both the simple agent simulation (Table 32, observation 3), and the BDI agent simulation (Table 33, observation 3) achieve a maximum mean price of £155333 and £145000 respectively, well below the experiment (Table 35, observation 3) and cognitive (Table 34, observation 3) agent simulations which achieve a max mean price of £170667 and £179833 respectively. This indicates that cognitive agents, much like real-world agents are interested in a larger amount of houses each round. A larger distribution of interest to more houses per turn is indicative of a decision-making pattern that values more than just the optimal solution at this moment/context but rather casts a wider net for houses that can help the agent achieve the majority of their criteria. This too showcases subjectivity in decision-making as a wider interest in houses outside the optimal range is indicative of taste and preference unique to that agent's perspective. Cognitive agents with their use of memory representation and storage, alongside their case-based decision theory, allows them to reinforce tastes and preferences through experience which aids in them making decision that go beyond satisfying a single, currently unfulfilled desire. Instead, decisions are made on the basis of what combination of desire prioritization has yielded the best results in the past.

This pattern of behaviour is also evident in the maximum price category that sees simple agent simulation (Table 32, observation 4) and BDI agent simulation (Table 33, observation 4) achieve a max price of £195000 and £185000 respectively while experiment (Table 35, observation 4) and cognitive agent simulations (Table 34, observation 4) hit a max price of £205000 and £200000 respectively. These figures of both mean and maximum price showcase the demand patterns for simple agents and BDI agents being less concentrated or fixated on specific houses in a consistent manner throughout the turns. On the other hand, both cognitive and experiment agents display high levels of persistent demand as their decision-making considerations are not determined purely on the current round context but rather, due to experience and memory in cognitive and real-world agents, they place interest for houses with attributes that in the past have served them well. This allows cognitive agents to exhibit a behaviour of house fixation regardless if that leads to a higher price and therefore lower chance of affordability for it. This behaviour is also exhibited by real-world agents which fundamentally opposed the notions of rationality as strategically, better alternatives may exist.

6.8.4 Histogram with Normal Distribution Fit analysis to identify elements of subjective rationality in demand patterns within each simulation (Frequency of price per house, demand distribution, StDev in different price brackets)

The research plotted the results of all simulations in a Histogram analysis with a normal distribution fit. This type of analysis reveals frequency of price and therefore demand levels for each house over the course of 30 rounds, allowing for a view in demand distributions and standard deviations per house in different price brackets.

The research can draw two main conclusions from this analysis. Firstly, the frequency of price per house and the resulting demand distribution is indicative of how each simulation perceives the value of each house. This is important as houses and agent attributes are maintained the same in each simulation, therefore any differences at demand distribution between each simulation is purely down to the agent's own decision-making mechanisms. This allows for a fair comparison between the real-world agents and computational agents. There are different distributions that may occur. A skewed data (either on the left or right side of the graph) indicates that the data is not normally distributed meaning that prices and general demand for houses is more in either the high or low value house price range. This means that a) agents do not differentiate enough between different house price bands and b) agents maintain demand pattern steady thus no reinforcing behaviour leading to limited to no subjective rationality involved in decision-making. A normal distribution or bell curve pattern to the frequency of price occurrence showcases a smoother price distribution, meaning agents appear to have optimal demand levels for houses around their mean price and are very sensitive to price increases and decreases. This showcases a very reactive pattern of behaviour that ensures agents maintain affordability in the face of evolving house prices. Multi-modal distribution of data has more than one peak meaning that the data represents more than one group of individuals. If a multi-modal distribution is observed in the analysis, it indicates that agents, due to their unique attributes, value/demand different ranges of houses according to how sufficient those houses within that range are in satisfying their needs. While the second group of agents require a more expensive or in-demand house to satisfy their needs. Essentially, the agents figured out which houses are enough to satisfy their criteria and, to a degree, focus their interest on them. It showcases individuality in decision-making and thus subjective rational thinking or behaviour by those decision-making agents in the simulation. When denoting distribution, the research will disregard any outliers, which are data values that are far away from others, usually located at the ends of the histogram graph. This is because outliers are minorities and can strongly affect results and therefore not representative of the majority of agent behaviours.

The second conclusion to be drawn by this data is normal distribution fit for the price of each house alongside the StDev of each house. The histogram analysis allows for the plotting of a normal distribution fit alongside the price frequency which showcases the range of demand for each house as well as its frequency of demand at each price point. The research has already analysed StDev but here, there is a comparison of deviation at different housing price points. If there is a difference in deviation between low value houses and high value houses, it is indicative of agents demand pattern. A low deviation at low value houses and high at high value houses showcases that agents have consistently low interest in low value houses (therefore mostly disregard them unless in dire need). It showcases how more agents operate and place interest at houses at high value ranges. On the other hand, a mostly even deviation at all price points indicates that agents operate and place interest on all houses, maintaining strong demand and interest for different house ranges depending on their unique attributes and perspectives. The latter is indicative of subjective rationality as agents do not only focus their attention to the houses that offer most utility but rather all houses that may solve at least some of their needs.

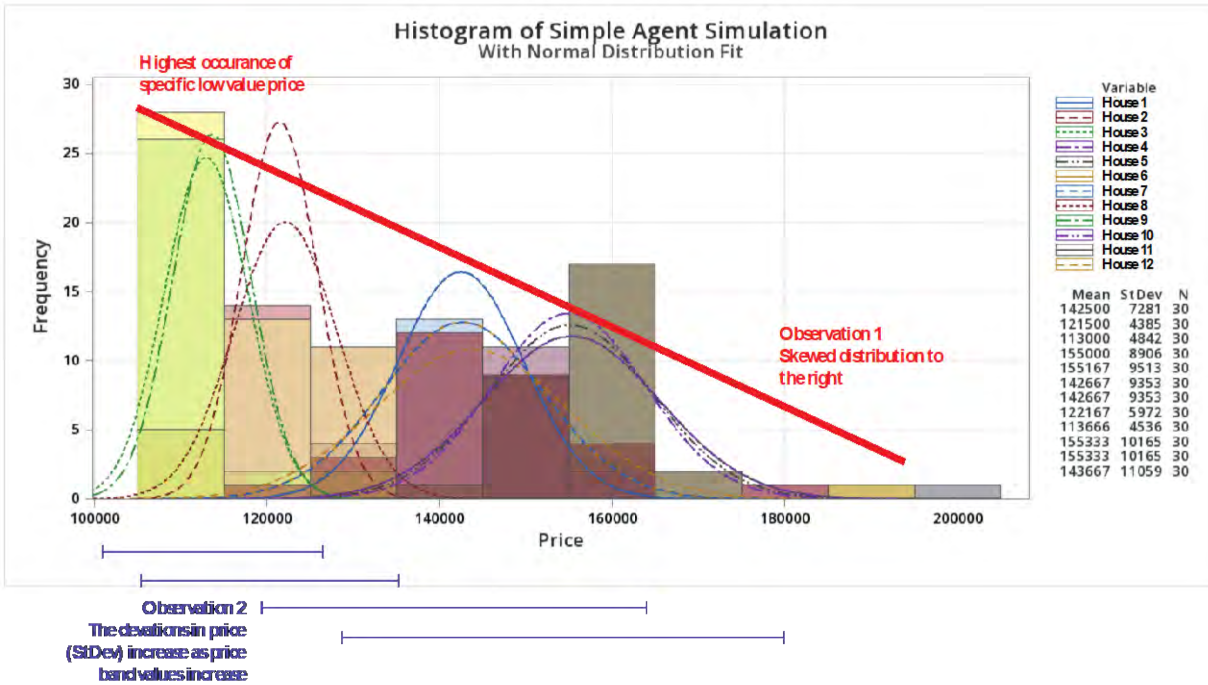


Figure 41: The figure showcases a Histogram for frequency of price occurrence for each of the 12 houses in the results of simple agent simulation. The figure also features a normal distribution fit for each house price frequency.

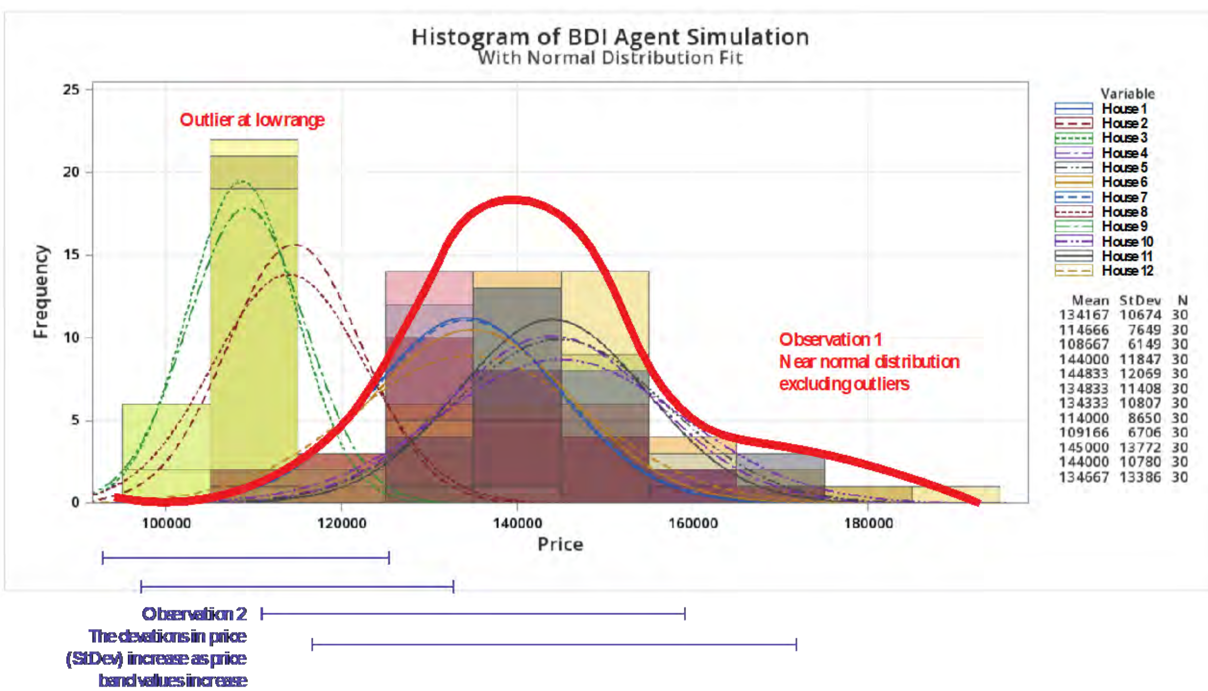


Figure 42: The figure showcases a Histogram for the frequency of price occurrence for each of the 12 houses in the results of the BDI agent simulation. The figure also features a normal distribution fit for each house price frequency.

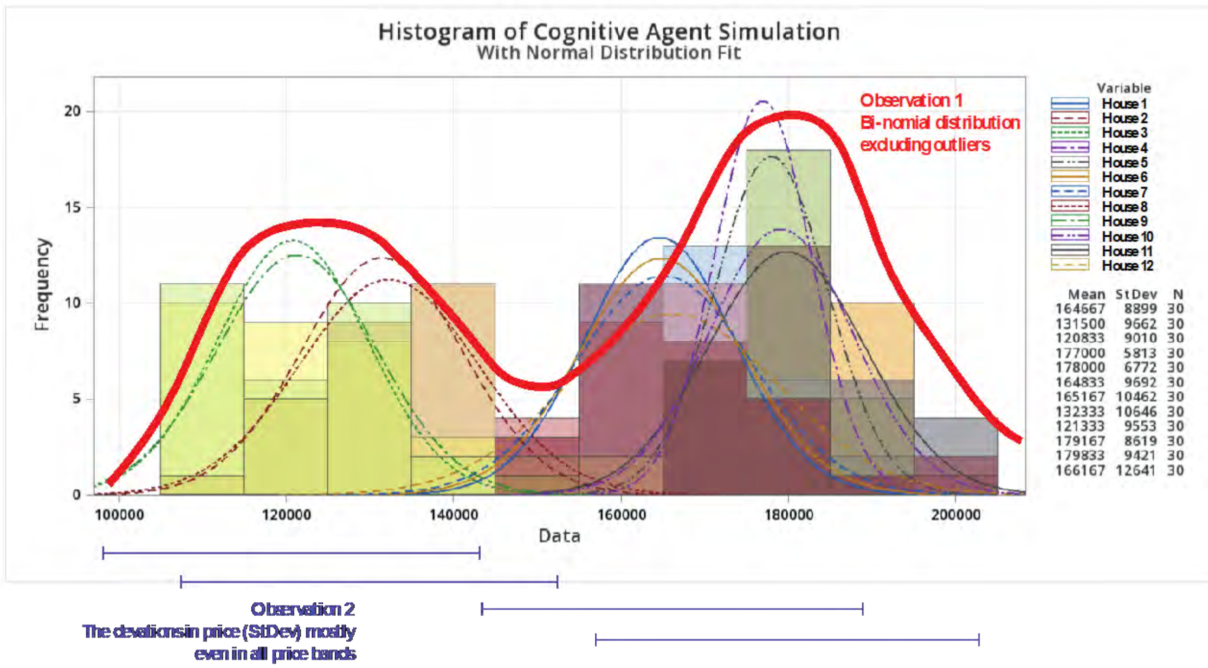


Figure 43: The figure showcases a Histogram for the frequency of price occurrence for each of the 12 houses in the results of the cognitive agent simulation. The figure also features a normal distribution fit for each house price frequency.

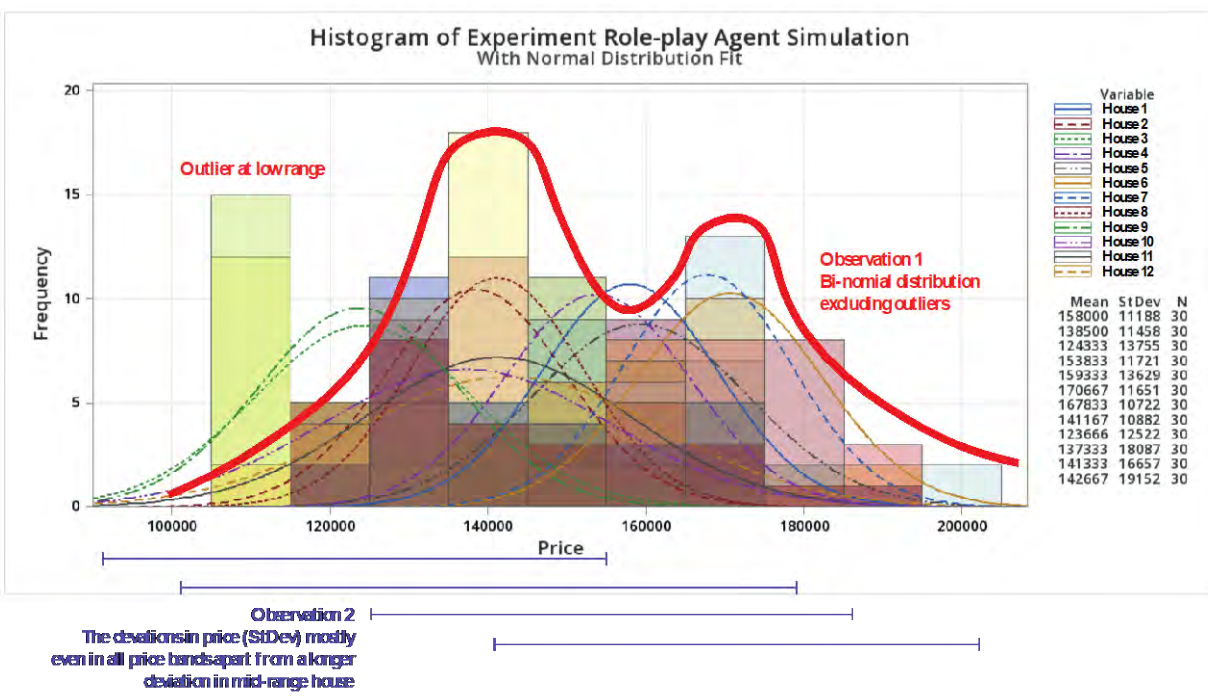


Figure 44: The figure showcases a Histogram for the frequency of price occurrence for each of the 12 houses in the results of the experiment role-playing agent simulation. The figure also features a normal distribution fit for each house price frequency.

