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A Data-Driven Approach towards a Realistic and Generic Crowd Simulation Framework

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Declaration of Authorship

I, Jacob Sinclair, declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Signed: ______________________________

Date: ______________________________

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Statement of the Contribution of Others

Nature Of Assistance	Contribution	Names
Supervision Support	Primary and Secondary Supervisor	Professor Ickjai Lee and Dr Art (Hemmaphan) Suwanwiwat
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Abstract

Crowd simulation is the simulation of a large number of entities that has the ability to interact with each other and their environment. Crowd simulation has provided an essential process in developing and analysing emergency management and response for police, military, mass event management, evacuations and traffic control. Developing a realistic agent based cognitive framework represents a crucial process in generating real-world data in an agent based crowd simulations. To achieve this gathering, real-world data is crucial in developing the realistic framework. There are three types of data that need to be considered: physical, mental and visual. Existing data gathering methods do not collect all three data types, but they provide a limited amount of data for an agent based simulations.

This thesis proposes a novel data gathering approach using a combination of Virtual Reality and Questionnaires as a means to gathering real-world data. This hybrid method collects all three data types, and is validated by comparing it to data collected from the real world. Two data gathering experiments (real world and our proposed method) were conducted to collect all three types of data for comparison. Experimental results show the proposed hybrid method can collect similar data to the real-world experiment, in particular for mental and visual data. Chi-square Goodness of Fit Test proves there is no significant difference between the real world and our proposed method. Whilst the test shows there is significant difference in physical data, in particular completed time. This is consistent with past studies, and we propose an adjustment factor for the completed time data that mitigates the gap between virtual space and real space. This allows the results collected to be input into the agent based simulations as real world data. Overall the proposed method is cost-effective, time efficient, reproducible, ecologically valid, and able to collect three types of data for an agent based crowd simulation model.

This thesis also proposes a realistic agent based framework for crowd simulations that can encompass the input phase, the simulation process phase, and the output evaluation phase. However, existing research has not used all three data types to develop an agent based framework since current data gathering methods are unable to collect all the three types. Instead randomly or manually generated

input data is run within the cognitive architecture, showing only its applicability in certain domain areas. Some past studies have been conducted by incorporating mental data (personality and emotion) into cognitive frameworks, however it is only through the low-level parameters.

The data collected from the hybrid data gathering method is incorporated into the agent based simulation model to provide realism and flexibility. The performance of the framework is evaluated and benchmarked to prove the robustness and effectiveness of our framework. Two types of settings are simulated (self-set parameters and random parameters) implementing several variations to demonstrate that the framework can produce real-world like simulation data. Experimental results demonstrate the effectiveness of the proposed agent based framework. A t-test demonstrates there is no significant difference between the data generated from self-set parameter agents and the data gathered from Virtual Reality and Questionnaires, proving the framework can produce approximate real-world data. While the data generated from random parameters shows a significant difference which suggests the framework has the potential to produce approximate real-world data of a larger size. A Chi-square Goodness of Fit Test proves there is no significant difference between the data gathered through the proposed data gathering and the data simulated by our proposed framework.

A crowd simulation case study is implemented using the proposed framework in an evacuation scenario. The case study shows the realism and flexibility of the framework in a different environment. Using the two setting types (self-set parameters and random parameters), we simulate three variations of the framework (set *vs.* random parameters, no knowledge *vs.* full knowledge of the environment, and low fidelity *vs.* high fidelity). The case study results show that realism and flexibility can be produced using our agent based framework by revealing unique behaviours unseen from the previous simulations. The results also show there is a significant difference between each scenario variation implemented. This reveals further validation that the agent based framework can provide flexibility and realism.

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List of Acronyms

ABFS Audio Based Fuzzy System.

ABM Agent Based Model.

ACT-R Adaptive Control of Thought-Rational.

AI Artificial Intelligence.

BDI Belief-Desire-Intention.

BDI-AMBER BDI Agent for Modelling Human BEhavior under Risk.

BDIP Belief-Desire-Intention-Policy.

BEI Belief-Emotion-Intention.

CLARION Connectionist Learning with Adaptive Rule Induction ON line.

fMRI functional Magnetic Resonance Imaging.

GOFS Goal Orientated Fuzzy System.

GPS Global Positioning System.

HiDAC High-Density Autonomous Crowds.

LTM Long Term Memory.

M Mean.

MBFS Movement Based Fuzzy System.

MFS Multilayered Fuzzy logic System.

OBFS Object Based Fuzzy System.

OCC Ortony, Clore and Collins.

OCEAN Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism.

PAD Pleasure, Arousal, Dominance.

SD Standard Deviation.

SOAR State Operator And Result.

STM Short Term Memory.

TIPI Ten Item Personality Measure.

VR Virtual Reality.

VR+Q Virtual Reality + Questionnaire.

Chapter 1

Introduction

1.1 Background

Crowd simulation is the focus of developing artificial objects (agents) either as individuals or groups that can generate and reflect realistic behaviours observed from the real world [1–3]. Crowd simulation provides us with a means to understanding real-world behaviours by allowing us to simulate the individual actions, social actions and interactions of autonomous agents [4, 5]. These unique agent behaviours can be seen as either collective groups (like social groups or organisations) or as an individual [6]. The advantage of running crowd simulations is, firstly, it can run a collection of heterogeneous agents each with their own unique characteristics and decision making processes [7]. By including their own unique characteristics and decision making, it will then subsequently provide us with the ability to display a variety of different realistic behaviours. Another advantage is that crowd simulations provide researchers a means to implementing psychological aspects (personality and emotions). Implementing psychological aspects into virtual agents can influence the way an agent makes decisions, moves and navigates through low level parameters (e.g. speed and radius). This is significant as it allows real-world data to be used in modelling crowd simulation agent based models, and can be used to reproduce real-life situations. Lastly, crowd simulation possesses the potential to be used as a means to help improve current and future situations in the real world [8]. For instance the improvement of evacuations within current building structures by having virtual agents escape a burning building within a set time frame. Another example is the simulation of different traffic scenarios based on the real world. This type of simulation can help provide a means of improving traffic flow in built up areas.

Crowd simulation has at present been used in many fields such as emergency management and response [8, 9], building design [10], and massive event traffic control [4]. Crowd simulation has also become very important in films [11] and video games [12] for animating high density realistic characters.

1.2 Motivation

One of the most important foci of research in crowd simulation is making virtual agents as realistic to human beings as possible. Modelling virtual agents as realistic individual human beings can also be called an agent based model [13, 14]. These agent-based models are capable of representing realistic behaviours. This is achieved by focusing on modelling each agent with their own movements, goals, ability to avoid collisions, and respond and adapt to various environments, situations and scenarios through a decision making process [15]. To achieve and develop this level of realistic agent-based models, it is important to gather data from the real world first [16]. Gathering data for agent-based models is of great importance. It provides us with data that can be used for the development of simulation models. To model realistic agents, scenarios and environments for crowd simulation, real-world data needs to be collected. Not only that gathering data allows researchers and developers to prove their project fulfils its intended purpose by evaluating and validating their model. In crowd simulation, evaluation provides proof that the model's performance and feasibility are acceptable at a certain standard. On the other hand, validation determines whether or not a researcher's virtual agent model displays realistic tendencies. Evaluation and validation not only provide proof that their project produces what it was intended to do, but also can prove their project can do something more or better than previous studies. There are three types of data that need to be considered when collecting real-world data [17, 18]. The three types of data are physical, mental and visual. Each data type represents a form of real world data that can be seen as individual behaviours. These individual behaviours can also be seen as a means to modelling by internal and external factors. An internal factor represents how each individual perceives the environment and behaves whilst an external factor is more about how an individual is perceived by others. The internal factors are captured through the use of physical and mental data, while external factors are collected from individual behaviours observed using visual data. Physical data are related to the body movements perceived through the scenes as opposed to the mind. Mental (psychological) data are related to the mind such as emotion and personality. Visual data represent how an individual is perceived by others normally through images and videos. By using a data gathering method that can collect all three data types, it provides a mean to implementing a data-driven approach to developing a realistic agent model. By employing a data-driven approach, an agent can be built based on real experiences and information collected and can be designed based on real actions and behaviours observed in the real world. Allowing us to produce a realistic agent that can represent real human beings.