Observation 1: Price frequency distribution analysis for each simulation

Viewing the histogram graph for simple agents (Figure 41, observation 1), there seems to be an even distribution of frequency of price levels for the price ranges between £120000 and £160000 with the exception of the lowest value of £110000 which has the highest frequency of any price range. On the other end of the scale there is the odd "one-off" occurrence of an individual price for a house reaching beyond £160000. This results almost resembles a right-skewed distribution of descending frequency of price occurrence as the price ranges increase. This matches with other analysis made on the results of the simulation that see simple agents, with utility maximisation and logic-based architecture, maintain steady levels of demands and interests in houses throughout the rounds. BDI agents (Figure 42, observation 1) on the other hand, apart from a similarly high low price range frequency of demand at £110000, there is a bell curve pattern to the frequency of price occurrence with a high point around the £140000 price mark. BDI agents have a random element to their decision-making due to their theoretical basis and therefore appear to reach lower levels of demand overall when compared to all simulations. However, the increased probability of agents not choosing a house due to its performance ensures a much smoother price distribution than any other simulation. This means agents appear to have optimal demand levels for houses around their mean price and are very sensitive to price increases and decreases. This showcases a very reactive pattern of behaviour that ensures agents maintain affordability in the face of evolving house prices. Reactivity however, does not necessarily mean subjective rationality as the agent's reactions adhere to general rules of self-interest. Similarly to BDI agents, experiment real-world agents (Figure 44, observation 1) achieve a high point in frequency at £140000 and an outlier spike at

£110000. However, unlike BDI agents, real-world agents have a second spike in frequency at £160000. This creates an almost double bell curve or bimodal distribution. In statistics, this type of distribution indicates that the data describes 2 individual groups within the spectrum. Some agents, due to their unique attributes value/demand more mid-price range houses as they could be sufficient in satisfying their needs while the second group of agents require a more expensive or in-demand house to satisfy their needs. This is in line with how the agent and house attributes where calibrated and unlike BDI and simple agents, the role-playing agents figured out which houses were enough to satisfy their criteria and, to a degree, focused their interest on them. This bimodal distribution pattern occurs similarly in the cognitive agent simulation (Figure 43, observation 1). In fact, it is even more distinct here with a clear division between two groups with the second peak occurring at £180000 which is much higher than any other simulation. This denotes that cognitive agents and case-based decision theory have the ability to focus interest on specific houses rather than distribute demand equally across them. It showcases individuality in decision-making that matches real-world agents.

Observation 2: Normal distribution fit of each price range analysis for each simulation

The normal distribution fit for the price of each house paints a similar picture in terms of decision-making patterns. StDev of each house price in simple agent simulation (Figure 41, observation 2) is different at low price range houses vs high price range houses. Specifically, low price-range houses see a smaller deviation in price which increases as the average house price increases. This pattern is similar to BDI agents' simulation (Figure 42, observation 2) that also sees StDev increase as the average house price increase. Both cognitive agents (Figure 43, observation 2) and experiment agent (Figure 44, observation 2) simulations maintain similar StDev at all price range with the exception of some outliers such as house 10, 11 and 12 in experiment simulation that has upwards of 70% StDev difference to all other houses. This might be an issue with real world agents not beginning to value houses further down the list until a later stage of the simulation forcing a higher StDev. However, the steady StDev in both cognitive and experiment agent simulations, even if they are relatively higher than simple and BDI agent simulations, showcases cognitive agents' ability to mimic role-playing agents decision-making pattern of figuring out which houses were enough to satisfy their criteria. This is indicative of how cognitive agents, similar to experiment agents, showcase elements of subjective rationality in the decision-making patterns.

6.8.5 Mean Price Graph to compare mean prices of each computational simulation against real-world agent experiment results (House mean price comparison)

The research derived the mean price of each house in the four simulations over the course of 30 turns. The results were placed in a graph to visually compare the differences in mean price and overall demand patterns for each simulation. The mean is the average value of the house and is calculated by adding up the price of each house at the end of every turn and then dividing it by 30. The research is able to draw one conclusion from this analysis. Real-world agents within the simulation and how they express interest/demand directly influences the price of each house. Though they are free to place interest on as many houses as they wish at each turn, both real-world agents and computational agents choose to limit their interest on houses that they wish to move in to in that round. This is where the comparison between the experiment mean price results and the computational agent simulation results is useful. If choices are made under objective rationality, only houses that are generally able to satisfy the majority of the agent's needs will be given interest resulting in overall lower mean price levels across the board. However, if choices are made under subjective rationality, anticipation of price changes, safety rating changes, experience and strategy comes into play when placing interest. This results in agents spreading their interest in more houses even if some of them may not fully satisfy their needs at the beginning of each turn but may results in a better outcome than what they have now. A more spread interest, results in a higher overall mean price across the board. The experiment simulation results therefore act as a benchmark for the computational simulations to showcase subjective rationality in their interest placing behaviour.

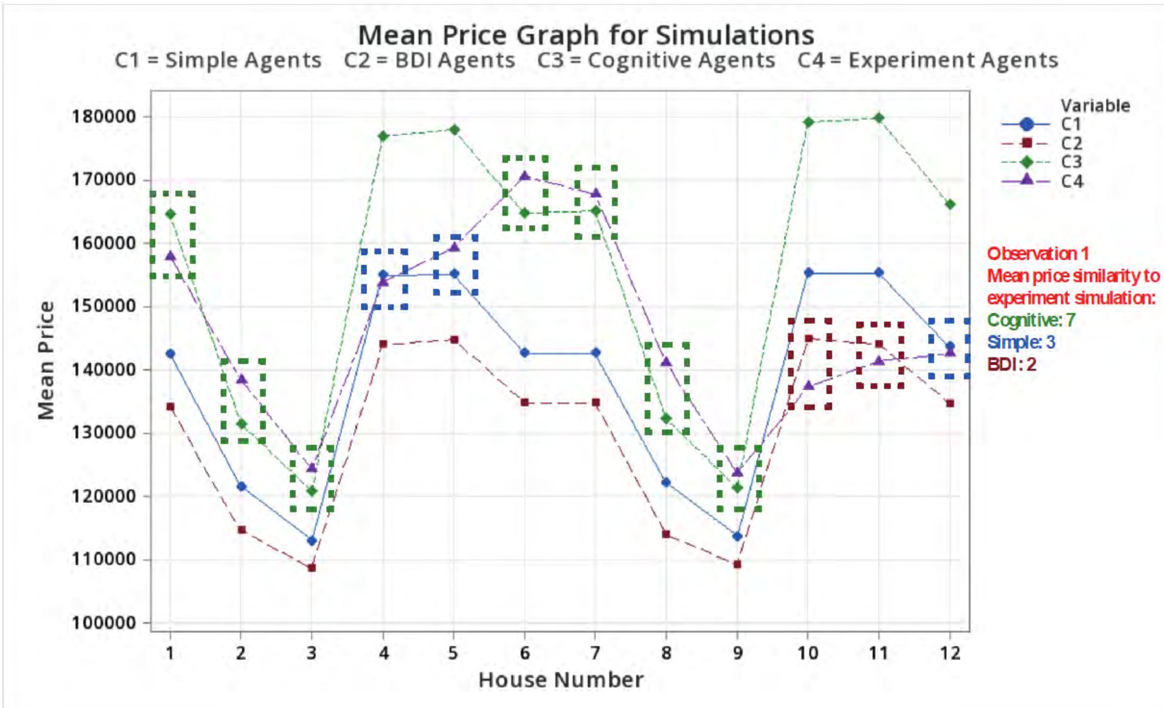


Figure 45: The graph maps the mean price of each house in each simulation over the course of 30 turns. This provides a way of comparing the overall demand for each house between each simulation.

Observation 1: Degree of similarity in mean prices for each computational simulation when compared to experiment simulation.

The graph (Figure 45, observation 1) reveals that 7 out of the 12 houses in the experiment real-world agent simulation match closest the values achieved by the cognitive simulation with simple agents achieving 3 out of 12 and BDI 2 out of 12. This indicates that throughout the 30 rounds, demand levels and by proxy price, from real-world agents aligns more closely to cognitive agents. The only houses that are vastly different between the two are houses 10, 11 and 12 and that may be explained by the massive StDev witnessed for those 3 specific houses which possibly skewed the mean value as agents drastically changed their opinion of those houses as the simulation progressed. Furthermore, the cognitive agents were the only ones able to match the relatively high mean values set by experiment agents. Looking at the other simulations results, the overall mean values for the simple agents are lower than those in experiment simulation, and the BDI agents perform the worst with mean values far lower than the rest. This is indicative of their overall demand pattern analysis in both the histogram analysis and descriptive statistics as maximum values for houses in the simple and BDI agent simulations are lower than the cognitive and experiment simulations. As mentioned before, both the cognitive and experiment agents display high levels of persistent demand for various houses as their decision-making considerations are not determined purely on the current round context but rather, due to experience and memory in cognitive and real-world agents, they place interest for houses with attributes that in the past have served them well. Therefore, the cognitive agents showcase subjective rationality in decisions made regarding the placement of interest.

6.8.6 Time Series Plot with LOWESS smoothing line.

The research run a time series plot of the results of each of the four simulations with a LOWESS smoothing line drawn on top of it to determine overall trends and patterns of demand over the 30-turn period. The active role-playing simulation results, as described in the previous section, provide some form of external validity for the three, computer ABMs. This section focuses on comparing the price evolution patterns evident in the time series plot analysis for the three different models, against the results of the laboratory experiment in order to judge their performance.

The time series plot provides us with a few conclusions that stem from different observations. These observations are made up of a LOWESS line, price bands, individual house valuations, maximum price fluctuations, minimum and maximum price values and lastly any convergent or divergent patterns between the different price bands (showcased through the LOWESS line). LOWESS (locally weighted scatterplot smoothing) smoothing line (Figures 46-49, observation 1), created by Cleveland (Cleveland, 1979) is a locally weighted polynomial regression analysis (Cleveland & Devlin, 1988). It aims to capture general patterns in the data while reducing noise and making minimal assumptions about relationships between the variables. The result is a line through the data points, used to visually assess trends and relationships. A flat or linear LOWESS line is indicative of a steady demand pattern and trend while a fluctuating or polynomial LOWESS line is indicative of shifting demand patterns through the course of the 30-turn simulation. Generally, shifting demand patterns are indicative of subjective rational decision-making as agents alter their preferences or reinforce their will and demand patterns over time through learning and experience.

Price bands (Figures 46-49, observation 2) are any distinct division in valuation of groups of houses within the simulation (these may be represented by LOWESS lines that follow the same value/trend of different houses). The number and degree of distinction between the various price bands is indicative of individual tastes and preferences. The more price bands that exist and the higher the distinction between lower and higher ones, the more subjective rational decision-making is exhibited by agents in the simulation. This is mainly due to a depiction of behaviour matching increased plurality of opinions (more price bands) and more reinforced and fixated decision-making (higher degree of distinction).

Individual house valuations (Figures 46-49, observation 3) are general observations on which particular houses are more or less valued in each simulation. The comparison between experiment agent simulation’s individual housing valuations and the three computational simulation’s valuations provides a measure of validity in terms of the computational agents having rational decision-making (i.e., agents not overvaluing low quality housing and not undervaluing high quality housing).

Maximum price fluctuation (Figures 46-49, observation 4) is the highest change in price for an individual house in the course of 30 turns. A low value here means that demand is relatively steady for the same house between rounds while a high value indicates a volatile shift in demand over time. The latter showcases notions of subjective rational decision-making as agents diverge from a decision pattern. This is due to subjective reasoning rather than objective utility since house attributes are constant other than price and safety rating. The utility rating for a house is expected to fluctuate but not enough to cause massive shifts in demand and therefore price. If such changes are noticed, then other elements are influencing the objective rational behaviour of the agents.

The value of the minimum and maximum price (Figures 46-49, observation 5) achieved by each simulation for a house is indicative of how high and low demand managed to reach for a single house in a simulation. A high maximum value indicates that agents have reinforced demand patterns, highly valuing a particular alternative. A minimum value above £100000 indicates that at all times, demand exists for all houses within the simulation.

Lastly, convergent and divergent patterns (Figures 46-49, observation 6) between price bands is the observed phenomenon of groups of houses (price bands) having their valuations move closer (convergent) or further apart (divergent) as the simulation goes on (over a 30-turn period). This can be observed through the LOWESS line as it allows for a much more visually clearer representation of moving averages within price bands. A lack of convergent or divergent patterns means that agents maintain steady differentiation between different houses and their attributes. Constant patterns of conversion and diversion is indicative of agents changing their demand patterns and valuing some attributes more or less as time goes on. The latter is indicative of subjective rational decision-making as agents begin to be influenced by experience, strategy and knowledge gain, making them alter their attitudes towards differently valued houses over time.

These conclusions are drawn from observations made on relevant figures with the research focusing on comparing the observations of computational agent simulations against observations made from the experiment real-world agent simulation results. It forms a benchmark for the different behaviours and allows for the research to comment on how well real-world behaviours are represented by the different agent theories and architectures.

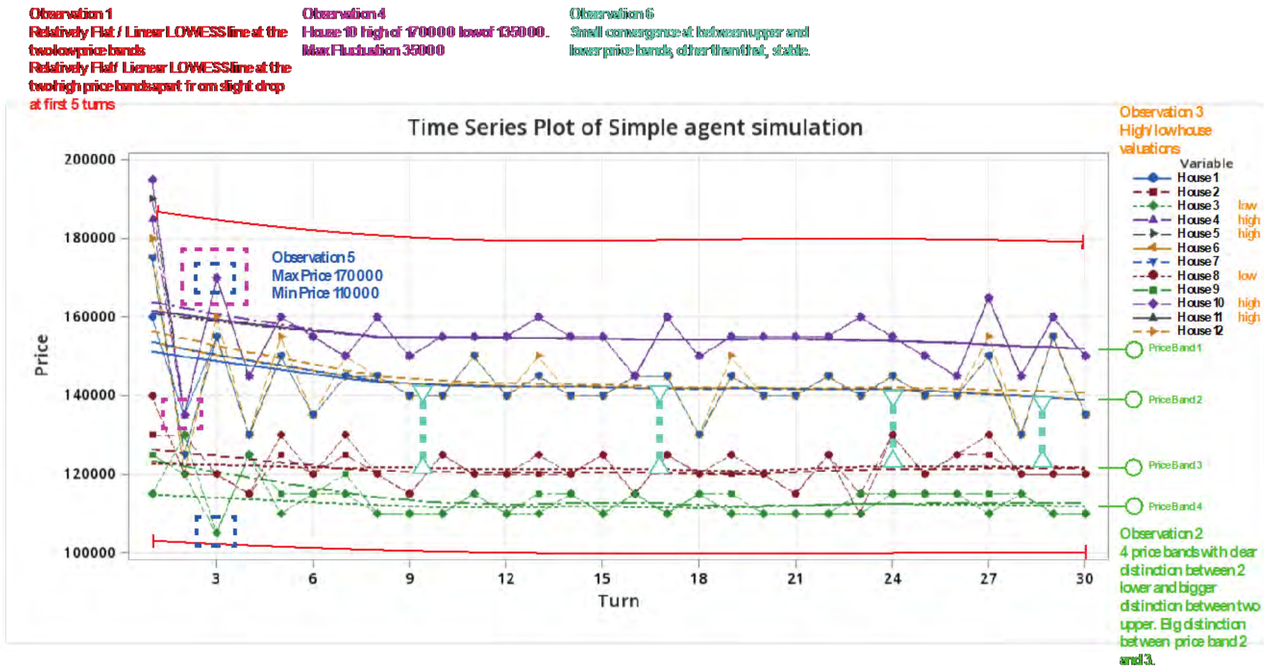


Figure 46: The graph showcases the price evolution patterns for the 12 houses in simple simulation results over 30 turns. A LOWESS smoothing line is drawn on top of the price change results to observe shifting trends.

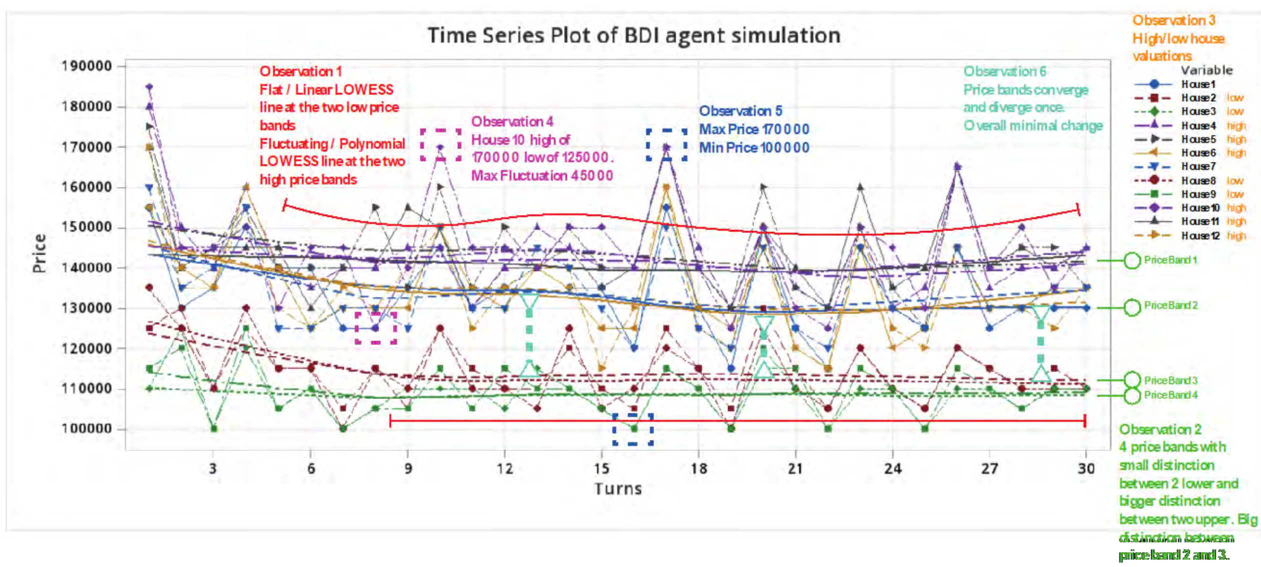


Figure 47: The graph showcases the price evolution patterns for the 12 houses in BDI simulation results over 30 turns. A LOWESS smoothing line is drawn on top of the price change results to observe shifting trends.