Two important features in developing realistic agents using a data-driven approach are: implementing psychological aspects and implementing a cognitive architecture. Psychological aspects such as personality and emotion play a significant role in displaying realistic agent-based models. These aspects can be used to make the agent appear and act more realistic by influencing the agent's decision making processes. Research has been attempted to create more realistic crowd simulations by implementing psychological aspects [19–21] into the virtual agents characteristics in order to influence the agent's behaviours. A cognitive architecture is a framework that has been created to provide similar decision making to the human mind. In order to achieve this, a cognitive architecture must consist of multiple components that can work together to make decisions and display realistic behaviours. These components can vary from knowledge/learning, storage of information (similar to how memories work) and even the processing of new information. By combining the two features with data collected, we can develop an agent-based model that can represent and display realistic behaviours.

1.3 Problem Statement

Typical crowd simulations are composed of three key phases: input, cognitive architecture model, and output. Where the input phase generates data (also known as data gathering phase) for a cognitive architecture model to process whilst the output phase involves output generation, evaluation and validation. However no overall framework encompassing these three key phases has been proposed to produce realistic simulations. Even though there have been approaches proposed in the field for making realistic agent-based models within crowd simulation [8, 22, 23], they share some common drawbacks.

First, traditional approaches focus on implementing, improving and developing variations of their cognitive simulation model, while at the same time neglecting the input phase and the output phase [13, 14]. Instead, the input data are randomly or manually generated to run a cognitive model to demonstrate its applicability in a certain domain area. This, in turn, makes it hard to validate or compare as realistic as no real-world data is being considered. Furthermore, some researchers have run multiple different types of data gathering methods, such as video recordings and real-world scenarios, to develop their agent based models. However, current data gathering methods are unable to collect all forms of real-world data for agent-based crowd simulations. This allows us to validate our models and simulation only to a certain extent. Limiting our ability to develop and validate an agent-based model from all possible perspectives when comparing to real human beings. Also, most of these current data gathering methods are cost and time inefficient. For instance, running a real-world experiment requires a lot of time to set up, find, and recruit participants to run. This can be a significant problem for researchers who are on fixed time to complete their project or have to run multiple data gathering experiments.

Second, there are some studies [8, 22, 23] that have attempted to improve the overall performance of their model by including richer input data such as psychological data (personality and emotion). However, the incorporation of the generated psychological data is primarily implemented through the low-level parameters of the cognitive architecture model. Low-level parameters focuses on basic input values that influence the agent's movements such as speed, collision radius, navigation and path finding. While high-level parameters are input values that focus on influencing the agents decision making such as behaviours and actions. Studies have incorporated psychological aspects into the high-level area of agent-based frameworks; however, this is normally within a single area [24]. By implementing psychological aspects to influence only a single module or area of the framework, we are limiting its influence over the framework and an unrealistic representation of the real world.

Third, these loosely coupled approaches are case specific, and not general enough to be used for various simulations. To the best of the authors' knowledge, there has been no agent architecture model proposed to tightly couple the collected mental (personality and emotion) and physical (speed and distance) into the cognitive architecture model for general purpose simulations.

Last, because of the random generation of input data, it is practically infeasible to quantitatively measure the performance of simulation output. Overall there lacks a flexible and adaptable framework that has been built using all forms of real-world data collected by the researcher, and has been validated using the data collected.

1.4 Aims of the research

The aim of this research is to make crowd simulation more realistic by employing a data-driven approach to inform and validate an agent based crowd simulation framework by collecting data through the use of VR+Q and a cognitive architecture. Specifically, this research has the following five aims:

1. Define a cognitive architecture with the integration of psychological (emotion and personality) aspects into the agent's high level decision making for simulating heterogeneous agents within a microscopic crowd simulation;

2. Implement an agent based crowd simulation framework that is based on the proposed cognitive architecture;
3. Design a generic agent based crowd simulation framework that can be used, in general, environment and scenario;
4. Design and implement a new data gathering method using VR technology to refine and validate the proposed crowd simulation framework;
5. Conduct user testings to collect data to inform and validate the proposed crowd simulation software framework under different application scenarios.

1.5 Limitations and Assumptions

Like all work in crowd simulation, there are numerous assumptions and limitations made to allow research similar to this to exist. The assumptions and limitations made in the course of this study are as follows:

- The word realistic in this study means that it showed similar results to real-world data collected, previous studies and/or expected results from theories of crowd behaviours;
- When gathering data from the participants, our goal is not to influence or change the participants' responses but to show they will produce similar responses based on the situation;
- Crowd behaviours are behaviours performed by individuals who have come together to form groups in crowd simulations;
- Personality is a static variable due to being a short-term simulation. If this was a long-term simulation, it would be considered as a dynamic variable;
- Emotions are changed based on a person's decisions and situation happening around the environment and is affected by others;
- Emotional facial expressions and appearances are not considered, although they are an important aspect, they are not in the scope of this project;
- The focus of individual characteristics, hobbies and gender are not considered although they are an important aspect in developing realistic crowd simulation. However, they are not in the scope of this project;

- The focus of comparing and implementing different cultures and nationalities are not considered although they are an important aspect in developing realistic crowd simulation. However, they are not in the scope of this project;
- The focus of social interaction and groups is not within the scope of this project. Although they are an important aspect in developing realistic agents in crowd simulation;
- The focus of individual data comparison between agents and real people is not in the scope of this project. The focus is on crowd data comparison between agents and real people;
- The focus of comparing the data based on an individual's VR experience is not in the scope of this project. The focus is on crowd data comparison which is an average of all individual's VR experience.

1.6 Contributions

This research will fill the current research gap by devising an agent based crowd simulation framework by gathering real world data in an effective and efficient manner. This research also considers the theoretical background of cognitive architectures and the influences of psychological aspects (personality and emotion). The research contributions are broken down into two groups: data gathering and the agent-based framework.

1.6.1 Data Gathering Contribution

- To identify a set of important data gathering features for agent-based simulations;
- To propose an ecologically valid and time/cost efficient method to capture physical, mental and visual data for agent-based simulations;
- To provide experimental results demonstrating the robustness of the proposed method with respect to the real-world data gathering approach;
- To propose an adjustment factor for completed time physical data in order to mitigate the real world space and the virtual world space;
- To conduct a statistical significant test to prove the validity of data collected by our proposed method.

1.6.2 Agent Based Framework Contribution

- Propose a flexible agent based simulation model that systematically incorporates the collected physical, mental and visual data;
- Evaluate, validate and benchmark the performance of our proposed model to prove the robustness and effectiveness of our framework;
- Propose an overall agent based simulation framework for realistic crowd simulations encompassing the input phase, the agent architecture model phase, and the output validation phase;
- Propose a generic agent based simulation framework that can be implemented in different scenarios and environments.

1.7 Thesis Outline

This thesis has a total of eight Chapters including Introduction. Following the Introduction Chapter is Literature Review in Chapter 2. Chapter 2 provides a review of relevant existing approaches, methodologies and issues to developing realistic crowd simulation. The first section discusses the current microscopic approaches used to develop crowd simulations. This is followed by current cognitive architecture models and how they have been used in previous crowd simulation studies. In the next section, we present the review and discussion of different data gathering methods that have been used in crowd simulation. This section is followed by a review and discussion of psychological aspects. Lastly, we present a summarisation of all the important aspects discussed throughout the literature review and describe how they have not all been utilised together effectively.

Chapter 3 discusses the overall agent based framework. This section covers the break down of the project into three phases and discusses how each phase is solved in the next four Chapters. Chapter 4 presents the experimental design for gathering real-world data. This section discusses the approach and methodology used to collect the data for the development of the agent based crowd simulation framework.

Chapter 5 discusses the design of the AI architecture for the agent based crowd simulation model and how it is computed. This chapter defines each module of the framework and the methodology used to develop the computational model. How the data gathered, in the previous chapter, is implemented into each module is also discussed. Chapter 6 analyses and reveals the results of this study. The first section analyses and compares the data gathering methods, and validates the method used from collecting real-world data for the agent based crowd simulation framework. The next section analyses and validates the agent based crowd simulation framework using the AI architecture by comparing it to the data collected during the data gathering phase.

Chapter 7 discusses a crowd simulation case study using the AI architecture. This chapter validates the framework's ability to be flexible and adaptable to different environments and scenarios. This is discussed and analysed through the scenario, the data collected and the results of the case study. Chapter 8 discusses the overall outcome of the project and explains future developments for this project. The following Table 1.1 displays a breakdown of intellectual contributions by relevant authors for each chapter in this thesis.