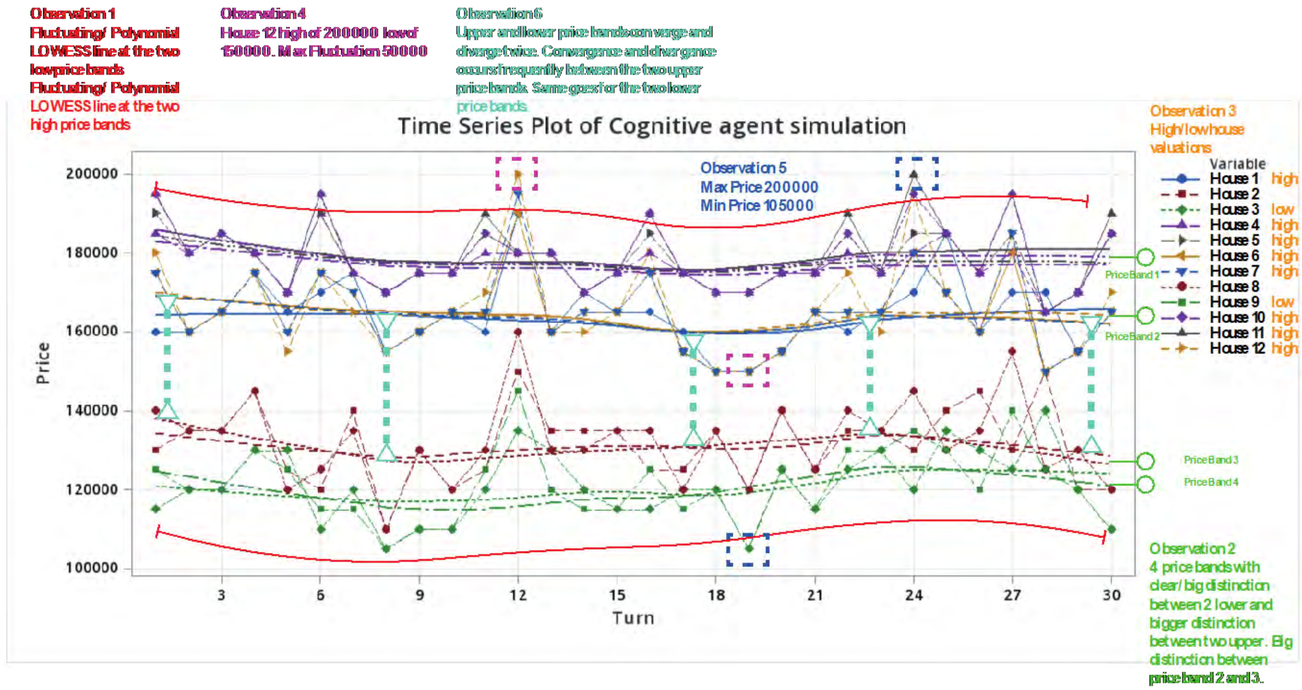


Figure 48: The graph showcases the price evolution patterns for the 12 houses in Cognitive simulation results over 30 turns. A LOWESS smoothing line is drawn on top of the price change results to observe shifting trends.

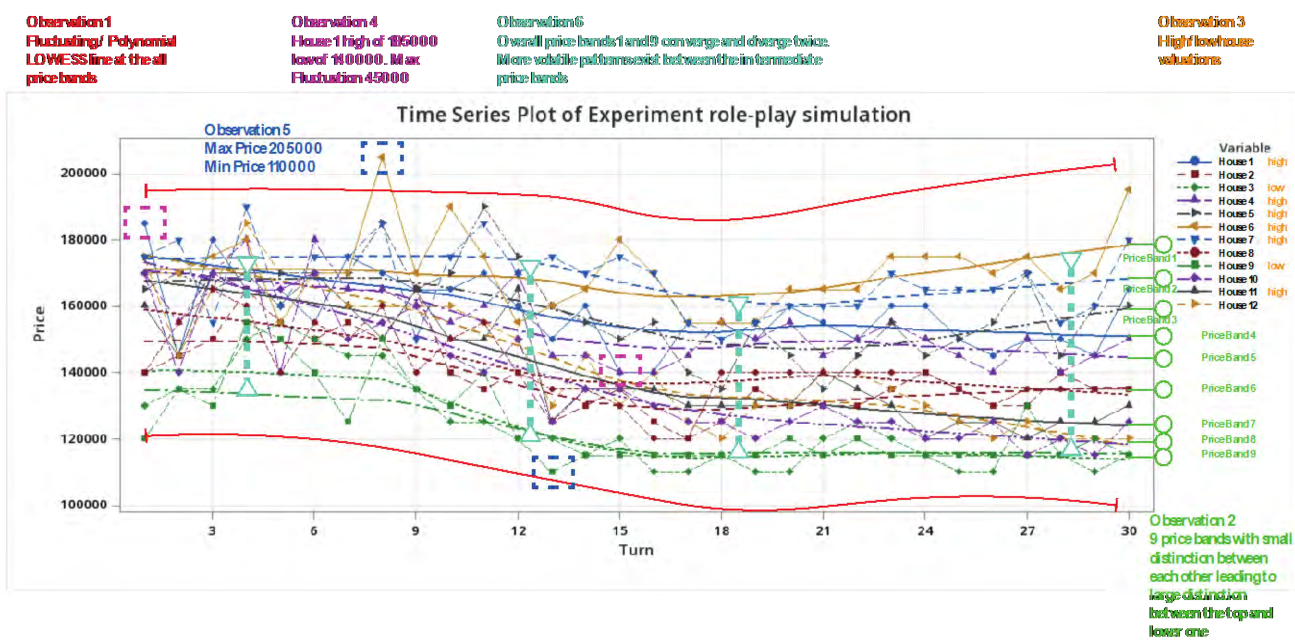


Figure 49: The graph showcases the price evolution patterns for the 12 houses in Experiment role-play simulation results over 30 turns. A LOWESS smoothing line is drawn on top of the price change results to observe shifting trends.

Firstly, the research compares the simple agent model (Figure 46) time series plot results with the laboratory experiment (Figure 49). It is evident that, the simple agents' results have the least in common with the active role-playing simulation. The four price bands (Figures 46, observation 2), exhibited by the LOWESS smoothing line, that are distinct in the simple agents' model, does not feature in the laboratory experiment, which exhibits 9 price bands (Figures 49, observation 2). However, both simulations seem to value, for the most part, the same houses higher and lower. For example, in both simulations, houses 3 and 9 are always at the very lower end of the price range while houses 6 and 7 are some of the most highly valued and demanded (Figures 46/Figure 49, observation 3). Fluctuations in price is another aspect that does not match in the two simulations. Simple agents seem to have a relatively steady demand for housing, with one fluctuation of £35000 with the rest being around just £20000 max (Figures 46, observation 4), while the lab experiment undergoes much bigger price fluctuations of upwards of £45000 (Figures 49, observation 4). This is further conveyed by the LOWESS line that is relatively flat/linear in simple agent simulation (Figures 46, observation 1) and rather wave like / polynomial in the experiment simulation (Figures 46, observation 1). This signifies a shift in demand patterns for the experiment agents throughout the course of the 30 turns while on the other hand, a steady demand and valuation of each house for the simple agent simulation. The general trend in price is also different as houses in the laboratory experiment seem to diverge in price as the simulation goes on, with an ever-increasing gap between the most expensive house and the least expensive (Figures 49, observation 6). In the simple agents' simulation, no such trend exists, with a steady demand maintaining housing prices at the same or similar level throughout the simulation (Figures 46, observation 6). It is worth noting that at no point, in both simulations, does a house price fall to its base value of £100000, indicating demand exists for all houses at all times (Figures 46/Figure 49, observation 5). In fact, the simple agents maintain a minimum value of £110000 for the majority of the simulation while the laboratory experiment fluctuates heavily at the start, with minimum price of up to £130000 before settling to around £110000 at the latter stages of the simulation, past round 15. On the other end of the price range, the maximum price for any house in the simple agent simulation is £170000 while the laboratory experiment reaches prices of £205000. This is not constant for the latter with the prices steadily increasing as the simulation goes on. This shows a reinforcement in demand as agents in the laboratory experiment have the capacity to learn which house best satisfies their needs and increase demand for it. Simple agents lack the ability to learn and reinforce behaviour thus maintain a steady demand level with minimal fluctuations.

The second model for comparison, the BDI agents' model (Figure 47), has more in common with the laboratory experiment results (Figure 49) than the simple agents model. Similar to the laboratory experiment, there are major fluctuations throughout the simulation, with some differences in the trends. Though both have fluctuations of upwards of £45000 (Figures 47/Figure 49, observation 4), the BDI agents seem to follow a specific trend that sees prices peak and bottom every 3 turns during the latter stages of the simulation. This does not occur in the laboratory experiment where the initial rounds mimic, in part, the chaotic fluctuations of the BDI agents but then becomes a much more predictable trend after turn 10. Furthermore, BDI agents have 4 distinct price bands (Figures 47, observation 2), shown by the LOWESS smoothing line, that maintains in consistency throughout the simulation. This is in contrast to the laboratory experiment that has 9 distinct price bands (Figures 49, observation 2). However, when comparing the LOWESS smoothing line of the two simulations, both exhibit a polynomial/fluctuating line pattern that signifies a changing demand pattern for the high-value houses (Figures 47/Figure 49, observation 1). For BDI agents, the LOWESS smoothing line for the lower two-house price bands, consisting of 4 houses, does not have a fluctuating pattern to it but rather a linear one. This showcases that BDI agents exhibit a shifting demand pattern for high-end houses while a steady demand pattern for lower-valued houses. This duality in temporal patterns is unique to BDI agents as they seem more assured of the value of cheaper houses than expensive one. A similar pattern can be observed from the 2 lowest valued houses in experiment agent simulation as after turn 15, those two houses are the only ones that maintain a steady LOWESS line value (Figures 49, observation 1). It is worth noting that, similar to the simple agents, BDI agents and role-playing agents value specific houses more or less equally in terms of their demand (Figures 47/49, observation 3). Both the lower price range and the higher price range features similar houses in both simulation results. Unlike the simple agents and the laboratory experiment results, the BDI agents, at times, have no demand for specific houses resulting in that house's value to be baseline at £100000. This difference in prices between BDI and role-playing agents extends to the higher price brackets, with the BDI agents only ever achieving a maximum of £170000 value for a single house, while the role-playing agents achieve as high as £205000. These observations indicate that BDI agents, with their random element, seem to showcase similar chaotic fluctuations to the first 10 turns of the role-playing agents. However, as role-playing agents become more familiar with what housing attributes best enable them to satisfy all their goals, their decision-making changes to a more predictable with a steadier upwards trend that sees the majority of houses maintain their position in their respective individual price bands. It appears that the BDI agents somewhat account for notions of bounded rationality and subjectivity in decision-making through their probabilistic theoretical basis. This shows promise as it generally performs better than the simple agents when compared to the laboratory experiment results.

Lastly, the research compares the cognitive agents (Figure 48) with the role-playing agents in an attempt to establish the former's performance and ability to mimic their decision-making patterns. Both the laboratory experiment results and the cognitive agent ones, showcase major fluctuations throughout the simulation (Figures 48/49, observation 1). The four price bands, exhibited by the LOWESS smoothing line, that are distinct in the cognitive agents' model (Figures 48, observation 2), does not feature in the laboratory experiment, which in fact has 9 bands (Figures 49, observation 2). Both have max fluctuations of upwards of £45000 with cognitive agents actually achieving slightly higher maximum fluctuation of £50000 (Figures 48/49, observation 4). Unlike the BDI agents, the cognitive agents, similar to laboratory agents do not seem to follow a specific trend in fluctuations. In fact, the cognitive agents have constant conversions and diversions of house price bands which is similar to the laboratory agent results (Figures 48/49, observation 6). These are constant in the cognitive agent's results, but this does not occur in the laboratory experiment where the initial rounds feature in part chaotic fluctuations until it changes to a similar pattern of diversion and conversion after turn 10. It is worth noting that, similar to the simple agents, the cognitive agents and the role-playing agents value specific houses more or less equally in terms of their demand (Figures 48/49, observation 3). Both the lower price range and the higher price range features similar houses in both simulation results. Furthermore, both cognitive agents and role-playing agents maintain demand for lower-end houses at all times throughout the simulation (Figures 48/49, observation 5). In fact, the cognitive agents are the only computer agent model to mimic the minimum price hike of housing up to £125000 during a conversion of the housing price bands. Though the cognitive agents have more frequent convergence and divergence patterns throughout the simulation, they are the only computer agents capable of doing this based on the results. To elaborate, similar to trends observed in the role-playing agents, the cognitive agents showcase the ability to, at the same time, have the minimum price of a house to be at the maximum for the simulation while the maximum price of a house is at a minimum for the simulation and vice versa. The similarities between the role-playing agents and the cognitive agents continue in the higher price brackets, with the cognitive agents able to achieve a maximum of £200000 value for a single house, while the role-playing agents achieve a similarly high price of £205000 (Figures 48/49, observation 5). This showcases that the cognitive agents, with their ability to reinforce their decision-making patterns through memory representation and experience, imitate in part a role-playing agents' ability to learn and reinforce their decision-making patterns as the simulation goes on. As role-playing agents become more familiar with what housing attributes best enable them to satisfy all their goals, their decision-making changes, forcing a diverging of price bands for houses. This is very similar to the cognitive agents as they grow their memory and tastes based on what they experience with the four distinct house price bands changing by the end of the simulation to be more individualistic, similar to the role-playing agents. When comparing the LOWESS smoothing line of the cognitive agent simulation vs the experiment agents, both exhibit a fluctuating/polynomial line pattern that signifies a changing demand pattern for the high-value houses (Figures 48/49, observation 1). For the cognitive agents, the LOWESS smoothing line for the lower two-house price bands, consisting of 4 houses, maintains a polynomial pattern that convergence towards the end of the 30 turns. Thus, cognitive agents exhibit a shifting demand pattern for all houses irrespective of their value causing price bands to converge and diverge (Figures 48, observation 6). This volatility in LOWESS line pattern can be observed in the experiment real-world agent simulation that, apart from the 2 lowest valued houses, demand patterns fluctuate heavily while price bands converge and diverge at different time in the simulation (Figures 49, observation 6). It is worth noting that after turn 15, the real-world agents appear to have a divergent pattern of LOWESS line for all price bands as each house gains a more definitive value. Cognitive agents also showcase a divergence after turn 24 but not between each price band but rather between the two upper and the two lower price bands. This indicates the ability of the cognitive agents to simultaneously begin to demand and value more the houses that offer them better chances at satisfying their needs and beginning to minimise their demand for houses that will categorically not satisfy their needs. This creates a division in the customer base, similar to what was observed by the binomial curves in histogram analysis of both the cognitive and the experiment agent simulations. Both of these agents are able to subjectively decide and reinforce their demand patterns over time to meet their overarching needs not only their immediate needs which is what the BDI and the simple agents are programmed to do through their respective theoretical basis. Historic knowledge is not factored in for the BDI and the simple agent's decision-making consideration renders them unable to exhibit a distinct agent behaviour of being more interested in houses that you expect would better meet all their needs in the future as learned from experience.

6.8.7 Creation of a meta-table to judge computational agent likeness to real-world agents.

The research has created a meta-table that encompasses all findings from the analysis and judges each computational simulation outcomes to its likeness with the experiment role-playing simulation outcomes. Overall, it seems the cognitive agents have the most in common with the role-playing agents in terms of their results as they enable subjectivity in decision-making through their ability to make decisions based on memory. This shows promise as it generally performs better than simple agents which dominate the field at the moment. BDI agents also perform better than the simple agents in their ability to mimic the results of the experiment agents, which in some ways exceeds the ability of the cognitive agents to do so. However, on the whole, the cognitive agents appear to have them highest likeness as 17 out of the 27 parameters favour their results. The deciding factor here appears to be the unpredictability of other agent decisions that makes current utility maximisation and the BDI computational agents unable to truly deal with both the safety criterion and affordability criterion. In this case, both the cognitive and the real-world agents seem to have a weapon that aids them in this aspect, their ability to learn as they go through the simulation and note which houses have been more likely to meet those evolving needs. As such, it forces the agents to behave in a way of shifting order parameters similar to Haken's synergetics (Haken, 1980; Portugali & Haken, 2018). It sees them locked in valuing certain homes more and more as they better serve them in achieving their goals in the past while inevitable re-occurrences of similarly high levels of criterion satisfaction only serves to reinforce their decision-making causing an ever-growing demand for high-end housing. This goes on until affordability makes them seek alternatives which destabilises the market to a new order paradigm of low-value housing demand rises. This in turn changes as their needs are not met and they begin to value once again more high-end housing which begins to rise in price and eventually affordability urges them to consider once again alternatives. This constant cycle of reinforcement and break down is what causes convergence and divergence in demand patterns with spikes in demand for low-value houses being experienced at much higher levels in the cognitive and the real-world agents, both of which spike to levels up to £160000 while in the BDI and the simple agents, low-value homes never exceed beyond £130000.