Table 1.1: A Breakdown of intellectual contributions by authors

Ch.	Publications	Intellectual Contribution
1	None	Entirely the work of Jacob Sinclair
2	[In preparation] Sinclair, J, Suwanwiwat, H and Lee, I (2020), Microscopic Crowd Simulation from Input Data Gathering to Cognitive Architecture: A Review, Computer Science Review	Jacob Sinclair gathered the literature and wrote the paper. Ickjai Lee and Hemmaphan Suwanwiwat directed the paper design and edited the draft.
3	None	Entirely the work of Jacob Sinclair
4	[Submitted] Sinclair, J, Suwanwiwat, H and Lee, I (2019) A Virtual Reality and Questionnaire Approach to Gathering Real World Data for Agent Based Crowd Simulation Models. In: Virtual Reality – Springer	Jacob Sinclair designed the approach, wrote the code, conducted the experiments and wrote the paper. Ickjai Lee and Hemmaphan Suwanwiwat directed the paper design, edited the draft, and suggested methods for parameter testing and significance testing.
5	[Submitted] Sinclair, J, Suwanwiwat, H and Lee, I (2020) A Hybrid Data Gathering and Agent Based Cognitive Architecture for Realistic Crowd Simulations. In: International Journal of Human-Computer Studies, Elsevier	Jacob Sinclair designed the approach, wrote the code, conducted the experiments and wrote the paper. Ickjai Lee and Hemmaphan Suwanwiwat directed the paper design, edited the draft, and suggested methods for parameter testing and significance testing.
6	[Published] Sinclair, J, and Lee, I (2017) A generic cognitive architecture framework with personality and emotions for crowd simulation. In: Proceedings of the 12th International Conference on Intelligent Systems and Knowledge Engineering, pp.1-6.	Jacob Sinclair designed the approach, wrote the code, conducted the experiments and wrote the paper. Ickjai Lee directed the paper design edited the draft.
7	[In preparation] Sinclair, J, Suwanwiwat, H and Lee, I (2020), A data-driven realistic Crowd Simulation: A case study with emergency management, Simulation Practice and Theory	Jacob Sinclair designed the approach, wrote the code, conducted the experiments and wrote the paper. Ickjai Lee and Hemmaphan Suwanwiwat directed the paper design, edited the draft, ands uggested methods for parameter testing and significance testing.
8	None	Entirely the work of Jacob Sinclair

Chapter 2

Literature Review

This section provides the discussion of past studies and what has been implemented for the development and refinement of realistic agent-based models within crowd simulation. Section 2.1 discusses different types of basic crowd simulation models which focus on navigation behaviour. Navigation behaviour is the ability of path finding and multiple steering behaviours to allow agents to move around different environments. Section 2.2 discusses different cognitive architecture types. Section 2.3 explains the different types of data gathering methods. Section 2.4 discusses different types of psychological aspects such as personality and emotions that have been implemented into crowd simulation. Section 2.5 summarises the overall importance of incorporating all previous discussed sections to create realistic crowd simulations. It also discusses the current issues with past studies and how the proposed project will solve it.

2.1 Crowd Simulation

Developing realistic crowds is a very important and challenging problem in crowd simulation. This is because realistic crowd simulations require many different components such as group behaviour, cognitive modelling, motion synthesis, crowd movement and rendering [25]. Crowd simulation can provide many features for generating realistic motions and behaviours such as full-body bio-mechanics, facial expressions, gestures and motion dynamics [26]. Crowd behaviours are a level of intelligence combined with individual navigation to help an agent move along a calculated path in a crowd [27]. Depending on the level of intelligence a crowd behaviour model, they can either execute a series of local searches of the environment or consider the locomotion constraints such as turning movements and dynamic obstacles in the environment such as other agents and moving objects.

There are two types of approaches to crowd behaviours they are microscopic and macroscopic models. Microscopic models focus on the behaviour and decisions of an individual agent and the communication with other agents within a crowd, while macroscopic models focus on the system as a whole [9, 28]. Macroscopic models do not provide individual behaviours for agents, instead focus on crowd behaviours as movements. Macroscopic models can be used in predicting the flow of traffic and the capacity of a large-scale structure like stadiums [28]. However, macroscopic models are unable to simulate complex agent interactions [27]. The different types of macroscopic models are regression model, route choice model, queue model and gas-kinetics model.

Table 2.1: Microscopic and macroscopic comparison.

	Realistic Behaviours	Crowd Density	Computational Power	Agents Modeled
Microscopic	Yes	Low-High	High	Individual Agents
Macroscopic	No	High	Low	Groups

Both microscopic and macroscopic models contribute to crowd simulation in different ways (see Table 2.1). The microscopic model is efficient in presenting realistic behaviours as it focuses on modelling agents as independent beings with their own positions, goals, collision avoidance with static obstacles, respond to dynamic threats and ability to move itself towards its target [27]. While a macroscopic model is incapable of providing realistic behaviours due to its focus on the systems as a whole [9] and presenting crowd behaviours as movements [28].

When it comes to crowd density which is the number of agents in a single location, an approach can handle, macroscopic models are able to handle high density crowds. This is because macroscopic models have the ability to be used in predicting the flow of traffic and the capacity in large-scale structures [28]. While microscopic models are mostly used in low to medium density crowds [28, 29] it can also provide high density crowds, although it can cause unrealistic agent movements to appear such as shaking or vibrating [28, 29]. When it comes down to the computational efficiency, the macroscopic model requires less computing resources [30] compared to the microscopic model due to the fact that it considers a crowd as one entity or whole system that moves through the environment following global rules and crowd behaviours as movement. A microscopic model, on the other hand does require a high level of computational power since it needs to run each virtual agent as its own individual being. Even with this drawback, microscopic models are better than macroscopic models in providing realistic crowd simulations due to the ability to simulate complex agent interactions and individual behaviours.

2.1.1 Microscopic Models

Microscopic models define the space-time behaviours of individual agents [28]. Agents are modelled as independent beings that have their own positions, goals, and collision avoidance with static obstacles, response to dynamic threats and even steer itself toward its target [27]. Some of the different models are rule-based approach [28, 31], cellular-automata model [32–34], social force model [35–37], and agent based model [38–40].

2.1.1.1 Rule Based Approach

Rule-based approach uses rules and heuristics to determine what action an agent should take when various circumstances are presented to an agent [27]. For example if an agent is about to walk into a wall and there is a rule related to a wall to the right. The simulation would determine whether the agent should move left (or right) to avoid collision.

The most common rule based approach used is Reynolds' boids model [28, 31]. The boid model is a particle system with simulated entities called boids. A boid represents an oriented particle with three specific control rules: alignment, cohesion and separation. Each rule determines how an agent responds to other agents within a localised area. Alignment allows an agent to align themselves with other agents. Cohesion allows the ability to approach the position of nearby agents and form a group. While separation allows agents to maintain a set distance from other agents without crowding each other [31, 41]. Each rule allowed an agent to move based on the position and velocity of the other agents within their detection range. Bayazit et al. [42] used behavioural rules from Reynolds [31, 41] that allowed their agents to modify their own actions based on their current position and situation.

Loscos et al. [43] implemented the rule-based approach to simulate the decision-making of pedestrians when a collision is expected to occur. To prevent a collision, the simulated pedestrians would either slow down or stop completely. Certain parameters such as the direction of the path of each pedestrian, the velocity factor and the distance between the pedestrians are considered in the simulation.

Guy et al. [26] implemented the rule-based approach to demonstrate their application of entropy metric to evaluate the predictability of crowd simulation techniques in terms of similarity to real-world crowd data. In their applications each agent follows three behaviour based rules: steer towards the goal, steer away from the closest obstacle, and steer away from the closest agent. When an obstacle is very close or when a collision is imminent to an agent, the avoidance rules are given a higher priority over the steer towards goal behaviour.

The problem with the rule-based approach is that it is limited by the number rules created by the developer. Also the rule based approach either does not provide collision detection and repulsion or they adopt a conservative approach by employing waiting rules. Which is acceptable if working with low density simulations but lacks realism for high density or panic situations [29].

2.1.1.2 Cellular-Automata Model

Cellular-automata [32–34] was created by Von Neumann in 1940s, by creating the first self-replicating automata with pencil and graph paper. Cellular-automata is a two dimensional grid of cells with either single or multiple values at each cell [28]. The state of each cell is defined by the values of the variables at each cell. A cellular automaton evolves in discrete time steps. The state of each cell is affected by the values of variables of a defined number of the neighbouring cells [28].