	SIMPLE AGENTS	BDI AGENTS	COGNITIVE AGENTS
Price Bands	🔴	🟡	🟢
Maximum Value	🟡	🔴	🟢
Minimum Value	🟢	🔴	🟡
Mean	🟡	🔴	🟢
Q3 / Q1 Difference	🔴	🟡	🟢
Highest Value Homes	🔴	🟡	🟢
Lower Value Homes	🟡	🟢	🟡
Max Price Fluctuation	🔴	🟢	🟡
Price cross correlation first 15 rounds for high value house	🟢	🟡	🔴
Price cross correlation first 15 rounds for low value house	🟢	🟡	🔴
Price cross correlation after 15 rounds for high value house	🔴	🟡	🟢
Price cross correlation after 15 rounds for low value house	🔴	🟡	🟢
Decomposition seasonal fit (low value house)	🔴	🟢	🟡
Decomposition Trend (low value house)	🔴	🟢	🟡
Frequency of fluctuations (low value house)	🔴	🟡	🟢
Amplitude of fluctuations (low value house)	🔴	🟢	🟡
MAD (low value house)	🔴	🟡	🟢
Decomposition seasonal fit (high value house)	🔴	🟡	🟢
Decomposition Trend (high value house)	🔴	🟡	🟢
Frequency of fluctuations (high value house)	🔴	🟡	🟢
Amplitude of fluctuations (high value house)	🔴	🟢	🟡
MAD (high value house)	🔴	🟡	🟢
StDev	🔴	🟢	🟡
Frequency of price per house	🔴	🟡	🟢
Demand distribution	🔴	🟡	🟢
StDev in Different price brackets	🔴	🟡	🟢
LOWESS line pattern	🔴	🟢	🟢

🔴 Least Likeness 🟡 Moderate Likeness 🟢 Highest Likeness

Table 36: A summative table of analysis indicating the likeness of each result from each simulation to the results obtained and analysed from the real-world agent role-playing simulation experiment.

6.9 Chapter summary

In the chapter, the research sought to describe a methodology, namely active role-playing simulation conducted as a laboratory experiment, in an attempt to provide the three complex agent models with external validity. The reasoning and choice of this method is clearly explained at the first few sections of the chapter. Following that, the research outlines the design of the active role-playing simulation that includes the model design, experiment design, and participant information. All information surrounding the experiment is outlined and explained. Following the experiment run, all results are analysed and discussed including possible reasonings as to why the experiment got those emergent patterns. The active role-playing simulation results were then used to compare the results from the three different models, against the results of the laboratory experiment in order to determine their performance. All four simulation results were further analysed statistically using a variety of methods which included cross-correlation analysis of price over time, time series decomposition, histogram analysis, descriptive statistics, mean price analysis, and a time series analysis with LOWESS smoothing line. This cumulated to a Table of results (table 36) that summarized the findings of each computational simulation when compared to their results likeness with the experiment simulation.

The chapter establishes that the simple agents are the least similar to the role-playing agents while both, the BDI agents and cognitive agents establish in different ways, a higher potential to mimic the reasoning/patterns generated by the role-playing agents. This effectively proves their potential that merits further investigation and research into real-world application.

CHAPTER SEVEN: DISCUSSIONS

7.1 Discussion on results from the analysis of the four simulations

Discussion of relevance of results on modelling theory and ESU-AF1 findings towards a contribution to urban planning

In the literature review chapter, the thesis explored the current state of urban simulative models using the ESU-AF1 framework. This analytical approach revealed a series of prevalent theories used as the basis for these models. In combination with an analysis of the different generation of urban simulative models and their trends, the research revealed how disaggregated modelling based on McFadden's discrete-choice model (1978) currently dominates the field in Gen 3 models (explained in section 2.4.7). This generation of models are usually agent-based and predominately use utility maximisation (Iacono et al., 2008b) as the basis for their agents' decision-making mechanisms, forgoing previous macro-level theories such as Bid-Rent theory, Input-Output theory and Economic base theory. These decision-making agents form the basis of the Modelling Framework step (Figure 6) of an urban simulative model with their theoretical basis driving the set of assumptions for the interaction of agents within the model. The simple agent simulation created by the research mimicked this set of assumptions with the use of ordinal utility (section 4.7) in an attempt to compare the current state of these models to this research's innovative test models. Both the BDI and cognitive agent models created as part of this thesis attempt to push the assumptions dominating this step within urban simulative models while ensuring that they do not limit subsequent choices made at lower levels (section 2.4.5, figure 8). In other words, they act as direct alternatives to current OMoTs and are interchangeable within a Gen3 urban simulative model. The results obtained by running and comparing the three models (section 6.8) cemented this by revealing agents in all simulations had similar distinctions between different houses (Figure 46, 47 & 48 explained in section 6.8). Therefore, to some degree, these new models with their new architectures and theoretical basis, maintain the ability to rationally make decisions adhering to the overarching Rational Choice theory (Macmillan, 2008) framework that governs this step within urban simulative models (Figure 7). This means that the research **contributes to the field of urban planning and modelling through the creation of alternative location choice models that can be interchangeable within the current generation of urban simulative models.**

Secondly, **the empirical analysis of agent architectures/theoretical basis of urban simulative models, specifically agents making decisions on location choice offers unique insight to new and existing researchers in the field**. Elaborating on that, in chapter three, the analysis of current urban simulative model agents is presented (Table 4) with regards to agent architecture capacity. The interest here was solely in simulative models that include micro-simulations and agent-based interactions within their human system representations. As such, the evaluating variables for the cross-case analysis (Table 3) were the concepts and properties present in the agent architecture. The research analysed previously reviewed urban simulative model work in published reviews with the exclusion of all models with no micro-simulative aspects. This type of analysis provides a unique insight not only to what already exists in the state of art but the limitations of this area from a very fundamental level, the coded agent architectures. It builds on Ettema's critic of a distinct 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). It not only proves Ettema's point but infers in the conclusion in table 5, specific agent theories and architectures that may be used to address it. This is important as the two new computational complex agent models created by this research form an improvement to their utility maximization-based counterpart. The study of the urban environment necessitates the utilization of complex decision-making agents due to its inherent nature as a temporal process of change, characterized by self-organization, unpredictability, and human intervention. By examining the interactions among various components, elements, and agents within urban processes at a granular level, it becomes possible to observe emergent patterns that manifest across different spatial and temporal scales of behaviour. This approach aims to unravel the underlying logic behind urban patterns and flows, which cannot be comprehended through reductive methodologies alone (Sengupta, 2017).

Thirdly, the thesis incorporates those agent theories and architectures in the creation of two innovative computational agents (BDI and cognitive, explored in chapter 4). The research then proceeded to run and test these computational experiments, running them in a 30-turn simulation within a controlled virtual environment to record their results. The research also creates a third computational model, based on ordinal utility with simple agents representative of the logic-based architectures currently used in Gen3 urban simulative models (explained in section 2.4.7). Then, using a laboratory experiment with role-playing real-world agents as a means to validate and compare the results of the three models, demonstrated that the results gained by the experiments, question the theoretical foundations of urban modelling in two ways. **a) A different approach with new agent theories and agent architectures is viable within the field. B) The results showcase that it is not only worth exploring further but provides a possible evolution from utility maximisation theory as the basis for decision-making agents.** Elaborating on the second point, the development of two new disaggregate ABMs (in chapter 4) to simulate dynamically, the co-evolution of urban location choice and price patterns on real estate, showcase the potential of more complex agent architectures. Although the currently used theoretical base of utility maximization helps simulate some of the complex behaviours in human decision-making, it also falls in the trap of homogenising taste between agents. However, if we consider notions of self-organisation and emergent from a complexity perspective, applied to the urban realm (Batty, 2012; Batty & Marshall, 2012a; Portugali, 2006), then urban change is driven by the chaotic interactions of people, self-organising following some type of top-down or external influence and subsequently resulting in the emergence of a new urban pattern. **Therefore, more complex agent behaviours, with a subjective rationality theoretical basis rather than objective rationality, would better represent their real-life urban household counterparts.**

These disaggregated ABMs created in this thesis, consist of two new and novel agent architectures in urban simulative models, BDI agent architecture and Cognitive agent architecture. The creation of these simulative models features computerised agents demanding and exchanging houses in a simulated world. The contribution revolves around the models unique theoretical and agent architecture framework and their overall performance when compared to the results obtained through the lab experiment in chapter 6. This is particularly evident in Table 36 that indicates the likeness of each result from each computational simulation to the results obtained and analysed from the real-world agent role-playing simulation experiment. It proves calls in the literature to improve upon these agent decision-making mechanisms (Ettema et al., 2005) as in reality, people reinforce and change their decision patterns which currently causes limitations on the reliance of empirically-derived relationships (Verburg et al., 2002) when you have computational agents with fixed utilities. This is especially true when the population's own context and even attributes are constantly evolving, as is the case in any urban environment. However, this issue as well as the lack of impact of demographic changes to demand for dwellings (Ettema, 2011) appears to be improved with the use of both BDI and cognitive agents to a degree as it better represents their decision making patterns of real-world agents (section 6.8).

Discussions of planning evolution and the relevance of results obtained towards a contribution to Planning practise.

The three models begin to diverge when you further analyse them revealing different agent behaviours in each one. This is particularly important if we reflect on the literature review regarding the role of urban simulative models as tools for planners (Harris, 1965) (section 2.5). Their aim is to aid in investigating and proposing solutions to planning problems (Batty, 2009a) and they evolve alongside planning theories and practise whose own evolution is a reflection of the shifting values, meaning and actions of society (Allmendinger, 2009). Looking at the critics and real-world observations regarding the major planning theories dominating the field (section 2.5 figure 12), it is evident that planning has shifted from a rational comprehensive approach, where the planner's view is perceived as the objective truth in all situation, to a collaborative communicative rationality approach (Allmendinger, 2009), where the planner understands there is a plurality of perspectives and theirs is not the objectively correct one. As such, urban simulation tools need to adapt to enable the representation of individuals with unique tastes and preferences. Subjective rationalities are what account for choices of taste or for choices under uncertainty. To account for subjectivity, usually in urban simulative models, the demand for land is justified from survey data of homeowners and their activities in a particular period in time. This enables the empirical generalization for space choice of individual agents/homeowners in urban simulative models thus creating objectivity using a utility maximisation theoretical basis for agent decision-making. The issue here is the abandoning of subjectivity in this decision-making process. Though empirically assessed through the survey data, the validity of those decisions only stands for that moment in time for that particular population making decisions on those particular spaces. Therefore, the context in which those decisions have been made, including the individual's own perception, experience and values are not truly accounted for with the use of utility maximisation. This is reflected in the results obtained by the simple agent simulation when compared with the experiment agents (section 6.8), particularly the cross correlation of price evolution (Figures 26 – 31). Simple agents, during the first few rounds appeared to more closely match the demand patterns of real-world agents when compared to the results of the BDI and cognitive agents. However, as the simulation progressed, and real-world agents began involving their experiences and strategies within their decision-making patterns, this trend was broken, and simple agents began to have the least likeness with real-world agents. At that point, cognitive agents, with their ability to include experience and memory in their decision-making processes, began to outperform all other computational simulations. BDI agents remained a constant performer at all timeframes during the 30-turn simulation being second-best to either simple agents at the start or cognitive agents past turn 15. This showcases the architecture's and corresponding theoretical basis's ability to maintain a good level of performance regardless of changing individual perceptions and opinions of real-world agents over time.

The research conducted in this thesis **addresses a notable gap in the existing literature by providing novel contributions to planning practice and urban design. Specifically, it focuses on the development and enhancement of two tools that have the potential to significantly improve the understanding of complex urban situations. These tools enable planners to adopt more sophisticated approaches in testing various scenarios by manipulating key parameters.** By bridging this gap, the thesis equips planning practitioners with advanced methods that facilitate a more comprehensive analysis of urban environments, leading to more informed decision-making processes in urban design and planning. The first, is a model of BDI agent architecture that introduced desire prioritisation in the decision-making process of agents demanding space. Furthermore, this model incorporated individualism for the agents and the notion of subjective rationality by shifting the weightings of each desire for each agent to be unique to their perspective. To achieve this, the agent's creation drew from the theory of planned behaviour in order to calibrate each desire's appeal to the unique characteristics that make up each agent. The second tool is a model that makes use of cognitive agent architecture from the computer science as a means of including memory storage and representation in the decision-making process of agents demanding space. To achieve this, the agent's creation drew from cognitive theories that include Case-Based Decision theory and consumer behaviour theory to deal with decision-making under uncertainty and cognitive decision-making on subjective housing attributes. Contrary to existing models in the field that currently feature within a planning toolkit, these two unique urban simulation prototypes feature in two distinct ways a new method of modelling agents and their decision-making processes expanding the current utility maximization modelling techniques present in disaggregated urban simulative models. This effectively pushes the capacity of these type of simulations and unlocks the ability to answer more complex questions for the end-users which now form part of current planning practice as described in the previous paragraph (Sengupta, 2017).

Discussion on current issues with communicative rationality and the importance of results obtained in aiding the issue towards a contribution to planning and architecture/design in general.

Considering the evolution of urban simulative models as tools to solve planning problems, the current issue in communicative planning is that it fails to separate ends from means (Allmendinger, 2009). Even if communicative rationality is used by planners to determine end goals, the means are not defined and revolve around formal procedures that take precedent over end goal values. Issues with problem identification and definition by stakeholders, brought upon by incomplete information on context, values and alternatives, prevents ideal speech (Allmendinger, 2009). Therefore, even with communicative rationality, a clear agreement may not be possible between all parties as power in society is unequally distributed resulting in the lack of undistorted communication due to the existence of domination, repression and ideology. The results gained by the cognitive agents' simulation, revealed that they are capable of exhibiting subjective rationality patterns of behaviour. This was evident in their histogram analysis (Figure 43, observation 1) that showcased a binomial distribution, only present in the real-world agent simulation results (Figure 44, observation 1). As such, cognitive agents can make decisions based on their context that favour them as individuals rather than a collective, forming different groups within the population, each with their own values and needs. This exhibited behaviour is particularly important as it has the ability to aid communicative planning practice. Cognitive agents can act as context specific stakeholders and unbiased participants of collaborative planning in "live action" simulations and explorations of open discourse. They can resolve conflicting ideologies without the presence of power dominance as they are untouched by external forces and only focused on their own individual needs given their unique set of context and circumstances. Thus, they allow for the testing of the means with direct indication of end goal effects on different stakeholders improving the quality of planning decisions. Beyond solutions, they can also aid with problem identification through the unbiased interaction between subjective goals/means. In a design context, this knowledge is invaluable as it provides an insight into user preference and needs, making any proposal more valuable to that specific population by achieving the equitable distribution of future resources. This design element extends beyond large scale urban planning and policy, into architectural design of buildings and their association to each other, effectively improving the value of those designs through repeat testing and identification of demand born through the subjective means and goals of the population that makes up the social context around it. Therefore, the thesis contributes to planning and architecture/design **by introducing and testing these new computational agents which allow designers to both formulate accurate representations of problems and simulate the value of their future designs beyond the objective parameters of proximity and size.**

Discussion on the results capacity to answer the literature's need for improvement in agent architecture and capacity towards a contribution to economics and computer science.

The primary contribution of this study to economics and computer science lies in addressing an existing gap in the literature pertaining to the modelling of urban dynamics. The new BDI and cognitive architecture-based models and their perspective theoretical basis (explored in Chapter 4) adopted by this research are an original exploration and adaptation of theories and methods from these two disciplines in the field of urban modelling. The results of their performance, when compared to existing utility maximization agents (Table 36), challenges the current use of the theory and architecture and suggests possible better performing alternatives.

As explored in the literature, though the new wave of urban simulative models (section 2.4.7) builds on the notion of disaggregated modelling with more intricate behavioural aspects for agents and decision-mechanisms/variables there still exists a 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). There are limitations on the reliance of empirically-derived relationships (Verburg et al., 2002) and a lack of impact of demographic changes to demand for dwellings (Ettema, 2011). This aspect is reflected in the results of simple agent simulations when considering both the low StDEv (Table 32) and flat pattern of the LOWESS smoothing line (Figure 46). The aim of these agents is to build objectivity in an otherwise subjective decision within the real world. Evolutionary criteria such as shifting prices and changing safety ratings on each neighbourhood do little to deter from a utility maximisation agent's demand pattern as the majority of its utility is derived through the other six criteria. As explored in section 6.8, the difference between Q1 and Q3 numbers for all simulations, point to simple agents having the least likeness (Table 36) to real-world experiment agents, with cognitive (Table 34) and BDI(Table 33) agent simulations fairer much better. This is indicative of the extent of price deviations present in the simulations as simple agents with their use of ordinal utility maintain a much steadier housing value and demand fluctuation as real-world agents appear to drastically change their demand patterns as the simulation goes on. This aspect is better represented in both BDI and cognitive agent simulations with a Q1-Q3 difference closer to the real-world agents with the pattern maintaining when analysing STDev of the different simulation models. Simple agents have the least values of STDev on average followed by cognitive agents then BDI agents and lastly experiment real-world agents that have the highest STDev. Both Q1-Q3 differences and STDev reinforce the fact that real-world agents appear to have changing and reinforcing patterns of demand brought on by subjective rational thinking. In reality, people reinforce and change their decision patterns which causes limitations on the reliance of empirically-derived relationships (Verburg et al., 2002) especially when the population's own context and even attributes change. However, this issue as well as the lack of impact of demographic changes to demand for dwellings (Ettema, 2011) appears to be solvable with the use of both BDI and cognitive agents to a degree. Though, arguably, BDI agents' ability to shift their demand pattern heavily relies on their probabilistic nature of their theoretical basis as explored in section 4.5.1. This forms a limitation as agents do not necessarily have the capacity to adapt accordingly but rather shift the probabilities to resolve their agent architecture's chosen primary desire. Cognitive agents on the other hand have the capacity to naturally evolve their demand patterns to both their own shifting preferences and past experiences. This is reflected in their LOWESS smoothing line (Figure 48) having a fluctuating pattern rather than a smooth stable trend much like real-world agent simulation (Figure 49). BDI agents have a similar fluctuating LOWESS smoothing line (Figure 47) at the high value houses range but a much smoother and steadier one at the low-range house. This showcases the ability of this agent architecture to account for shifting situations such as evolving and chaotic price and safety patterns reducing reliance on survey demand data calibration (Rosenfield et al., 2013) and allowing for demand changes to occur should the simulation desire to shift agent demographics during the runs (Ettema, 2011).

Ettema et al. (2005) mentions that there is a distinct 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. Though the simulations do not have an element of negotiation, the introduction and testing of cognitive agents revealed that they do possess the ability to adjust their behaviour. An analysis of their LOWESS smoothing line showcases a divergence after turn 24 (Figure 48) between the two upper and two lower price bands. This indicates the ability of cognitive agents to simultaneously begin to demand and value more the houses that offer them better chances at satisfying their needs and beginning to minimise their demand for houses that will categorically not satisfy their needs. This creates a division in the customer base, similar to what was observed by the binomial curves in histogram analysis of both cognitive (Figure 43) and experiment (Figure 44) agent simulations. Both of these agents are able to subjectively decide and reinforce their demand patterns over time to meet their overarching needs not just their immediate needs which is what BDI and simple agents are programmed to do through their respective theoretical basis. Historic knowledge is not factored in for BDI and simple agent decision-making consideration and this renders them unable to exhibit a distinct agent behaviour of being more interested in houses that you expect would better meet all their needs in the future as learned from experience. The literature calls for the advantages of disaggregated behavioural approaches (Vorel et al., 2015), especially in urban land-use models that have a lot to benefit from ABM with intelligent agents (Huang et al., 2014). However, to the best of this researcher's and other researchers knowledge, currently there are no geographical spatial applications of advanced cognitive behaviours and agent architectures (Heppenstall et al., 2016). The research presented in this thesis has therefore not only attempted to address issues surrounding the lack of specific agent behaviours, but rather incorporate and introduce a massively new cognitive agent architecture framework accompanied by new to the field theoretical basis as ASU-AF1 revealed how no model uses Case-based decision theory (Figure 7). **The thesis has innovatively tested an agent architecture from computer science in the field urban simulation for the first while simultaneously testing the fitness of specific economic decision theories in determining demand for real-estate.**

The work contributes to the field of economics through the testing of different economic theories as the basis for decision-making mechanisms for computational agents vs a direct comparison with real-world decision-making agents in a controlled environment. The application of Utility Maximisation in the context of urban modelling can be criticised given the results of this study (Table 36). The research approach followed by this thesis showcased that when compared to real world human decision-makers in the same situation, some decision-making theories fared better than others. The laboratory experiment featured in chapter 6 enabled a direct testing of the performance of three decision-making economic/psychology theories when applied to the field of urban modelling. These theories tested are Utility Maximisation theory which has thus far been the gold standard in the field of urban modelling (Figure 11), Case-Based Decision Theory and Theory of Planned Behaviour. Out of the three theories, the analysis revealed that Utility Maximisation was the worst performing theory while Case-Based Decision Theory was the best performing decision-making theory when applied to an urban modelling context.

Furthermore, the thesis contributes to computer science through the comparison of different agent architectures when applied to an urban modelling context. The computational models created as part of this research (logic-based, BDI and cognitive) as well as the validation technique followed (active role-playing simulation), demonstrated that BDI and Cognitive agent architectures (Table 36) improve upon logic-based architectures when dealing with decision-making agents in an urban modelling context. The analysis revealed that Cognitive Agents are the best performing architecture when applied to an urban modelling context given the parameters set out within the controlled experiments/computational models.

7.2 Discussion on relevance of findings to other researchers

As explored in the previous section, the research has a number of key findings that are potentially of great interest to researchers in the urban modelling, computer science, economics and planning/architecture fields. Firstly, the thesis concluded that current real-estate models feature agent architectures that have a:

1. Lack of cognitive agents using memory storage and representation
2. Lack of collaboration between agents to achieve goals
3. Lack of belief, desire, intention agents (BDI)
4. Lack of pro-activeness traits

These findings establish a gap in terms of the number of computer science-based approaches implemented within an urban modelling field. This research tried to utilize some of these missing features, specifically the lack of cognitive agents and lack of BDI agents, in an attempt to evaluate their relevance and performance against traditional logic-based utility maximization agents. The results of all three models were assessed against role-playing agents to externally validate them. In doing so the research concluded that both cognitive and BDI agents outperform simple logic-based agents in mimicking human role-playing agents, with cognitive agents seemingly performing the best (Table 36). These conclusions offer great insight to future research in this area, providing proof that cognitive agents are well worth consideration for any modeler creating or incorporating a real-estate demand model within a wider urban simulative model. The lessons from this research may also be of use to strategic planners that are in the market for an urban simulative model to help them predict the effects of their own planning decisions/designs. By understanding the different decision-making theories and modelling techniques available, it can allow them to make a more informed choice depending on their own needs as well as data availability.

These finding are interesting, especially the outperformance of cognitive agents featuring memory storage and representation. According to both Axelrod (1997a) and Crooks et.al (2018), there are arguments against modelling a system with increased complexity. However, it appears that additional agent attributes such as those in BDI agents and cognitive agents, help the model in outperforming simple logic-based agents. This finding is in line with other researchers' findings in the literature of urban simulative models seeking to harness the advantages of disaggregated behavioural approaches (Vorel et al., 2015) with ever-more advanced agent modelling and techniques.

Considering recent attempt to improve agents in real-estate demand modelling (Fatmi et al., 2017; Fatmi & Habib, 2018; M. Habib et al., 2011; M. A. Habib & Anik, 2021; Hong et al., 2012;

Jokar Arsanjani et al., 2013; T. Li et al., 2020; Wang & Waddell, 2013b; Yao & Wang, 2021), this research work focuses solely on the decision-making mechanisms and compares between different theoretical basis and agent architectures. Unlike the references above, this research focuses on investigating the performance of different models rather than the creation of a single real-estate model for application. As such, the conceptual models of this research will act as guides in the creation of new, innovative complete real-estate models, tested in a real-world application for other researchers. It offers encouraging results in the application of both a) BDI agents with a Theory of Planned behaviour basis and b) cognitive agents with a Case-Based Decision theory basis in real estate modelling, that other researchers can take forward.

CHAPTER 8: CONCLUSIONS

8.1 Overview of thesis

8.1.1 Context and ideas that bind the thesis.

In a poll ordered by the Commission for Architecture & the Built Environment in the summer of 2002, 81% of people mentioned that they are interested in how the build environment looks and feels. They agreed that building/space design impacts quality of “daily life, professional productivity, educational attainment, physical well-being, levels of crime and house values”(Lipton, 2002, p. 2). The value of a house plays a crucial role in assessing the overall impact of design on various aspects mentioned earlier and beyond. In light of this, the objective of this PhD research was to enhance the evaluation and prediction of demand and, consequently, the value associated with a particular design or space. This was achieved by focusing on improving agent decision-making within urban simulative models, which are commonly utilized for this purpose.

The fundamental issue with judging / predicting an individual’s decision in any situation heavily relies on whether the empirical generalization by which the prediction scenario’s rules are based on, were constructed under a “subjective” rationality or “objective” rationality. The distinction here is important because an objective rationality choice is scientifically, factually correct or right. The decision maker himself on the other hand, directly influences the correctness or justification for a subjective rationality choice.

Such subjective rationalities are what account for choices of taste or for choices under uncertainty. Here lies the gap in measuring value and demand for land/space/design in urban simulative models. Currently, the demand for land is justified from survey data of homeowners and their activities in a particular period in time and used to project decisions using theories stemming from objective rationality. However, the evolution of economic theory, predominantly in the area of consumer behaviour, established how a range of internal determinants, relating to one's own motivations, and external determinants, relating to outside factors have the possibility to influence decision-making on an individual level (Gibler & Nelson, 1998). The subjective rationality behind consumer behaviours relating to land / building / space / design choices creates the issue with the current theoretical applications for urban simulative models. It is primarily trying to create objectivity in an otherwise subjective rational choice. This lack of ability to account for subjectivity has been further magnified with recent disruptions caused by the Covid19 pandemic as current urban theories of agglomeration are unable to explain new patterns of housing choice. It further lacks the ability to incorporate any aspects of design that go beyond calculable physical building attributes and proximities. Architectural design is more than the creation of a measured collection of rooms within a plot with specific proximities to different amenities.

8.1.2 Main issues and debates in this subject area and what the research addresses

The new wave of urban simulative models (Gen 3 as seen in Figure 11) builds on the notion of disaggregated modelling with more intricate behavioural aspects for agents and decision-mechanisms / variables. The literature clearly indicates that researchers in the field of urban simulative models are seeking to harness the advantages of disaggregated behavioural approaches (Vorel et al., 2015).

This research investigates the potential of new disaggregated behavioural techniques with the ultimate aim to improve agent decision-making mechanisms to allow for subjective rationality. These improvements include notions of cognition, judgment and decision-making processes, consumer behaviour and the role of experience in decision-making through the use of Case-based decision theory (section 4.6.1) and Theory of Planned behaviour (section 4.5.1). These theories were applied to novel simulative models of housing demand using previously unexplored agent architectures for the area that includes BDI agent architecture and cognitive agent architecture. A third model was created using logic-based agent architecture that acts as the control experiment with both the theoretical basis and agent architecture mirroring that of a typical module of its nature within the wider literature (section 4.7). All three models run a computer simulation in a virtual environment featuring 3 neighbourhoods, 12 houses and 24 agents seeking to choose a house that best satisfies their needs. The aim is primarily to test the potential of the new theories and agent architectures used within the three models.

The capabilities of the new agents created gets tested through a laboratory experiment featuring an active role-playing simulation where people replace the very agents in the computer simulation and make decisions on their behalf. The participants of the experiment are given the same attributes and roles as their counterparts in the computer simulations while being placed in the same virtual environment with the same choices and objectives. The experiment seeks to validate the potential of the new theoretical basis and agent architectures created as part of this research. Furthermore, it ensures that the potential of the novel computational models created warrants further research and application to real world scenarios.

8.1.3 Reasoning for researching decision-making mechanisms in urban simulative models based on recent developments in the field.

Considering new publications in the field, it’s evident that there is ongoing research into decision making mechanisms for agents within urban simulative models. Fatmi and Habib (2018), have recently proposed a new prototype for the integrated transport, land-use and energy (iTLE) model (M. A. Habib & McCarthy, 2021)(M. A. Habib & Anik, 2021) that incorporates how life circumstances of agents affect their location choices. This particular model is based on the theory of residential stress that suggests that residential stress triggers a household’s decision for moving to a residential location - generated by changes in life-stages, dwelling characteristics, and neighbourhood attributes (Fatmi et al., 2017). This is based on fuzzy logic-based location search model and its implementation in the iTLE model, simplified using a multinomial logit model to address the utility equations that determines probability of entering the market and choosing a specific residential space. These utilities evolve using coefficients that change as the agent's life-stages change. This seeks to create some form of subjectivity in decision-making based on the life cycle of people, however the agent architecture basis is still logic-based and still attempts to create objectivity in decisions though by adding some more caveats in terms of life-circumstances.

Other recent attempts featured egalitarian bargaining, Nash bargaining, and utilitarian principles (Yao & Wang, 2021) that sought to incorporate group decision-making within the household location choice dynamic. This features a Latent class discrete choice modelling approach which incorporates personality traits for agents that sees them having higher or lower tendency towards egalitarianism in collaborative decision making (Yao & Wang, 2021). Other attempts, seeks to improve on a classic utility maximization location choice model with the addition of reference-dependent theory (T. Li et al., 2020). These attempts demonstrate emerging research into the area and how this thesis' contribution, with the look into both innovative theoretical basis and agent architecture can aid in improving decision-making mechanisms in the field.

Keeping the progress of urban simulating models through Gen 1, Gen 2, and Gen 3 (as described in Chapter 2 and concluded using the ESU-AF1 model) in mind, it is evident that urban modelers sought to innovate within the field for decades. The direction of innovation is clear as the field moves ever-further away from aggregated theoretical calculations and assumptions towards disaggregated modelling with a call from established researchers in the field to investigate cognitive agents capable of adjusting their behaviour (Ettema et al., 2005). Agents for simulating housing search and choice while incorporating negotiation between developers and potential buyers in a dynamic context (Ettema et al., 2005) with researchers in the field urban simulative models currently seeking to harness the advantages of disaggregated behavioural approaches (Vorel et al., 2015). If we consider the current developments in the field stated above, there is still a lack of innovation within the agent architecture with most developments adjusting utility maximization equations in an attempt to incorporate subjectivity in the decision-making mechanisms. Therefore, it was vital for this research to push innovation in the field further by borrowing from computer science as well as economics to introduce new to the field computational architectures and theoretical basis for decision-making mechanisms. This is an attempt to create a Gen 4 series of urban simulative models that move to incorporate further conditions and dynamic preference weighting depending on agent perspectives at different points within the simulation.

8.2 Revisiting the research objectives and questions.

The research established a set of objectives and questions that emerged from an initial literature review. Using the ESU framework to assess urban simulative models, a number of observations regarding the literature became clear. Firstly, there was a clear move from macro-simulation to micro-simulation for the field. ABM was at the forefront of this with its application mainly confined to the module within urban simulative models that dealt with location choice. Thus, this research aimed to innovate within this module that, for the most part, forms perhaps the most important part of a larger LUTI-type model. Of course, these modules are sometimes standalone models themselves, therefore, the research's first aim/objective was to classify these using an umbrella term and then create a definition for it.

1) Classify real-estate demand urban simulation models.

The term real-estate demand was invented by this research in an effort to establish a term for all models and modules that would be investigated. A 'Real-Estate Demand' urban simulation model is part of the spatial interaction model family that incorporates a range of different urban simulation models such us urban growth and land-use. The main characteristic of this model is the ability to assign value, both monetary and otherwise (demand), to buildings/land/plots (space).

This definition adequately describes all models and modules that abstract real-estate markets and their processes. This enabled the research to move towards a review of real-estate demand models in an attempt to understand the current literature around them.

2) Undertake a systematic review of real-estate demand models analysing their theoretical basis, model scale, decision factors and spatial interaction modules.

To achieve the second objective, the research created, in collaboration with other researchers, the ESU-AF1 analytical framework. It allowed the research to understand and categorise the incorporation of theoretical assumptions at various points in a simulative urban model.

After the research has assessed both the theoretical basis and the operationalized models of theory that are used to apply it within urban simulative models, the focus switched solely to real-estate demand models that used ABM or microsimulation. These models represented the current attempts to harness the benefits of disaggregated modelling within the field. The research proceeded to set a goal to evaluate the agent architectures behind these models in an attempt to understand whether the field fully utilized the capabilities of such models by making use of all possible attributes afforded by such modelling techniques.

3) Evaluate current agent architectures in use for real-estate demand models and assess any limitations that may exist.

The research used a cross-case analysis, to assess existing models on their agent architecture capacities, directly answering the question set by the research.