STEPS [9] and EXODUS [9] are examples of cellular-automata models that have been implemented into crowd simulation. STEPS is a cellular-automata model that allows an agent to occupy one cell at each given time and allows agents to move in the preferred direction only if the next cell is empty. EXODUS uses a 2D grid to map geometry of a building. The grid provides nodes that can be connected with eight other surrounding nodes. The parameters that affect the agent's movement are speed, shortest distance to a goal, other agent positions on the grid and agent's current position.

Pelechano et al. [29] stated that the cellular-automata model restricts agent movements when the density of a crowd is high. Even though it is fast and easy to create, it does not provide agent interaction and only models homogeneous interactions amongst agents. The constraint of one agent per cell can also produce unrealistic crowd behaviours [27].

2.1.1.3 Social Force Model

Social force model [35–37] was proposed in the 1995 by Helbing and Molnar for simulating pedestrian motion [28, 34]. Social force models are able to simulate forces such as repulsion, attraction, friction, dissipation and fluctuations [27, 28]. Social force models can describe pedestrian agent's behaviour in a more realistic manner although they were developed to be as simple as possible [28]. Pelechano et al. [19, 28, 29] presented a HiDAC, which is a parameterised social forces model that relies on psychological and geometrical rules. HiDAC allows simulating high-density crowds of autonomous agents moving in a natural manner in a dynamically changing virtual environment. The parameters used to affect an agent's behaviour in HiDAC are [19, 28]:

- Leadership – the percentage of leaders in a crowd;

- Trained – the percentage of agents that have trained knowledge of the area among the leaders;
- Communications – decide whether an agent can communicate or not;
- Panic – the percentage of agents that will display panic when something dangerous occurs;
- Panic propagation – the percentage of agents with high level of probability of displaying panic behaviours when seeing other agents panicking;
- Impatience – the percentage of agents that will avoid restricted areas when other paths are available;
- Falling – the percentage of agents with a high probability of losing their balance when under severe pushing;
- Pushing threshold – the percentage for each min to max distance allowed from other agents in which repulsion forces won't affect them;
- Right preference – the percentage of agents that will try to move towards the right when facing opposite flow;
- Avoidance – the percentage for each magnitude indicating how long an agent will try to avoid other agents by walking around.

Guy et al. [26] also used the social force model to demonstrate their application of entropy metric. The social force model was used to compute the path of each agent in the environment by adding various forces to each agent that depends on the positions and velocities of all nearby agents. For example, an agent receives a repulsive force pushing it away from any neighbours and from any walls or obstacles nearby. The size of the force will decrease gradually based on the distance. Each agent will in addition have a goal velocity used to calculate the desired speed and direction.

The problem with the social force model is that in most implementations, it makes the agents look like they are shaking in response to multiple imposing forces in high-density crowds [28]. This causes the simulation to be unrealistic, as it does not match normal human behaviour. It is also believed that the social force model represents an approach that produces simulations that appear like particle animation rather than human movement [29].

2.1.1.4 Agent Based Models

ABM are computational models of autonomous agents designed for simulating their actions and interactions with the purpose of viewing assessing their behaviours and effects on a system as a whole. ABM primary focus is on implementing behavioural rules for modeling each agents behaviour [38]. These behavioural rules are to represent those of human beings. The ABM allow agents to have the ability to examine their surroundings, make decisions based on their situation such as following another agent or avoiding objects within the environment [38, 39].

Park et al. [38] proposed a collision avoidance behavior model for ABM. The behaviour model implemented was based on psychological findings of human behaviours. The psychological aspects applied were to cover all phases of the ABM low-level parameters such as sensing, collision prediction, collision avoidance steering, locomotion, and space-keeping.

Dawson et al. [40] implemented a dynamic agent based model for effective flood incident management processes. It was developed to provide a new understanding into flood events and how it can be used for policy analysis and other practical applications. A list of behavioural rules was implemented to define how each agent and the flood management organisations will behave.

ABM's provide researchers with advantages when being implemented into their simulations [39]. Firstly, ABM's are able to capture unique behaviours and emergent phenomena within different simulations and scenarios. Secondly, an ABM is flexible, as it allows the researcher to determine the level of complexity for the agent and provides a natural framework structure for tuning the complexity. Even though ABM's have the ability to simulate realistic human behaviours, it is just a shell of something bigger. ABM's provide a heterogeneous agent in the behavioural level however they do not provide a clear framework that can handle individual characteristics and the decision making level.

2.1.2 Discussion

Crowd behaviours provide a simple level of intelligence that works together with individual navigation to provide virtual agents with the ability to move across a calculated path within a crowd. However, crowd behaviours are developed only for the behavioural level of an agent's AI and not the characteristic or decision making level. In order to create a realistic agent, an architecture that provides a structure for all three levels is required. The ABM provides the best means to achieving realistic agents as it provides flexibility in its design allowing more functionality to be integrated into the framework.

One approach to developing realistic agents using ABM is the integration of a cognitive architecture explained in the next section. Cognitive architectures provide a structure developed to handle the characteristic, decision making and behavioural levels of an agent's AI.

2.2 Cognitive Architecture

Cognitive architectures are frameworks that have been designed to represent the process of the human mind. Cognitive architectures consist of multiple components designed to work together to display realistic behaviours. These components can include a storage of information (such as memory) and the process of attaining and providing knowledge [44]. Research into integrating cognitive architectures has spread into multiple fields of studies such as artificial intelligence, cognitive psychology, neurobiology and crowd simulation [44].

There are many different types of cognitive architectures each with their own unique structure, strengths and weaknesses. The six most common cognitive architectures developed to date are BDI [45], SOAR [46], ACT-R [47], CLARION [48], ICARUS [49] and Subsumption [50]. BDI is an architecture that was designed to analyse and plan in real-time environments. SOAR is one of the first cognitive architectures designed. It was developed to handle an assortment of jobs of an intelligent agent through a simple method of learning from experience [44, 46]. ACT-R was developed to model the human cognition from data gathered by experiments in cognitive psychology and brain imaging. CLARION is a hybrid architecture that was designed to simulate jobs in cognitive and social psychology. ICARUS was designed for physical and embodied agents by integrating perception and actions with cognition [44, 48]. Subsumption is used for behaviour based robotics and is seen as a new approach to artificial intelligence.

2.2.1 Belief-Desire-Intention (BDI)

BDI architecture is one of the most used framework in developing intelligent autonomous agents in agent-based crowd simulations. The BDI was designed based on the studies of psychology and intentional systems [44]. BDI was developed as a system that has the ability to analyse and plan in real-time dynamic environments. BDI was designed to allow agents to be able to react to changes and communicate within their environment at the same time as attempting to achieve their goals. In addition BDI has the capability to respond to new conditions, situations or goals in real-time [44].

The belief state runs how an agent perceives its surrounding environment through information including itself and other agents. The belief state updates itself based on the information gathered by the perception of the environment and the implementation of the intention state [44]. The desire state represents the goals or objectives that a BDI agent aims to achieve. A BDI agent completes its desired goal by successfully performing the required action or description of the goal. The intention state represents the actions that a BDI agent is obligated to perform in order to achieve its desires [44].

The BDI framework provides agent based crowd simulations with the ability to perceive agent's decision making process in a more realistic manner [51, 52]. The BDI framework allows virtual agents to possess a varying amount of knowledge regarding their environment and their neighbouring agents [53]. This knowledge determines the virtual agent's beliefs and allows them to determine what desires they wish to achieve. Jason Tsa et al. [53] implemented the BDI framework into their multi-agent evacuation simulation tool called ESCAPES. This was implemented to provide their agents with the ability to determine what behaviour the agent should display based on the knowledge gather from the environment and other agents. ESCAPES has been used by other researchers to implement their own evacuation scenarios [54] and compare their own methods to other methods researched [55].

The BDI framework has been enhanced within agent based simulations by incorporating psychological aspects like personality and emotions into the BDI framework [21, 51, 52]. By incorporating personality and emotions into the BDI framework, it has allowed virtual agents to appear more realistic in their decisions and beliefs. Zoumpoulaki et al. [21] implemented an emotional state into the agent's beliefs allowing them to affect the agents decision making process. They also implemented a personality module and emotion module that also affects the agent's decision making process within the BDI framework. Other studies have implemented the personality and emotions into their research in their own way. Vasudevan and Son [24] implemented an emotion module into the BDI framework which affects the agent's beliefs and desires based on time pressure and the agent's confidence. T. Bosse et al. [56] implemented a modified version of the BDI framework that replaces the desire module with an emotion module. T. Bosse et al. [56] BEI is implemented for collective decision making based on an individual agent's mental state and also the interaction with other agents.