The summed-up conclusions of the cross-case analysis, in terms of current lacking agent attributes, were as follows:

1. Lack of cognitive agents using memory storage and representation
2. Lack of collaboration between agents to achieve goals
3. Lack of belief, desire, intention agents (BDI)

4. Lack of pro-activeness traits

This provided the research with clear agent architecture objectives to hit with the creation of new conceptual complex agent models. It also set the limitations in identifying new theoretical basis for the computational models to be created by this research. These theories needed to utilize the agent attributes that are currently lacking in the field in an attempt to evaluate if their use would yield sufficient benefits when compared to what is currently in use.

4) Build simplified computational urban simulation models for real-estate demand with a range of theoretical basis for agent decision-making processes.

The research created three distinct computational ABMs of real-estate demand. Each model consisted of 24 agents in a virtual environment made up of 3 neighbourhoods and 12 houses. The first model featured the Theory of Planned Behaviour and utilised BDI agent architecture to determine agent decision-making i.e. housing choice. The second model featured Case-Based Decision theory and utilised cognitive architecture with memory representation and storage influencing agent decision-making. The third and last model featured a classic utility maximization agent using Ordinal Utility theory and a logic-based architecture. This model was not meant to be innovative, it featured a common modelling method and theoretical basis and acted as the means to compare the performance of the other two models in relation to what the field currently used. These models were defined using the ODD+D protocol to allow for a universal description of their capacities that could be understood by the wider research community. Following a series of parameter sweeping experiments aimed at enabling the models to yield comparable results, the three model outputs were analysed and assessed. The main form of assessment was the emergent pattern of price evolution of housing as it was directly dependent of agent demand/decision-making. Due to the models being conceptual and not applied to a real-world site, there were no data by which to generalize the results of the analysis. Therefore, the research opted to create a method that would externally validate these results. This came in the form of a laboratory experiment that would enable the three models' performances to be compared against real-world people decision-making in the form of role-playing agents.

5) Run a human role-playing simulation/game laboratory experiment with 24 participants playing assigned imaginary roles to externally validate the models.

The human role-playing simulation laboratory experiment approach was designed and executed using 24 willing participants. The approach provided the research with the means by which to externally validate the performance of the three models. Though a laboratory experiment has its downsides, primarily the limitation of factors under consideration, the research opted for that one as opposed to a real-world test as it enabled the focus on known parameters influencing decision-making and thus creating an even playing field of comparison for all three models.

6) Draw conclusions on the capacity of new computational agent simulation models to display patterns of behaviour befitting subjective rationality through statistical analysis of results and their comparison with role-playing simulation.

The research compared the performance of three different computer ABMs (simple agents, BDI agents, and cognitive agents) against the results of a role-playing simulation laboratory experiment that simulated a housing market (section 6.8). The discussions (chapter 7) revealed that the simple agent model has the least in common with the laboratory experiment, as it lacks the ability to learn and reinforce behaviour, resulting in a steady demand with minimal fluctuations. The BDI agents model shows promise in accounting for bounded rationality and subjectivity in decision-making, with its probabilistic theoretical basis, showcasing similar chaotic fluctuations to the first 10 turns of the role-playing agents. However, as the role-playing agents become more familiar with housing attributes that best enable them to satisfy their goals, their decision-making changes to a more predictable, steadier, less chaotic fluctuating trend. The cognitive agents model performs the most similarly to the laboratory experiment, with steady fluctuations throughout the simulation and constant conversions and diversions of house price bands.

8.3 Discussion of findings from the empirical studies

The research conducted a cross-case analysis of a number of agent-based real estate demand models in an attempt to investigate the agent architectures used to determine it. This revealed a number of conclusions that are summed up below:

1. Lack of cognitive agents using memory storage and representation
2. Lack of collaboration between agents to achieve goals
3. Lack of belief, desire, intention agents (BDI)
4. Lack of pro-activeness traits

Considering the wider literature within urban simulative model discipline, there have been criticisms of real-estate demand models (sometimes mentioned as location choice in the literature) and call for improvements. These range from a 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 (P. H. Verburg et al., 2002), lack of impact of demographic changes to demand for dwellings (Ettema, 2011), a lack of calibration methods for parameter values to ensure best fit of model (Kii & Doi, 2005) and a lack of cognitive agents capable of adjusting their behaviour while incorporating negotiation between developers and potential buyers in a dynamic context (Ettema et al., 2005). The literature clearly indicates that researchers in the field urban simulative models are seeking to harness the advantages of disaggregated behavioural approaches (Vorel et al., 2015). Furthermore, it is evident that some of the conclusions derived from the empirical studies, such as lack of cognitive agents, collaboration between agents and pro-activeness traits are echoed by other researchers in the field that call for the improvement of ABM for real-estate demand models. This showcases the importance of this research, as it attempts to test the performance of some of these lacking agent architecture features while introducing a number of, new to the field, agent theories that can make use of them.

This research forms the initial steps at incorporating BDI and cognitive agents in real-estate demand model through a conceptual modelling approach in a controlled, virtual environment that enables a fair comparison between the new innovative complex agent models and both their logic-based and their role-playing agent counterparts. In doing so, the research creates the basis of understanding the performance of these models against what is commonly used in the literature and real-world human decision-making. Determining their usefulness in a range of real-world applications remains to be seen, however, the empirical studies of this research, which include the analysis of models using the ESU-AF1 framework, provides the first attempt to acknowledging both the current agent architecture attributes used today and the agent theory that limits its potential. This quantifiable approach of qualitative computational aspects enables future researchers to investigate the progression of the field and real-estate demand models in terms of agent capacity and coding.

Some ABM researchers, especially in the field social science, view ABM as a primarily a means of representation, with little regard of how that is implemented in a computer program (Polhill et al., 2019). Though they acknowledge that some environments and languages are more convenient than others, their primary concern is the end results in the form of behavioural representation of a social system/entity. This research disagrees with this type of thinking as the agent architecture and agent attributes directly influence the level of representation. Andrew Crooks et al. (2017) mentioned the need for an appropriate level of complexity for a model that is justified by the target system it strives to represent. An excessively complex ABM may be harder to understand than the system is tries to emulate. Though that may be the case, it should not deter the use of different agent attributes that, at first seem more complex, as they may yield better results. Axelrod (1997b) poses the “Keep it Simple, Stupid” (KISS) approach that argues for models to be as simple as possible at first with additional complexity being added only if the model fails to adequately represent the system. Edmonds and Moss (2004) however, pose the “Keep it Descriptive, Stupid” (KIDS) approach that argues for a model to start by reflecting all evidence and knowledge about the system, regardless of complexity, while removing unnecessary features iteratively as you progress. This research agrees with the KIDS approach that would allow for the use of a full range of agent attributes initially, to represent the system, in this case location choice for households in a real-estate demand model. This approach does not inhibit the potential of system representation to simple agent attributes though simplification of the system may be needed as the modeler progresses through the modelling process in order to remove unnecessary complexity.

Regardless of the modeler’s individual views on model complexity, what is evident from the results of the empirical studies is that there are underutilized agent architecture attributes that have the potential to improve performance and system representation. Without modelers adequately exploring these and attempting their implementation, it is impossible to judge their usefulness and value. It is therefore imperative that future research continues to push for more complex agent behaviours in real-estate demand models in a perpetual quest for better agents and better model performance.

8.4 Reflecting on the discussions of the simulation model development and simulation/laboratory results.

8.4.1 Extent of generalizability of results obtained and reflections on methodological choices.

The focus of this research was on testing different complex agent models for residential location choice modelling within urban simulative models, using a laboratory experiment as the testing ground. The aim was to assess the generalizability of these models beyond the controlled environment of th**e** laboratory **experiment**.

The modelling focus is primarily on agent decision-making, with less emphasis on the **level of abstraction** of the virtual environment or the exact replication of market forces compared to real-world scenarios. The experimental setup deliberately employed simplified market dynamics to accentuate the effects of agent decision-making on housing prices. Consequently, the impact of environment fidelity and market forces on the generalizability of results was deemed negligible **to the validity of the results**. The laboratory experiment, juxtaposing human decision-makers with computational agents, successfully facilitated a comparison of different agent architectures. The outcome, highlighting the superiority of cognitive agents over logic-based counterparts, was externally validated through the role-playing simulation. Notably, the behaviour of role-playing agents closely mirrored that of cognitive agents, underscoring the validity of the findings.

However, the aforementioned decisions of the research in both the use of an active role-laying simulation / laboratory experiment as the means of validation and the simplification of market dynamics and processes in real-world location demand scenarios bring forth key limitations. Firstly, the choice to simplify market dynamics and exaggerate the impact of demand on price of house was done to limit the research scope of this study. Understanding market dynamics and researching the nuances of real-estate markets as well as providing a suitably high-resolution abstraction of it in a computational environment while experimenting with more complex agent dynamics and data needs proved too big of a challenge for a single PhD study. Therefore, the research had to focus on what it sought to investigate, in this case, the introduction of more subjective rationality in agent decision-making within location-choice models. An alternative of this approach would have been to use an existing urban simulative model and just change the location choice component with the new agents while employing it to a real-world setting. However, this limited the usefulness of these agents and their performance in a real-world setting to that particular urban simulative model's package and limitations. The research wished to test a new range of agent theories and architectures, unattached to existing modelling frameworks that could be employed for a range of simulation purposes that extent beyond a single modelling package's capacity. The choice, therefore, was to limit the degree of fidelity to market dynamics. This ultimately changed the aims of the research by limiting the ability of the novel agents to be employed in a real world setting for validation purposes. As such, the research pursued the path of a laboratory experiment as the means of validation, knowingly limiting the validation of the agents to purely their decision-making mechanisms in this particular controlled environment. Though the results of it provides merit of employment of said novel agent theories and architectures in a real-world setting, it also provides key limitations to the work. Notably, the model itself cannot be tested in a real-world setting without the introduction of further / truer market processes. These need to be coded within the model as updated processes and interaction for the agents. Therefore, any further research will require an element of market knowledge and abstraction before employing the novel agents to a real-world setting. These need for changes does not extend to the agent theory, architecture and coded mechanism of decision-making which can be redeployed as such. This brings forth a second limitation of the research's choice of level of abstraction and validation, the extent by which the agents perform similarly better than their standard counterparts in a different setting. Though the research proved that the decision-making of both the cognitive and BDI agents performs better than industry standard utility maximising agents when compared to real people decision-making, the fact that the test environment is limited in both market processes and complexity of considerations, encourages further examination on their ability to replicate this result in a different setting.

8.4.2 Reflection on the discussion of results

This thesis extensively explored the landscape of urban simulative models, using the ESU-AF1 framework and qualitative analysis of existing real-estate demand models. It also delved into agent architectures, proposing innovative cognitive and BDI models to address existing limitations. These new models were compared against traditional utility-based models, revealing their potential to offer nuanced insights into planning and design challenges.

The discussion reflected on the evolving nature of planning theories, noting the current shift towards collaborative communicative rationality. Based on the results obtained by the study, the introduction of cognitive agents was highlighted as a means to shore up some of the shortcomings of this theory by potentially offering to mitigate power imbalances and enhance the quality of planning decisions through unbiased discourse of computational agents acting on behalf of their real-world counterparts. The agents have shown a level of cognitive intelligence through the statistical analysis of their results, able to imitate pattern behaviours exhibited by their real-world counterparts in a controlled environment. This brings hope that further research, leading to the implementation of cognitive agents in a real-world setting, can help improve urban planning processes.

A missed opportunity to explore this potential further was during the creation and running of the laboratory experiment. I made a decision to directly compare the results of the experiment and the results of the different computational agent simulations using a range of statistical analysis. This placed a limitation on what was recorded and evaluated to determine reasoning for decision-making. During the course of running the laboratory experiment, participants expressed some of their reasonings for making specific choices in the housing market. Though the environment was controlled and the market processes heavily abstracted from reality, participants role-playing still made decisions on reasons other than maximising their criteria. For example, after failing to procure a highly coveted house that would ensure they satisfy the maximum number of criteria, some participants expressed their desire to instead choose a lesser alternative that had a higher probability of successful purchase. This choice, as they mentioned, was to ensure that their family of 4 had at least a home to live in as they have been homeless for the last 5 rounds. This change in strategy and the subjective reasoning behind it would have been a very useful aspect of the results had it been recorded in a formal manner. Here lies the missed opportunity because, what led to real world agents forming bonds and affiliations to lesser than objectively better alternatives, and the process of cognitive agents behaving the same, has not been explored in this research. The emergent patterns are similar though the process and mechanisms that led to them are not fully recorded and discussed. This was perhaps beyond the scope of this study as the market and real estate environment differed from a real-world alternative. This missed opportunity does however inform future research into cognitive agents for urban simulations. For to truly calibrate and implement such agents in a real-world setting, the mechanisms that lead to subjective reasoning in a real-estate market need to be explored using qualitative research methods and then abstracted and implemented computationally using cognitive agents.

This reflection ties in with the thesis' identified shortcomings in current urban simulative models, particularly regarding the incorporation of spatial attributes and demographic influences on housing demand. The introduction of cognitive and BDI agents was posited as a step towards addressing these limitations and enriching behavioural modelling in urban planning. Simple utility agents have limitations in representing real-world agents, whereas cognitive and BDI agent simulations perform better. Real-world agents have shifting patterns of demand influenced by subjective rational thinking. The combined use of BDI and cognitive agents can resolve the limitations of empirically derived relationships and demographic changes to housing demand to some extent. BDI agents' demand patterns rely heavily on their probabilistic nature, while cognitive agents can evolve their demand patterns naturally to their shifting preferences and past experiences. Although the simulations do not include negotiation, which is another current shortcoming revealed through the literature review, cognitive agents have demonstrated the ability to adapt their behaviour. Disaggregated behavioural approaches are increasingly preferred in urban land-use models, which can benefit from intelligent agent application. The discussion highlighted the importance of exploring new theoretical and agent architecture frameworks to improve decision-making mechanics in urban simulative models. It discussed the two innovative computational agents (BDI and cognitive) and compared them to a current simple ordinal utility-based model with the results suggesting that the new models provide an alternative to current models and offer unique insight into the limitations of the field. The discussion concludes that the new agent architectures explored in the thesis (BDI and Cognitive) have the ability to contribute to planning practice and urban design by allowing planners more advanced methods to test scenarios by changing parameters and unlocking the ability to answer more complex questions for the end-users. However, before this is the case, as mentioned in the previous paragraph, it is important to research further and capture the true mechanisms of subjective reasoning within the urban simulative models. What this research proves is that cognitive agents are capable of providing a means by which to incorporate complex behaviours and reasonings within a model but these need to be researched and abstracted adequately in order to maximise user benefit.

8.4.3 The thesis' contributions to knowledge

The contributions of knowledge achieved for this thesis are split to four different disciplines between urban simulative modelling, planning and architecture, economics and finally computer science. This section summarises the contributions identified in chapter 7 where references to literature review and analysis are used to further contextualise these contributions.

Contribution to urban modelling

Contributions to urban simulative modelling are two-fold. Firstly, **the empirical analysis of agent architectures/theoretical basis of urban simulative models, specifically agents making decisions on location choice offers unique insight to new and existing researchers in the field**. Elaborating on that, in chapter three, the analysis of current urban simulative model agents is presented. Human behaviour is a complex subject to understand. This however does not stop modellers from simulating human systems in an urban environment. A series of assumptions allows for an abstraction of reality to create a digital representation of the human entity. Urban simulative models incorporate human systems to various degrees and scales. The interest here was solely in simulative models that include micro-simulations and agent-based interactions within their human system representations. As such, the evaluating variables for the cross-case analysis were the concepts and properties present in the agent architecture. The choice of cases cross-analysed stems from previously reviewed urban simulative model work in published reviews with the exclusion of all models with no micro-simulative aspects. This type of analysis provides a unique insight not only to what already exists in the state of art but the limitations of this area from a very fundamental level, the coded agent architectures.

Secondly, the thesis demonstrated that the results gained by the experiments, question the theoretical foundations of urban modelling in two ways. **a) A different approach with an expanded theoretical and agent architecture is achievable within the field. b) It is worth exploring and is required to switch away from utility maximisation theory as the basis for decision-making agents.** Elaborating on the second point, the development of two new disaggregate ABMs (in chapter 4) to simulate dynamically, the co-evolution of urban location choice and price patterns on real estate, showcase the potential of more complex agent architectures. These disaggregated ABMs consist of two new and novel agent architectures in urban simulative models, BDI agent architecture and Cognitive agent architecture. The creation of these simulative models features computerised agents demanding and exchanging houses in a simulated world. The contribution revolves around the models unique theoretical and agent architecture framework and their overall performance when compared to the results obtained through the lab experiment in chapter 6. The outcome of the empirical study in chapter three being a lack of representation of BDI and cognitive agent architectures provided the challenge for creating these two architectures in parallel with a third, rule of inference architecture as a representative of the majority of current urban models in order to compare the inputs and outputs of all three models.

All outcomes and analysis of the new simulation models was validated through an active role-playing simulation. The use of people, role-playing agent roles, making the decisions between choices in the same situation/context as their computational agent counterparts in a controlled virtual environment, allows for a direct comparison of results. This adds external validity to the computational agents created by providing an initial test of their performance. At the same time, it concludes by showcasing both cognitive and BDI agents outperforming simple logic-based agents, signifying the importance of using these agent attributes and theoretical basis in future research.

Contribution to Planning and Architecture

The work in the thesis contributed to planning practise through the introduction of new tools/improvement of current tools that can aid in the method by which they are understanding a situation better, allowing planners more advance methods to test scenarios by changing parameters. The first, is a model of BDI agent architecture that introduced desire prioritisation in the decision-making process of agents demanding space. Furthermore, this model incorporated individualism for the agents and the notion of subjective rationality by shifting the weightings of each desire for each agent to be unique to their perspective. To achieve this, the agent's creation drew from the theory of planned behaviour in order to calibrate each desire's appeal to the unique characteristics that make up each agent. The second tool is a model that makes use of cognitive agent architecture from the computer science as a means of including memory storage and representation in the decision-making process of agents demanding space. To achieve this, the agent's creation drew from cognitive theories that include Case-Based Decision theory and consumer behaviour theory to deal with decision-making under uncertainty and cognitive decision-making on subjective housing attributes. Contrary to existing models in the field that currently feature within a planning toolkit, these two unique urban simulation prototypes feature in two distinct ways a new method of modelling agents and their decision-making processes expanding the current utility maximization modelling techniques present in disaggregated urban simulative models. This effectively pushes the capacity of these type of simulations and unlocks the ability to answer more complex questions for the end-users which now form part of current planning practice as evident by the empirical work in the thesis.

As such, cognitive agents can make decisions based on their context that favour them as individuals rather than a collective, forming different groups within the population, each with their own values and needs. This exhibited behaviour is particularly important as it has the ability to aid communicative planning practice. Cognitive agents can act as context specific stakeholders and unbiased participants of collaborative planning in "live action" demonstrations of open discourse. They can resolve conflicting ideologies without the presence of power dominance as they are untouched by external forces and only focused on their own individual needs given their unique set of context and circumstances. Thus, they allow for the testing of the means with direct indication of end goal effects on different stakeholders improving the quality of planning decisions. Beyond solutions, they can also aid with problem identification through the unbiased interaction between subjective goals/means. In a design context, this knowledge is invaluable as it provides an insight into user preference and needs making any proposal more valuable to that specific population and a better fit for that physical area/space. This design element extends beyond large scale urban planning and policy, into architectural design of buildings and their association to each other, effectively improving the value of those designs through repeat testing and identification of demand born through the subjective means and goals of the population that makes up the social context around it. Therefore, the thesis contributes to planning and architecture/design through once again through the **introduction and testing of these new computational agents which allow designers to both formulate accurate representations of problems and simulate the value of their designs beyond the objective parameters of proximity and size.**

Contribution to Economics

The work contributes to the field of economics through **the testing of different economic theories as the basis for decision-making mechanisms for computational agents vs a direct comparison with real-world decision-making agents in a controlled environment.** The application of Utility Maximisation in the context of urban modelling can be criticised given the results of this study. The research approach followed by this thesis showcased that when compared to real world human decision-makers in the same situation, some decision-making theories fared better than others. The laboratory experiment featured in chapter 6 enabled a direct testing of the performance of three decision-making economic/psychology theories when applied to the field of urban modelling. These theories tested are Utility Maximisation theory which has thus far been the gold standard in the field of urban modelling, Case-Based Decision

Theory and Theory of Planned Behaviour. Out of the three theories, the analysis revealed that Utility Maximisation was the worst performing theory while Case-Based Decision Theory was the best performing decision-making theory when applied to an urban modelling context.

Contribution to Computer Science

The contribution to computer science is in the form of a research finding stemming from the **comparison of the potential of different agent architectures when applied to an urban modelling context**. The computational models created as part of this research (logic-based, BDI and cognitive) as well as the validation technique followed (active role-playing simulation), demonstrated that the performance of BDI and Cognitive agent architectures is better than logic-based architectures when dealing with decision-making agents in an urban modelling context. The analysis revealed that Cognitive Agents are the best performing architecture when applied to an urban modelling context given the parameters set out within the controlled experiments/computational models.

8.5 Further limitations and recommendations for future research

This should provide a critical reflection on the work presented in the thesis, highlighting important lessons learned, how challenges arising during the research were dealt with and informed, for example, changes in aims or objectives, identify unexpected or missed opportunities and their potential implications, and key limitations of the work. It should further provide an explanation of how these aspects will inform future research, particularly when the developed cognitive agent is utilised to explain real world contexts.

This thesis provides the building blocks for an ABM method capable of assessing more than quantitative aspects of planning and architectural design in ex ante analysis. By incorporating theories and agent architectures with the capacity to allow for subjective decision-making based on taste, experience and uncertainty, designers will be able to engage with Futures that are arrived through more complex considerations than what current objective/rational models are capable of offering now.

Architecture and planning go beyond quantitative aspects of spatial design. Practitioners and researchers in the field learn about quality of space, spatial strategies, materiality, importance of design detailing and other aspects that, given the number of alternatives, appease different client tastes and desires. These qualitative aspects of taste vary depending on the design scale, from urban master planning to a single building design. Some seek to satisfy benchmarks for environmental design, others aim to aesthetically please users or offer a passive experience through a range of architectural techniques. As of yet, real-estate demand models have not had the capacity to incorporate such complex consideration in their agent decision-making process. Part of this, is the difficulty in calibrating and assessing subjective decision-making in a real-world context. This research, sought to establish cognitive and BDI agent architectures that enable an alternative to utility maximization equations for decision-making. The main reasoning was to provide a method by which such subjective decisions can be calibrated not in terms of objective utility value but measures of positive experience or orders of prioritization allowing for more complex agent behaviours leading to better informed future scenarios.

This thesis does not attempt to directly incorporate qualitative aspects of design within the agent's decision-making, but rather provides a framework through which subjective notions of experience, memory representation and prioritization of objectives is enabled. In doing so, this thesis achieves two things. Firstly, it showcases the merit of using such ABM techniques against traditional logic-based architectures, externally validated through a laboratory experiment. Secondly, it provides a framework that future researchers can build upon to include attributes associated to taste in agent decision-making.

The lack of qualitative variables for agent consideration within the models, brings forth limitation to the research, mainly around the lack of real-world representation/application and small size of the environment used to test the models. Regarding the former, the thesis created conceptual models to test performance in a controlled, virtual environment in order to ensure all relationships within the model are determined by known and modelled factors. This helps in the external validation of the models through a laboratory environment as the only aspect under question is the decision-making of the agents and nothing more or hidden. When applying these conceptual models in a real-world application, other issues pop up that require both an improvement in the code to incorporate a range of new variables and a new calibration method capable of assessing the value of set variables to match real-world data. In order to overcome this limitation, future research requires knowledge in urban economics as to abstract the processes of residential mobility and choice, the identification of complex pattern behaviours in a real-estate market such as loss aversion which falls in the realm of behavioural economics, and an ethnographic study of the model's real world application area to determine the context and attributes of agents. These attributes need to extend beyond neoclassical assumptions of income and demographic but rather personal perceptions and level of expertise of the individual in the market itself.

Regarding the limitation of a small environment, there could be changes in the decision-making of agents and the relationships as the world/context scales up and more variables are added in these conceptual models. This will require further calibration and data analysis to consider the effect in both desire prioritization and experience value for both BDI and cognitive agents. Herbert Simon's notions of "bounded rationality" a cornerstone of behavioural economics (Marsh & Gibb, 2011), provides a view of how scaling up the environment can impact agent decision-making. A larger set of choices that the agent needs to search through raises the question of whether the agents can achieve perfect knowledge. This aspect is a key limitation to the work in this thesis as all agents have perfect knowledge of all alternatives, though in the case of cognitive agent, the agents themselves have shifting priority preferences for the different variables. This means that when conducting further research into the application of cognitive and BDI agents in a real-world setting, there needs to be an introduction of some form of limitation to the search scope of alternatives by the agents. This type of mechanism needs to be informed through an ethnographic study that, for example, determines the experience levels of consumers within a real-estate market that sets the limit to their search range.

The thesis therefore proposes future research in the field that builds upon this work. Considering the limitations of this research, the research warrants the real-world application of both BDI and cognitive agents based on the Theory of Planned Behaviour and Case-Based Decision theory respectively. This will allow for researchers in the field to incorporate variables that cause subjectivity in decision-making and test their effect in value/demand for a variety of spaces and dwellings.

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Appendix

Equation 1:

```
def issafe(self):

  avg = 0

  for h in self.hs:

    for agent in agents:



      if agent.h == h.id:

        avg = avg + agent.i
```

```
        else:
            pass

    avg = avg / int(len(self.hs))
    safety = []
    for h in self.hs:
        for agent in agents:
            if agent.h == h.id:
                if (avg + 10000 >= agent.h) and (avg - 10000 <= agent.i):
                    safety.append(True)
                else:
                    safety.append(False)
            else:
                pass
    safetyrating = True
    if False in safety:
        safetyrating = False
```

```
        else:
            pass
        return safetyrating
```

Equation 2:

```
def closetowork(self):
        workprox = True
        if self.h == "none":
            workprox = False
        elif self.h != "none":
            for house in houses:
                if self.h == house.id:
                    if house.n == "a":
                        if neighbourhooda.w == True:
                            workprox = True
                        else:
                            workprox = False
                    elif house.n == "b":
```

```
                if neighbourhoodb.w == True:
                    workprox = True
                else:
                    workprox = False
            elif house.n == "c":
                if neighbourhoodc.w == True:
                    workprox = True
                else:
                    workprox = False
            else:
                workprox =False
    else:
        workprox = False
    return workprox

def closetoschool(self):
    schoolprox = True
```

```
if self.h == "none":
    schoolprox = False
elif self.h != "none":
    for house in houses:
        if self.h == house.id:
            if house.n == "a":
                if neighbourhooda.sc == True:
                    schoolprox = True
                else:
                    schoolprox = False
            elif house.n == "b":
                if neighbourhoodb.sc == True:
                    schoolprox = True
                else:
                    schoolprox = False
            elif house.n == "c":
                if neighbourhoodc.sc == True:
```

```
                        schoolprox = True
                    else:
                        schoolprox = False
                else:
                    schoolprox =False
        else:
            schoolprox = False
        return schoolprox

    def closetopark(self):
        parkprox = True
        #print(self.h.n)
        if self.h == "none":
            parkprox = False
        elif self.h != "none":
            for house in houses:
                if self.h == house.id:
```

```
if house.n == "a":
    if neighbourhooda.p == True:
        parkprox = True
    else:
        parkprox = False
elif house.n == "b":
    if neighbourhoodb.p == True:
        parkprox = True
    else:
        parkprox = False
elif house.n == "c":
    if neighbourhoodc.p == True:
        parkprox = True
    else:
        parkprox = False
else:
    parkprox =False
```

```
    else:
        parkprox = False
    return parkprox
```

Equation 3:

```
if self.ba == True and self.sn == True and self.pbc == True:
            true_desire = desire
        elif self.ba == True and  self.sn == True and self.pbc == False:
            if chance > 25:
                true_desire = desire
            else:
                true_desire = "not_willing_to_change"
        elif self.ba == True and  self.sn == False and self.pbc == True:
            if chance > 25:
                true_desire = desire
            else:
                true_desire = "not_willing_to_change"
        elif self.ba == False and  self.sn == True and self.pbc == True:
```

```
    if chance > 25:
        true_desire = desire
    else:
        true_desire = "not_willing_to_change"
elif self.ba == False and  self.sn == False and self.pbc == True:
    if chance > 50:
        true_desire = desire
    else:
        true_desire = "not_willing_to_change"
elif self.ba == True and  self.sn == False and self.pbc == False:
    if chance > 50:
        true_desire = desire
    else:
        true_desire = "not_willing_to_change"
elif self.ba == False and  self.sn == True and self.pbc == False:
    if chance > 50:
        true_desire = desire
```

```
    else:
        true_desire = "not_willing_to_change"
elif self.ba == False and  self.sn == False and self.pbc == False:
    if chance > 75:
        true_desire = desire
  else:
        true_desire = "not_willing_to_change"
```

Equation 4:

```
if housea.pc <= housea.pi:
    agent.cd = desire_in_question
elif housea.pc >= (housea.pi * 1.05) and housea.pc < (housea.pi * 1.15):
    if housechance <= 10 and (agent.ba == True and agent.sn == True and agent.pbc ==
True):
        agent.cd = "not_willing_to_pay"
    elif housechance <= 20 and (agent.ba == True and agent.sn == True and agent.pbc ==
False):
```

```
    agent.cd = "not_willing_to_pay"
elif housechance <= 20 and (agent.ba == True and agent.sn == False and agent.pbc ==
True):
    agent.cd = "not_willing_to_pay"
elif housechance <= 20 and (agent.ba == False and agent.sn == True and agent.pbc ==
True):
    agent.cd = "not_willing_to_pay"
elif housechance <= 30 and (agent.ba == False and agent.sn == False and agent.pbc ==
True):
    agent.cd = "not_willing_to_pay"
elif housechance <= 30 and (agent.ba == True and agent.sn == False and agent.pbc ==
False):
    agent.cd = "not_willing_to_pay"
elif housechance <= 30 and (agent.ba == False and agent.sn == True and agent.pbc ==
False):
    agent.cd = "not_willing_to_pay"
elif housechance <= 40 and (agent.ba == False and agent.sn == False and agent.pbc ==
False):
    agent.cd = "not_willing_to_pay"
```

```
        else:
            agent.cd = desire_in_question


    if housea.pc >= (housea.pi * 1.15) and housea.pc < (housea.pi * 1.25):
        if housechance <= 20 and (agent.ba == True and agent.sn == True and agent.pbc ==
True):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 30 and (agent.ba == True and agent.sn == True and agent.pbc ==
False):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 30 and (agent.ba == True and agent.sn == False and agent.pbc ==
True):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 30 and (agent.ba == False and agent.sn == True and agent.pbc ==
True):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 40 and (agent.ba == False and agent.sn == False and agent.pbc ==
True):
            agent.cd = "not_willing_to_pay"
```

```
        elif housechance <= 40 and (agent.ba == True and agent.sn == False and agent.pbc ==
False):
          agent.cd = "not_willing_to_pay"
        elif housechance <= 40 and (agent.ba == False and agent.sn == True and agent.pbc ==
False):
          agent.cd = "not_willing_to_pay"
        elif housechance <= 50 and (agent.ba == False and agent.sn == False and agent.pbc ==
False):
          agent.cd = "not_willing_to_pay"
        else:
          agent.cd = desire_in_question
      if housea.pc >= (housea.pi * 1.25) and housea.pc < (housea.pi * 1.5):
        if housechance <= 30 and (agent.ba == True and agent.sn == True and agent.pbc ==
True):
          agent.cd = "not_willing_to_pay"
        elif housechance <= 40 and (agent.ba == True and agent.sn == True and agent.pbc ==
False):
          agent.cd = "not_willing_to_pay"
```

```
    elif housechance <= 40 and (agent.ba == True and agent.sn == False and agent.pbc == True):
        agent.cd = "not_willing_to_pay"
    elif housechance <= 40 and (agent.ba == False and agent.sn == True and agent.pbc == True):
        agent.cd = "not_willing_to_pay"
    elif housechance <= 50 and (agent.ba == False and agent.sn == False and agent.pbc == True):
        agent.cd = "not_willing_to_pay"
    elif housechance <= 50 and (agent.ba == True and agent.sn == False and agent.pbc == False):
        agent.cd = "not_willing_to_pay"
    elif housechance <= 50 and (agent.ba == False and agent.sn == True and agent.pbc == False):
        agent.cd = "not_willing_to_pay"
    elif housechance <= 60 and (agent.ba == False and agent.sn == False and agent.pbc == False):
        agent.cd = "not_willing_to_pay"
    else:
```

```
        agent.cd = desire_in_question

    if housea.pc >= (housea.pi * 1.5) and housea.pc < (housea.pi * 2.00):

      if housechance <= 40 and (agent.ba == True and agent.sn == True and agent.pbc ==
True):

        agent.cd = "not_willing_to_pay"

      elif housechance <= 50 and (agent.ba == True and agent.sn == True and agent.pbc ==
False):

        agent.cd = "not_willing_to_pay"

      elif housechance <= 50 and (agent.ba == True and agent.sn == False and agent.pbc ==
True):

        agent.cd = "not_willing_to_pay"

      elif housechance <= 50 and (agent.ba == False and agent.sn == True and agent.pbc ==
True):

        agent.cd = "not_willing_to_pay"

      elif housechance <= 60 and (agent.ba == False and agent.sn == False and agent.pbc ==
True):

        agent.cd = "not_willing_to_pay"

      elif housechance <= 60 and (agent.ba == True and agent.sn == False and agent.pbc ==
False):
```

```
            agent.cd = "not_willing_to_pay"

        elif housechance <= 60 and (agent.ba == False and agent.sn == True and agent.pbc ==
False):

            agent.cd = "not_willing_to_pay"

        elif housechance <= 70 and (agent.ba == False and agent.sn == False and agent.pbc ==
False):

            agent.cd = "not_willing_to_pay"

        else:

            agent.cd = desire_in_question

    if housea.pc >= (housea.pi * 2.00):

        if housechance <= 50 and (agent.ba == True and agent.sn == True and agent.pbc ==
True):

            agent.cd = "not_willing_to_pay"

        elif housechance <= 60 and (agent.ba == True and agent.sn == True and agent.pbc ==
False):

            agent.cd = "not_willing_to_pay"

        elif housechance <= 60 and (agent.ba == True and agent.sn == False and agent.pbc ==
True):

            agent.cd = "not_willing_to_pay"
```

```
        elif housechance <= 60 and (agent.ba == False and agent.sn == True and agent.pbc == True):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 70 and (agent.ba == False and agent.sn == False and agent.pbc == True):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 70 and (agent.ba == True and agent.sn == False and agent.pbc == False):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 70 and (agent.ba == False and agent.sn == True and agent.pbc == False):
            agent.cd = "not_willing_to_pay"
        elif housechance <= 80 and (agent.ba == False and agent.sn == False and agent.pbc == False):
            agent.cd = "not_willing_to_pay"
        else:
            agent.cd = desire_in_question
    else:
        agent.cd = desire_in_question
```