The BDI framework has not only been enhanced by integrating personality and emotions but by also modifying the framework to include new modules. K. Vasudevan et al. [24] enhanced the current BDI framework to allow the functionality to model human behaviours under risk; called BDI-AMBER framework (BDI Agent for Modelling Human BEhavior under Risk). K. Vasudevan et al. [24] used the BDI-AMBER to create innovative techniques for developing precise crowd simulations. The BDI-AMBER framework works using five modules (Goal Seeking, Belief, Emotion, Desire and Decision Making). The goal seeking module sets the goals within an agent. The belief module contained a perceptual processor which gathers data from the environment using the agent's senses and the characteristics of the agent to provide the set beliefs within the agent. The emotion module dealt with aspects that influence the whole BDI-AMBER framework [24]. The two main aspects within the emotion module are time pressure and confidence evaluator. The desire module determined what the agent needs which are determined based on the current goal. The decision making module provided the intentions by planning and performing the actions required in achieving the agents goals [24].

Du Lei et al. [57] presented the BDIP that incorporates predictions within the BDI framework. The BDIP model provides a better basis for decision making in emergency evacuation management than the original BDI model. They incorporated predictions into the BDI framework due to the fact that agents always predict the future state of a situation. However, studies into the predictive power of agents has been ignored. The prediction module estimated the future state of situations which means that the prediction module is the cause of advanced computing about the goal of emergency evacuations [57].

However, these methods only allow the personality and emotions to either affect the framework in a single module or affect certain modules under a single circumstance. This can be considered unrealistic as psychological aspects affect characteristics that influence and produce behaviours, actions and decisions by evolving by biological and environmental factors.

2.2.2 State Operator And Result (SOAR)

SOAR is a classical artificial intelligence framework and one of the first cognitive architectures designed. SOAR's main objective is to handle a full range of capabilities of an intelligent agent from simple routines to complicated problems through a general method of learning from experience [44]. This provides SOAR with a wide range of problem solving methods and also allows virtual agents to learn all aspects of a particular task in order to accomplish them.

The SOAR architecture provides agent based crowd simulations with agents that can analyse and adapt to a continuously changing environment. This is completed through a unique decision making process that can solve problems by learning different aspects of an agent's task and adapting in order to complete them. M. Lhommet et al. [58] implemented SOAR into their agents to provide a decision making process in order to simulate a crisis. Which provided emerging crowd behaviours from the individual agent behaviours based on emotional contagion. M. Lhommet et al. [58] enhanced their SOAR architecture by adding an appraisal module designed to deal with the events of appraisal, social relationships and emotional contagion of the agents. Although the SOAR architecture was implemented into M. Lhommet et al. project, they provide very little discussion on how SOAR was implemented into their project and why SOAR was chosen.

2.2.3 Adaptive Control of Thought-Rational (ACT-R)

ACT-R used empirical data that has been gathered from experiments in cognitive psychology and brain imaging to design and model human cognition [44]. With a thorough understanding of human cognition, ACT-R provides researchers with a step by step simulation of human behaviours. ACT-R framework has been used in the prediction of activation patterned within the brain with the aid of fMRI [44]. Even though the ACT-R architecture has not been used in agent-based simulations, it has provided inspiration to researcher's agent-based design by adapting some of its concepts. Munchow et al. [59] developed a WALK agent architecture based on the inspiration of the ACT-R architecture. The WALK agent architecture incorporated a declarative memory for long-term knowledge from the ACT-R architecture [44, 59].

2.2.4 Connectionist Learning with Adaptive Rule Induction ON line (CLARION)

CLARION is a hybrid architecture [44, 48]. CLARION focuses on analysing and learning by incorporating implicit and explicit memories. CLARION has been integrated for simulating jobs in cognitive psychology, social psychology and artificial intelligence applications. However, CLARION has not been implemented into agent-based simulations even though it can provide assistance into simulation of psychological tendencies in artificial intelligence.

2.2.5 ICARUS

ICARUS was designed for physical and embodied agents. ICARUS provides this by integrating perception and actions with cognition [49]. ICARUS is a cognitive architecture that also combines reactive execution with problem-solving, symbolic structures with numeric utilities and provides learning structures and utilities in a cumulative method [44]. This cognitive architecture has not yet been implemented into crowd simulation this could be due to ICARUS being a large complex architecture.

2.2.6 Subsumption

Subsumption was designed as a cognitive architecture that is used in behaviour based robotics, and has been seen as a new approach to artificial intelligence. Subsumption uses an incremental and bottom-up approach to achieve its goals and solve problems of extensibility, robustness and achieving multiple goals [44].

This approach has not been implemented into agent-based simulations. This could be due to being designed for behaviour based robotics and not virtual agents.

2.2.7 Other Architectures

Although BDI, SOAR, ACT-R, CLARION, ICARUS and Subsumption are the six most common cognitive architectures, there have been other minor types of cognitive architectures that have been implemented or created into crowd simulations. H. Abdelhak et al. [60] implemented a cognitive emotion agent architecture that allows their agents to perceive the environment, analyse the situation, make decisions and perform the appropriate action based on their decisions. M. Lyell et al. [61] implemented a cycle of observation-cognition-action into hybrid pedestrian agents. This cycle includes emotions that are triggered by the events received through the perception stage. A. Guye-Vuillème et al. [62] developed their own high-level architecture that is designed to drive an agent's goals, beliefs and actions in a socially realistic approach. W. Shao et al. [63] implemented a cognitive model into their autonomous agent to allow them to have the ability to apply knowledge in order to perceive and implement goals. W. Ali et al. [64] developed a platform call MAGs based on cognitive capabilities such as perception, knowledge, memorisation and making complex decisions. N. Fridman et al. [65] implemented an extended version of the social comparison theory to deal with cultural differences in the behaviour of pedestrians and also deal with differences during evacuation scenarios. W. Chao et al. [66, 67] created the IMCrowd system architecture that has the ability to simulate social behaviours of heterogeneous agents in different communication scenarios. Even though there have been other cognitive architectures designed in previous studies, they have been developed within a particular scenario or have been design to be used in certain scenarios.

2.2.8 Discussion

Many different types of cognitive architectures have been developed over the last few years. But most have been developed for other purposes rather than agent-based crowd simulations. For this proposed study, an enhanced version of the BDI architecture will be implemented into the agents since it is the most widely used and popular cognitive architecture. In addition, the BDI architecture was chosen because of its ability to analyse and plan in real-time situations, allow agents to react to changes and communicate within an environment at the same time as trying to achieve its goal. Although the BDI architecture does provide these capabilities, there are still some areas that can be implemented to improve the realism of the agents such as tight coupling and high level implementation. To implement these missing capabilities and develop the BDI architecture, collecting data from people in the real world is required.

2.3 Data Gathering

The purpose of data gathering is to provide data that can be used for the development of simulation models. In order to model realistic agents, scenarios and environments for agent-based simulations; real-world data needs to be collected. Researchers have used many different methods to collect real-world data in the field of agent-based behaviours, this section reviews major approaches in the field.

2.3.1 Important Data Gathering Features

There have been many studies in microscopic or agent-based simulations to generate more realistic crowd simulations [15, 68–70] (refer to survey papers for more details [71–73]). They typically focus on computational enhancement [68], incorporation of additional features into simulations such as psychological/physical factors [17], or applications in a particular domain such as pedestrian simulation or emergency management [8, 13, 74]. Even though the importance of data generation for agents has been well recognised to produce realistic agent-based simulations [73, 75], not much research [76] has been conducted on data gathering or data collection for agents in agent-based simulation.