Equation 5:

```
for agent in agents:
    list_priorities = [agent.epark, agent.ework, agent.escho, agent.esafe, agent.esuit, 
agent.eaffo]
    list_priorities.sort(reverse = True)
    list_houses = []
    list_pprint.append(list_priorities)
    print list_houses


    for house in houses:
        if house.o == "none":
            list_houses.append(house)
    print list_houses
    for priority in list_priorities:
        if len(list_houses) == 1:
            choice = list_houses[0]
            choice.o = agent.id
```

```
    agent.h = choice.id
    break
else:
    pass
if priority == agent.epark:
    for house in list_houses:
        if house in neighbourhooda.hs:
            if neighbourhooda.p == True:
                pass
            elif neighbourhooda.p == False and len(list_houses) > 1:
                list_houses.remove(house)
        elif house in neighbourhoodb.hs:
            if neighbourhoodb.p == True:
                pass
            elif neighbourhoodb.p == False and len(list_houses) > 1:
                list_houses.remove(house)
        elif house in neighbourhoodc.hs:
```

```
                if neighbourhoodc.p == True:
                    pass
                elif neighbourhoodc.p == False and len(list_houses) > 1:
                    list_houses.remove(house)
```

Equation 6:

```
list_house_price = [hap, hbp, hcp,hdp,hep,hfp,hgp,hhp,hip,hjp,hkp,hlp]

list_desires = [a1cd, a2cd, a3cd, a4cd, a5cd, a6cd, a7cd, a8cd, a9cd, a10cd, a11cd, a12cd, a13cd,
a14cd, a15cd, a16cd, a17cd, a18cd, a19cd, a20cd, a21cd, a22cd, a23cd, a24cd]

list_ownedhouse = [haowne, hbowne, hcowne, hdowne, heowne, hfowne, hgowne, hhowne,
hiowne, hjowne, hkowne, hlowne]

list_owners = [haoe, hboe,hcoe,hdoe,heoe,hfoe,hgoe,hhoe,hioe,hjoe,hkoe,hloe]

  with open('Cognitive_Agents.csv', mode='a') as csv_file:
      fieldnames = ['is house owned at start','owner at start','agent priority','agent choice at
round end','house_price', 'is house owned at end', 'house owner at end']
      writer = csv.DictWriter(csv_file, fieldnames=fieldnames)


      writer.writeheader()
      writer.writerow({'is house owned at start': list_ownedhousestart,'owner at start':
list_ownersstart,'agent priority': list_pprint,'agent choice at round end':
```

list_choice_id,'house_price': list_house_price, 'is house owned at end': list_ownedhouse,

'house owner at end': list_owners})

Table of results for empirical analysis:

Variables	**Autonomy: Agent decision do not require user input and are based on agent's own inner state (Lin *et al*>, 2007)**	**Mental Mechanism: Agent has mechanism to realise intentions by achieving goals**	**Adaptation / Adaptability: Ability of an agent to adjust activities according to a dynamically changing environment**	**Concurrency: Agent can perform multiple tasks at the same time**	**Communication: Agent has methods or mechanisms or protocols that enable / define agent interactions**	**Collaboration / Teamwork: An agent has methods to cooperate with other agents to achieve goals**	**Agent Abstraction: Methodology has theory to describe agents using high-level abstraction**
Source	0= Agent has no control over its activities	Internal Architecture: Agent architecture used to determine range of Attitudes	0= Agent has no response to a changing environment	0= Agent can only perform a single action at a time	0= Agent has no defined interactions with other agents	0= Agent has no capacity for collaboration	0= Agent behaviour is not informed by theory
	5= Agent has some self-control features but still relies on external input for some decisions / proactive / reactive activities	1= Agent has a reasoning mechanism based on a set of inference rules / logic based/ symbolic representation	5= Reactive, agent perceives their environment and timely responds to changes to it	5= Agent can perform a number of tasks in a single family of activities at the same time	5= Agent has capacity for interaction with same type of agent or non-direct interactions	5= Agent has capacity to collaborate with same type of agents to achieve goals	5= Agent behaviour is informed by high-level abstraction of reality (maybe some aspects informed by theory?)
	10= Agent has control and is responsible for all of its own activities with no need for external input / command.	1= Agent has direct mapping of actions to environment changes / reactive	10= Proactive, agent does not only respond to environment changes but exhibit goal-oriented behaviour by taking initiative and pro-actively adjusting actions in anticipation for change.	10= Agent can perform a range of tasks in a range of activity families at the same time	10= Agent has capacity for interaction with same & different type of agents	10= Agent has capacity to collaborate with same and different type of agents to achieve goals	10= Agent behaviour is informed by a low-level abstraction of reality (maybe all aspects informed by theory?)
		1= Agent has belief, it has a world view / perception					
		1= Agent has desires, motivation or options the agent has to carry out actions in order to achieve a desired world state					

		1= Agent has intention, commitment towards a desire and belief, auctioning to bring about the desires					
		1= Agent has memory storage, long / short term memory storage of world state					
		1= Agent has representation of memory / learning capacity, realising if a choice made was to its satisfaction or level of satisfaction					
SIMPOP	10 = ONLY INITIAL INPUT NEEDED	1 = INFERENCE / TRANSITION RULES, 0, 0 ,0 ,0, 0, 0	5 = Grows / trades in accordance to environment	5 = can perform economic activities in different sectors utilising different raw materials for each function at the same time	5 = can trade with other settlements	5 = can trade with other agents	5 = principles of self-organisation theory as applied to large-scale geographical systems
MUSSA	5 = LAND USE DATA IS MANUALLY CHANGED	1 = INFERENCE / BID CHOICE UTILITY BASED DECISIONS, 1 = CHANGE TO AVAILABLE LOT THAT MAXIMISES PROFIT, 0, 0, 0 = STOCHASTIC PROCESS OF WILLINGNESS TO PAY, 0 ,0	0= Agent does not perceive environment	0	5= Agents engage in bidding wars	0	5 = bid-choice theory / utility and informed by surveying of households
CommunityViz	10 = ONLY INITIAL INPUT / DATA NEEDED	1 = INFERENCE RULES THAT GOVERN DECISIONS WITH A PROBABILISTIC ELEMENT, 1 = AGENT IS REACTIVE TO ENVIRONMENT CHANGES (QUALITY OF LIFE IN THE AREA), 1 = perception changes by changing world belief, 0, 0, 0, 0	5 = Agent monitors changes to the environment and changes actions	0	5 = Agents hire other agents	0	5 = informed by high level theory of complexity / surveys
PUMA	10 = ONLY INITIAL INPUT / DATA NEEDED	1 = RULES OF INFERENCE / LOGIC BASED, 0, 0, 0, 0, 0, 0	5 = Agents perceive their neighbourhood status changes which changes their decision-making / utility factor for that location	5= agent can relocate and find a new job location at the same time (location-based choices)	5= Agents influence other agent decision indirectly through neighbourhood status, congestion and other externalities as well as firm locations and sizes affecting job locations and amount of jobs for household agents	0	5 = informed by utility maximisation theory and survey
SYPRIA	10 = Only input	1 = RULES OF INFERENCE / LOGIC BASED, 1 = ENVIRONMENT CHANGES DIRECTLY AFFECTS INSTITUTIONAL EFFECT ON HOUSEHOLD POPULATION, 0, 0, 0, 0, 0	5 = Agent perceives their environment and is affected by it / conforms to it	0	5 = Institutional agents communicate on production of goods	5 = Institutions Collaborate to influence population of households	5 = informed by aagrarian theory, household survey
ILUMASS (IRPUD	5= The decisions made are somewhat predetermined by survey data	0, 1 = Agent is reactive moving in accordance to environment changes, 0, 0, 0, 0, 0	5 = Agent reacts to environment changes	5 = agent can grow, marry, have children, relocate and change transpor	0	0	5 = informed by survey data

				t habits in a turn			
LUCITA	10 = Decisions solely by agent	1 = Agent decision-making is linked to 3 if statements, 0, 0, 0, 0, 0, 0	0 (environment does not change)	5 = agents grow and produce at a number of cells each turn	0	0	5 = informed by behaviours observed by on the ground studies
OPUS / UrbanSim 2013	10 = Agents decide automatically	1 = Agent decisions are based on rules of inference drawn from probabilities taken from surveys, 0, 0, 0, 0, 0, 0	0 (no change to environment)	0	5 = non direct interaction through demand and supply of property affecting price and affortability	0	5 = agent behaviour informed by survey that results in probabilities of choice drawn for each cycle.
RLCM 2015	10	1 = Agent decisions based on multinomial logit models of agent attributes and target attributes, 0, 0, 0, 0, 0, 0	0 (no change to environment)	0	0	0	5 = based on survey data using open platform for urban simulation
ILUTE / 2013	10 = Agents decide and act autonomously	1 = Multinomial models made decisions on how act (enter market or not) based on wider economic environment, personal changes (marry, divorce has kids grow up), 0, 0, 0, 0, 0, 0	5 = Some response to global economic variables changing	10 = Agent can grow, bid, move, sell (being both the seller and buyer at the same time)	5 = agents interact through a buyer / seller auction type system where the seller chooses from a range of bids	0	5 = choices attributed to survey data
ettema 2011 (closest to cognitive agent)	10 = Agents act autonomously	1, 0, 1 = it has a universal set of beliefs and perception on the average market price per unit of size for household of type x, 0, 0, 1 = somewhat universal storage of average prices that updates the beliefs / world view perception, 0 = it has no way of evaluating a choice made	5 = agents' perception of optimal utility based on the changing market and household attributes causes a decision of whether or not to enter the housing market	0	5= They indirectly sell and buy houses from each other by setting house prices and offer prices but not engage in bidding	0	5 = some economic theory on Willingness to buy / willingness to accept not directly implemented but Bayesian procedure dictates updated beliefs and activities generally based on some relevant

								research study
UrbanSim (2003)	10 = Agents act autonomously	1 = location choice made through rules of inference linked with attributes of house / household, 0, 0, 0, 0, 0, 0	0	5 = agent grows in demographic attributes (marry evolve), enters household market and look for employment at the same time	0	0	5 = Agent decision-making drawn from urban sociology, urban economics and urban geography
ILUTE 2001	10 = Agents act autonomously	1 = Agents decide when to enter the market based on triggering effect, 0, 0, 0, 0, 0, 0	0	5 = agent is the buyer and seller of property at the same time	5 = agent communicates vacancies and bids for residential property with other agents	0	5 = validation and calibration of agents through aggregate market behaviour comparison for model results. Some theoretical backing on the market processes of agents
PECAS 2003	10 = Agent (zones) evolve autonomously	1= Activity allocation is made through reasoning mechanisms, 0, 0,0, 0 ,0 ,0	5 = Reactive change to allocation / demand for specific space within the zone through input - output table method	0	0	0	5 = Some theoretical basis
Abraham, Hunt 2005	10 = Agent acts autonomously	1 = Offer - accept based on inference rules of utility and random variables, 1 = agent responds to excess demand by reducing / increasing price, 0, 0, 0, 1 = agent stores the demand in past simulation, 0	5 = Agent reacts to changing average price based on demand (Auctioneer)	0	5 = Agents interact via auctioneer to buy and sell goods in offer bundles	0	5 = Based on economic notion of the auctioneer acting as the middleman between demand and supply
SE(3)M / BLUM	10 = Agent acts autonomously	1 = Probability and employment values / transport cost matrix determine population / household location, 1 = changes in employment and travel cause reactions of population, 0, 0, 0, 0, 0	5 = Agents react according to base economic theory / zonal changes to economic activity	0	0	0	5 = Based on economic base theory, bid rent theory and

							gravity models
Kii 2005	10 = Agent acts autonomously	1 = Agents act in accordance with utility algorithm / reasoning mechanism, 1 = Agents react to neighbourhood effects / changes as its part of their logic statements, 0, 0, 0, 0, 0	5 = Agents change their logic statement to changes in their neighbourhood	0	5 = Agents interact indirectly, with their types causing repulsive or attractive forces changing neighbourhood effect	0	5 = Agent location / behaviour informed by economic theory (utility maximisation and bid rend theory)
RELU-TRAN	10 = Agent acts autonomously	1 = Agents act according to maximising their utility and make choice of zone and whether to be employed, how much space to buy and goods to purchase based on logic reasoning mechanisms, 0, 0, 0, 0, 0, 0	5 = All agents adapt their decision-making based on zonal changes formed by past agent decisions.	0	0	0	5 = Behaviour based on previous work on decision-making
Agent iCity	10 = Agents act autonomously	1 = Agent decision making is based on a set of logic statements, 1 = decisions to move are a direct response mapped to environmental changes such as neighbourhood income, neighbourhood average dwelling price, proximity score, 0 ,0, 0,0 ,0	5 = All agents initiate activities based on changes to their neighbourhood	0	0	0	0

Appendix item 2:

Recruitment Letter:

Chronologically, before participants are briefed on the experiment, they must be approached and accept to be involved in this study. This requires a recruitment email outlines the invitations send out to potential participants.

Sample Recruitment Email for role-playing experiment participants.

Dear [*name*],

My name is Solon Solomou, and I am a researcher at the Manchester School of Architecture. I am writing to invite you to participate at role-playing experiment for my PhD project ‘Towards new complex agents for simulating residential location choice in Urban simulative models’.

You're eligible to be in this study because you [*insert description*]. I obtained your contact information from [*source*].

If you decide to participate in this study, you will take part in a single workshop for the experiment (date to be confirmed depending on participant availability). The experiment will be organized online and will be recorded. You will be asked to sign a consent form at the beginning of the experiment.

Your participation in the experiment is voluntary. You can choose to be in the study or not. If you'd like to participate or have any questions about the study, please email me at s.solomou@mmu.ac.uk

Thank you very much.

Sincerely,

Solon Solomou

Instructions to participants:

Activity Information Sheet

Research project title:
Towards new complex agents for simulating residential location choice in urban simulative models
Research investigators:
Solon Solomou

About the Project

This is a PhD project proposing new complex agents with their unique sets of behavioural theories for simulating household location choice. Chosen participants will act out and make the same decisions as the different complex agents, in the same environment with the same context. This means that participants' roles are the agents themselves with the same motivations, background and criteria for satisfaction.

About the workshops

You have been invited to participate at this active role-play simulation.

The aim of this activity is to serve as external validity for the different complex agents created as part of this research project. This is achieved by determining the fit of their theoretical basis through direct comparison with the decision you will make in this simulation.

As far as possible, your contribution will be kept confidential. You will have an opportunity to remove any information you have provided from the simulation results. Taking part in the study is voluntary. You may choose not to take part or subsequently cease participation at any time. You will receive no payment for your participation. The data will not be used for commercial purposes.

For more information

If you have any further queries about the workshop, please, contact us:

Solon Solomou

s.solomou@mmu.ac.uk

Workshop Consent Form:

Agreement to participate in a recorded role-playing workshop.

Title of Project: Towards new complex agents for simulating residential location choice in urban simulative models

Name of Researcher: Solon Solomou

Please, . . .

1. I confirm that I have read and understood the information sheet. dated ../../…. for the above project and have had the opportunity to ask questions about the workshop procedure.

2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason to the researcher.

3. I understand that my responses will be recorded and used for analysis for this research project.

4. I give/do not give permission for my workshop recording to be archived as par[illegible]s. research project, making it available to future researchers.

5. I understand that my responses will remain anonymous.

6. I agree to take part in the above research project.

7. I understand that at my request a transcript of my responses can be made available to me.

___________________ ______________

Name of Participant Date Signature

S. Solomou ______________

__________ ______________

Researcher Date Signature

To be signed and dated in presence of the participant.