Various data collection approaches will be discussed in Section 2.3.2, and here we identify several important features that need to be considered in order to gather data for agent-based simulations. These include cost effectiveness, time efficiency, reproducibility, ecological validity, and experimental control [76]. Cost effectiveness refers to how much money will be required in order to conduct the particular data gathering method. Whilst time efficiency refers to how long a data gathering method will take in order to gather enough data for the project. This can be from the amount of time it takes to recruit participants all the way to running the data gathering experiment. Reproducibility refers to whether the method employed is able to be replicated in a real, virtual or simulated format. Ecological validity is whether the data gathering method used can be seen as a means to representing a real-life situation. For instance, asking participants to watch a virtual simulation and comment on it to gather data cannot be considered ecologically valid [20]. While having people participated in a virtual environment [74] that represents the real world can be considered ecologically valid. Experimental control is whether the experiment or observation method can be controlled by minimising the effect of unwanted variables (such as influences from outside the experiment). This often provides an increase in the reliability of the data. In addition to these five important features, it is important to capture and model three data types including physical, mental (psychological including personality and emotion), and visual data for agent-based simulation. There could be some more features such as real-time [71], however we focus on these five important features along with the three data types in this study.

2.3.2 Data Gathering Methods

2.3.2.1 Video Recordings

A video recording is a visual copy of an event or situation that happened in the real world. This method provides low time efficiency and cost effectiveness due to the fact that the entire real-world event is pre-recorded and all that this required from the researcher is to collect the data [77]. Video recordings provide ecological validity as it is based on real life events, which can be hardly reproduced in a virtual simulation that can help compare and validate agent-based models. For instance, Fridman et al. [54] used video recordings of pedestrian cultures taken from five different countries (Iraq, Israel, England, Canada and France) to gather data on individual cultural parameters (personal space, base walking speed, avoidance side and group formations). This data was then used in modelling virtual pedestrians and displaying the impact of the cultural parameters on crowd dynamics.

However, the experimental control of video recordings is impossible as they are pre-recorded events forcing the researcher to accept unknown variables to their work. Video recordings can only provide real-world data and behaviours through the use of physical and visual data. For example Sakellariou et al. [78] gathered data using video recordings of pilgrims performing the ritual of Sa'yee. The data gathered from the videos were used to provide characteristic behaviours (visual data) of crowd and real-world parameters (physical data) to be used in their simulations. However, it cannot provide mental data as there is no interaction with the people within the videos making it impossible to determine their personality or emotion.

2.3.2.2 Real World Scenarios

Real-world scenarios are situations, which have already happened in the real world, that are to be modelled into simulation scenarios by researchers to prove their project can simulate the same or similar results. For example, Tsai et al. [55] gathered data using a crowd panic on the streets of Amsterdam and Greece protest to develop their simulation environment in order to compare their model to other research models. Shao and Terzopoulos [63] reconstructed the original Pennsylvania train station in New York City with virtual agents to demonstrate realistic human activity.

A real-world scenario has a low cost effectiveness and time efficiency to a project since it requires a significant amount of time to run. This method cannot be reproduced as a means of comparing and validating research data to real-world data collected from the scenario. However, this data gathering method has no experimental control due to be based on events that have already happened in the real world. Although real-world scenarios can provide physical data and visual data (if combined with other methods such as video recordings), most researchers implement this method only for modelling their scenarios. Many researchers also used this method in their research to compare their results to the real world instead of developing realistic agent-based models using real-world data [55, 79]. Real-world scenarios cannot provide a way of mapping agent personality and emotions due to acquiring information on the people in the scenarios would be required.

2.3.2.3 User Studies

A user study is the examination of the performance, characteristics and behaviour of the users. User studies are run in two ways: first is the method that allows the researcher to run controlled real world scenarios and the other is having real people evaluate their product, design or simulation. For example, Guy et al. [20] implemented a user study which required their participants to view 3 different scenarios and to describe the behaviour of a particular agent. The data gathered from the user study was used to map the parameters of various personality traits. The cost to run a user study varies based on the extent of the scenario: for instance acquiring a location and purchasing equipment to represent the scenario. User studies do have a low time efficiency due to the fact that it takes time to acquire a location, recruit enough participants and run the entire scenario.

User studies are controlled experiments to some degree as the scenario and environment is built around the researcher's project and can only provide data that the researcher requires. This also means the researcher can reproduce the entire method in a virtual format for validation later on. This method does provide ecological validity, however; it can also be perceived as not a true ecological validity due to it being based on a real-life situation developed and controlled by the researcher. This method does not provide all data types. Visual data can be collected using the perception of the researcher or the participants; whilst physical data can be obtained from either using equipment that has GPS or by using real-life participant's reactions or responses to virtual agents and behaviours to collect data. Mental data can be collected through questionnaires, for instance Guy et al. [20] asked their participants to describe what psychological behaviours the agents were producing within a virtual user study.

2.3.2.4 Questionnaires

Questionnaires consist of a chain of questions whose purpose is to gather information from the respondents. For instance, Jia and Yun [80] implemented a multiple-choice questionnaire to simulate a scenario of a plant fire emergency. The purpose of the questionnaire was to test the decision making ability of the staff under stress. The data gathered from the questionnaires were analysed to model the agent's risk assessment, decision making and stress ability on the agent's decision making [80].

Questionnaires provide a cost-effective approach to collecting data as it does not require a lot of money to print out multiple copies of the same questionnaire. Also these days most questionnaires could be uploaded online so that many people can participate without any extra cost. The time it takes to run this method varies as it depends on how many participants are required and how difficult it would take to find them. The data collected can be replicated within agent-based simulations. It requires computational modelling that can either run data statically, or the data can be replicated through a process built within the agent model. This method can be considered ecologically valid as it does represent real life responses from real people. However, this data cannot be considered as real-life actions or behaviours performed by real people. This is because it can only provide a hypothetical situation and not a real-life situation. The researcher has full control over the experiment as they determine what questions and answers can be obtained. For example, a multiple choice question forces the participant to select one of the answers created by the researcher. Even open-ended questions are controlled by the researcher as it focuses primarily on the area of the project. Questionnaires cannot provide visual data unless used with another method (such as video recordings or user studies) and cannot provide any physical data as the participants are not asked to do anything other than answering questions. This method does provide the best means to gathering mental data as it directly asks the participant questions that can be used to determine personality or emotions.

2.3.2.5 Virtual Reality

VR requires real people to move through a virtual world where the researcher can gather data on the person's movements, actions, behaviours and decisions [81]. Kinateder et al. [82] created a VR platform to design microscopic algorithms for realistic simulations. This research gathered data on the users and virtual agent's interaction and trajectory through the environment which was analysed and compared to other VR methods. VR varies when it comes to cost effectiveness, for instance, a virtual simulation can be run using only a mobile phone and a VR headset or it can be run by purchasing a VR setup system such as Oculus Rift (https://www.oculus.com/) or Vive (https://www.vive.com/). VR is quite time efficient, as it does not take long to setup and you only require an empty room in which the participants can move around without bumping into physical objects.

The scenario and environment can be easily replicated as it is already a virtual setup. This method is ecologically valid as you can create realistic real-life environments to scale and real-life situations within a virtual world. The benefit of making real-life environments to scale in VR is that it allows researchers and developers to create any environment from around the world and have people immersed within them without having to physically go there. Another benefit is that by making real-life environments in VR it provides a sense of realistic physical presence to the user allowing them to believe they are actually there. VR can also provide the participants with the ability to interact with the environment. VR allows the researcher to control the experiment so that they can collect accurate data being influenced by external variables. Simultaneously VR can also allow the participant to have control by giving them the freedom to move around and make their own decisions, just like in the real world. VR can gather visual data by allowing the researcher or the participant to observe an event from a third person perspective. Physical data such as speed, distance and time can be collected using the VR device as a GPS tracker. While mental data cannot be directly collected using the VR method, but it can be used in conjunction with other methods.

2.3.2.6 Comparison and Discussion

Table 2.2 reports comparison of data gathering approaches with respect to those five important features as well as three data types as discussed in Section 2.3.1. Approaches including video recordings, real-world scenarios and user studies are cost ineffective and time inefficient and they are unable to capture three types of data simultaneously. Approaches such as questionnaires and VR are solid candidates mostly satisfying identified important data gathering features for crowd simulation. But they fail to capture all three types of data by themselves. This motivated this study to propose a hybrid approach combining questionnaires and VR methods together to capture all three types of data. The VR provides the researcher the ability to collect physical and visual data, while a questionnaire covers the collection of mental data. Still, in order for the mental data to be effective in agent based crowd simulation models, an understanding of different psychological aspects and their mapping is required.

Table 2.2: Comparison of data gathering approaches.

	Video	RW Scenario	User studies	Questionnaires	VR
Cost effectiveness	Low	Low	Low	High	Medium-High
Time efficiency	Low	Low	Low	Medium-High	Medium-High
Reproduciblity	Low	Low	Medium	High	High
Ecological validity	High	High	Medium	Low	Medium-High
Experimental control	Low	Low	Medium	High	High
Visual data	High	High	High	Low	High
Mental data	Low	Low	Low	High	Low
Physical data	High	High	Medium	Low	High

2.4 Psychological Aspects

Psychology represents the scientific study that focuses on the mental functionality and behaviours. Psychological aspects such as personality and emotion play a significant role in human decisions and behaviours. Implementing psychological aspects into virtual agents is believed to be able to create individual differences among the agents causing them to appear more realistic.

2.4.1 Personality

Personality is a combination of physical, emotional and social features that define an individual. Personality provides individual differences based on three important characteristics; they are decision making, emotions and behaviours. For example, introverted people generally prefer having a greater interpersonal distance from others as they don't feel comfortable interacting with other people. They also tend to be resistant to any visual interaction with others. People who are a mix of neurotic and introverted possess more self-control, rigid behaviours and tend to display an increase in uncoordinated movements [28].

The implementation of personality into the study of crowd simulation provides researchers with the ability to create heterogeneous agents by providing realistic behaviours. Personality has been integrated into agents to represent agent characteristics and map agent behaviours and emotions. Different personality models have been developed and implemented into crowd simulation to produce heterogeneous agents.

2.4.1.1 OCEAN Personality Model

The OCEAN model is one of the most popular models used in crowd simulation [19, 21, 27, 58, 61, 83–85]. The OCEAN model represents five dimensions of personality used to define human personality. OCEAN stands for openness, conscientiousness, extraversion, agreeableness and neuroticism. Openness is the imaginative and creativeness characteristics of a human. Conscientious is the level in which a person is organised and careful. Extraversion is the level of outgoing and sociable a person will be. Agreeableness is the level of kindness shared with other people. Finally, neuroticism is the emotional instability and the tendency to experience negative emotions.

The OCEAN model has provided researchers with the ability to map personalities to agent behaviours [19, 27, 83]. M. Kapadia et al. [27] mapped each attribute of the OCEAN model to the low-level behaviour parameters within the HiDAC crowd simulation system. This provided the HiDAC system with the ability to model individual differences by giving each agent different psychological and physiological attributes. F. Durupınar et al. [83] implemented a personality-to-behaviour mapping between the OCEAN model and low-level behaviours such as walking speed and pushing. F. Durupınar et al. performed the mapping between the two as they believe that low-level behaviours such as these are functions of personality and due to the OCEAN model providing one-to-one mapping between low-level parameters and personality traits.

The OCEAN model has also been utilised as a way of affecting or mapping emotions [58, 61, 84, 85]. M. Ntika et al. [84] implemented the OCEAN model to determine the agent's empathy parameters. The OCEAN model was employed to calculate the empathy value of the agents which determined how vulnerable an agent is to changing an emotional state. L. Saifi et al. [85] combined the emotion model OCC with the personality OCEAN model. The combination was made to specify the predisposition of each agent's ability to feel every emotion and calculate the intensity of these emotions.

Although the OCEAN model is popular and has provided mapping to agent behaviours and emotions in crowd simulation, there is a lack of implementation of personality as an individual entity within an agent and its influence on the agents decision making and other modules [21]. A. Zoumpoulaki et al. [21] implemented a personality module as an individual entity that incorporates the OCEAN model into the BDI framework. The OCEAN model is implemented within the module to affect and influence the agents decision making, emotional reactions, behaviours and help address issues of diversity [21]. By considering personality as an individual entity, it can provide a comprehensive framework that can be used in a more dynamic setup allowing it to influence and be influenced by an agent.

2.4.1.2 Personality Traits

Personality traits are one of the most popular personality models used in crowd simulation [3, 20, 37, 60, 86–88]. Personality traits are habitual patterns of behaviours, thoughts and or emotions. It is believed that humans display an immense number of different personality traits and some of these traits are considered to be the core of an individual's basic personality [20].

Personality traits have been integrated into crowd simulation by connecting and mapping the traits to agent's parameters. For example, S. J. Guy et al. [20] integrated the Eysenck 3-Factor personality model and the six personality trait theories (aggressive, assertive, active, impulsive, shy and tense) into crowd simulation to simulate heterogeneous crowd behaviours. Based on the perceived personality data collected from a user study, in which people were asked to watch videos of different crowd simulation scenarios, each personality trait was mapped to agent's parameters such as neighbour distance, maximum number of neighbours, planning horizon, radius and preferred speed. The simulation demonstrated that these personalities would not only affect an agent's decisions, but also the resulting behaviours will affect other agents. For instance, shy agents would stay behind and allow the other agents to exit first. Similarly, in an evacuation scenario when a group of aggressive agents is formed, each agent would slow each other down causing them to exit the building slower than the other agents with different personalities.

V. Kountouriotis et al. [37] modelled high parameterisation of an individual agent, each with their own physical and psychological traits. These traits ranged from mass, top speed, acceleration, leader or follower personality, and the ability to be a part of a group such as friends or family. Turkay et al. [88] proposed a behavioural model for crowd simulation, which incorporates the personality trait aggressiveness and carefulness. The model uses analytical behaviour maps to control agent behaviours with agent-crowd interactions. In their simulation, an agent's behaviour is composed of its behaviour state and behaviour constants. Behaviour state is determined by the behavioural values assigned to each cell in the 2D grid behaviour map. Agents in the same cell will share the same behavioural values. These values can be altered temporally and spatially representing agent-crowd interactions. Behavioural constants are agent-specific values presenting the agent's personality attributes.

Although personality traits are a popular method used in crowd simulation, it does not provide a comprehensive framework. Not only should it implement a mapping to the agent's low-level parameters but also to their decision making module, emotions and behaviours. Personality traits also raise many questions on whether the mapping of each personality type is valid based on how the data are gathered.

2.4.1.3 Roles and Profile Models

Other smaller personality models have also been incorporated into crowd simulation. One model is representing personality types as different agent roles [23, 33, 52]. N. Pelechano et al. [33] specified different personality types by assigning different roles to each agent within the simulation such as trained personnel, leaders and followers. This will allow each individual agent to exhibit their own behaviour. Another model is personality characteristics [56]. T. Bosse et al. [56] used personality characteristics such as expressiveness, openness, and tendency to absorb or amplify mental states to represent their agents.

Lastly, a model representing passive and pushy as personalities [89, 90]. P. M. Torrens et al. [90] implemented two different personality profiles called passive and pushy. Passive agents were more relaxed when it came to collision detection such that they easily produce collisions. Passive agents also displayed the tendency of stopping and letting other agent pass by them. Pushy agents, on the other hand, were set to maintain their desired speed at all costs, producing space only when a the edge of a collision. These models provide limited capabilities to crowd simulations as they cannot influence or represent all areas within an agent such as agent parameters, decision making, emotions and behaviours. We need to adopt a holistic approach to implement and understand the influence of personality.

2.4.2 Emotion

Emotions are personal characteristics that are influenced by mood, personality and motivation. Emotions are commonly known to affect facial expressions. Emotions can influence an agent's ability to perceive, learn, behave and communicate within an environment [91]. Mood can be considered as a state of mind or even an emotion. It can also affect many behaviours and decisions made by an agent [28]. Emotions are implemented into crowd simulation to provide realistic heterogeneous agents. Emotions have the ability to affect a virtual agent's decision making, behaviours and influence other virtual agents. There have been many different models that have implemented emotions into crowd simulation such as representing emotion as individuals, the OCC model, PAD and many more.

2.4.2.1 OCC Model

The OCC model is a popular method that provides a hierarchy that classifies 22 different emotion types (admiration, anger, disappoint, distress, fear, fearsConf, gloating, gratification, gratitude, happyFor, hate, hope, joy, love, pity, pride, relief, remorse, reproach, resentment, satisfaction, shame) [92]. The OCC model hierarchy also contains three branches that represent the 22 emotions; they are

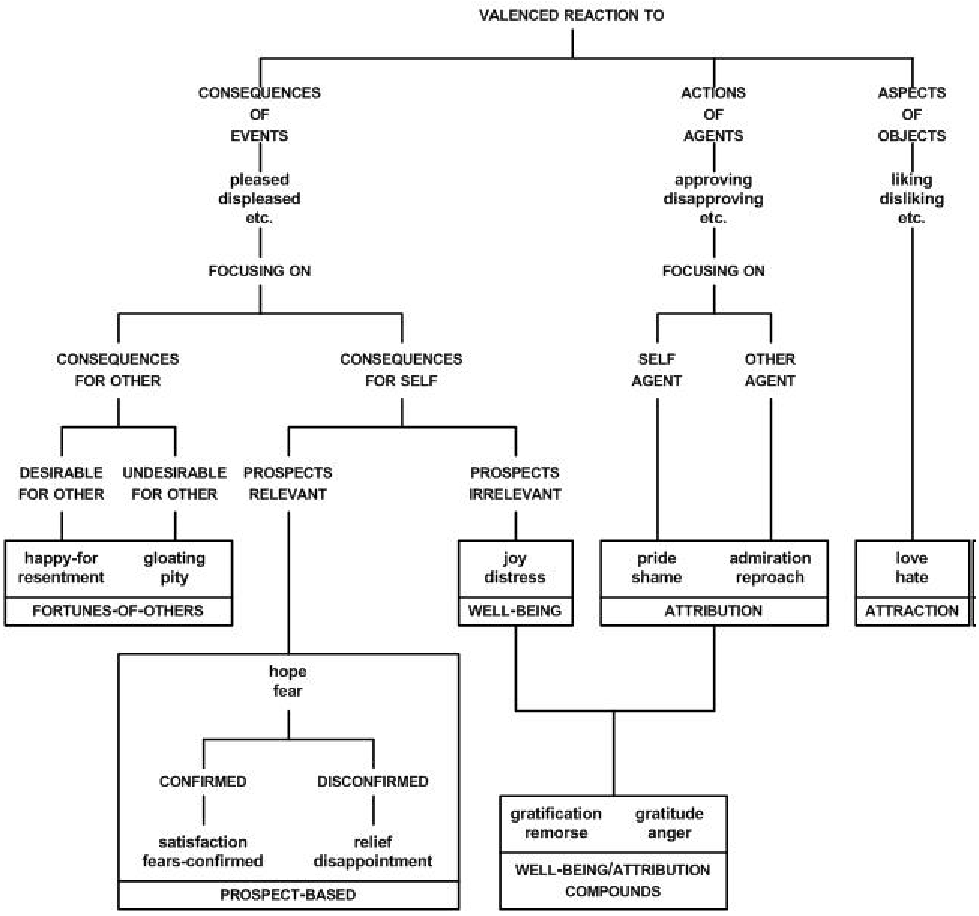


Figure 2.1: OCC model [92].

consequences of events (e.g. joy, pity, etc.), actions of agents (e.g. pride, reproach, etc.) and aspects of objects (e.g. love, hate, etc.) (see Figure 2.1).

The OCC model has been implemented into crowd simulation to provide multiple functionalities to produce realistic agents [17, 21, 58, 83, 85, 93–96]. M. W. Baig et al. [94] implemented the OCC model into their framework to describe causes of emotions for learning, classification and for calibrating the model. Their approach involved the cognitive triggering of emotions due to the three branches of the OCC model events, agents and objects. Because of this, the OCC model makes the assumption that emotions are developed based on consequences of certain cognitive methods and their clarification. A. Zoumpoulaki et al. [21] implemented an emotion model based on the OCC model. Their approach to emotion is based on modelling five positive/negative emotions as coupled pairs (Joy/Distress, Hope/Fear, Pride/Shame, Admiration/Reproach and SorryFor/HappyFor). The first three coupled emotions focus on affecting the agent itself while the other two focus on how other agents affect them.

The OCC model provides a robust approach to developing emotions into crowd simulation by providing multiple functionalities to developing realistic agents. However, there are so many ways to implement this model that there is no solid method that provides the most realistic representation for agents.

2.4.2.2 Individual Emotions

Individual emotions are basic emotions such as happy, sad, fear, stress, etc., that can be visually and physically represented by people. Individual emotions can provide virtual agents in crowd simulation by acting out the emotion through their behaviours and movements.

T. Bosse et al. [56] implemented the emotion fear into their cognitive architecture BEI. They use fear to affect an agent's beliefs which affect the agent's biasing; for example, adapting their openness to other agents, development extent and positioning within the environment. At the same time, the effect of beliefs can also influence an agent's fear which causes the fear of other group members to be place on their own.

L. Jia et al. [80] implemented a stress ability that affects the decision-making behaviour of individual agents in evacuation scenarios. They implemented two kinds of stress abilities: high stress ability and low stress ability. High stress ability agents had the ability to analyse and calmly judge on their own and tend to act based on their own decisions; while low stress ability agents tend to be unable to make up their own judgements instead, they choose to follow other people's decisions. Although individual emotions can provide agents that appear realistic, they are more difficult to implement. This is because of having to produce the emotions from scratch instead of having a model that can be used in crowd simulation.

Individual emotions can also be represented as emotional levels [22, 53, 91, 97–100]. An emotional level represents an individual emotion that can increase and decrease its intensity. Stamatopoulou et al. [91] implemented one of the basic emotions, horror in their crowd simulation. Horror was represented by six different horror levels: calm, alarm, fear, terror, panic and hysteria. An agent's horror level changed based on the situation and the environment. For example, when a calm agent perceives there is danger the horror level increases and its horror level will be changed from calm to alarm.

Nguyen et al. [99] used a mood-X behaviour table that maps particular mood levels to a list of expected behaviours. The mood studied by Nguyen et al. [99] was aggression. The levels of aggression used were avoidance, neutral, curious, aggressive posture, aggressive non-lethal and aggressive lethal action. Each aggression level was linked to a specific list of expected behaviours. For example, at neutral level, the expected behaviour of an agent is wandering, at avoidance level, the agent's expected behaviours include throwing rocks, pushing, hand-to-hand fighting, and shooting. Although representing individual emotions as emotional levels presents a way of determining how intense the agent should present that emotion, it does not provide emotional propagation and a model that can be used in crowd simulation.

2.4.2.3 PAD Model

PAD is a model that describes and measures emotional states [60, 101]. This is produced using three dimensions in PAD, firstly the pleasure/displeasure scale which measures how pleasant a person's emotions might be. Secondly, is the arousal/non-arousal scale which measures the intensity of the emotions. Lastly, the dominance/submissiveness scale which represents whether a person's emotions are controlling and dominant or controlled and submissive in nature [101].

X. Jiang et al. [101] implemented the PAD model into their crowd simulation to map both the agent's emotions and personalities into a unified space to create their Hidden Markov Model with emotion and personality. The mapping determined the relationship between basic emotions such as fear, angry, happy, bored, curious, sleepy, dignified and elated and PAD space.

H. Abdelhak et al. [60] used the three-dimensional emotion space PAD to specify emotion. They added a personality type which provides a dynamism to the evaluation of basic emotions. But also employs the agent's decision making process to navigate on PAD space based on relevance, arousal and dominance intensities.

Although the PAD model provides a mapping between basic emotions and itself, how the data is gathered for the mapping can represent an issue. The PAD model also does not provide the ability to influence an agent's decision making, behaviours and parameters. This is because of being developed as a method that describes and measures emotional states.

2.4.2.4 Other Emotion Models

Other studies have incorporated their own smaller emotion models into crowd simulation [17, 24, 102–105]. N. Xiang et al. [102] implemented a dynamic emotion transmission into their crowd simulation model to process continuously co-arising emotions. Emotion transmission is when agents emotions are triggered by other agents based on their personality and situation in their environment. In this simulation the agents were spectators whose emotions were triggered by other spectators based on their personality and the results of a sport game.

K. Vasudevan et al. [24] implemented an emotion module that influences areas of their BDI-AMBER framework. The emotion module provided two main areas:

time pressure and confidence evaluator. Time pressure kept track of the time since the start of an emergency and the targeted time set by the agent for their escape. The confidence evaluator influenced whether the agent will re-evaluate its existing goal or change its goal to a new one.

Although these emotion models are affective in their own projects they do not provide a model that can cover all areas of emotions to display realistic agents in crowd simulation.

2.4.2.5 Emotion Propagation

To make emotions in crowd simulation realistic, agents must be able to propagate their emotions to other agents. Two models have been adopted to propagate emotion in crowd simulation: emotion contagion [32, 55, 66, 67, 84, 106, 107] and panic propagation [36, 107–109].

L. Fu et al. [32] modified the macroscopic SIR model to a microscopic model to allow the integration of emotional contagion with individual movements. The purpose of implementing emotion contagion was to understand how panic can propagate through a dynamic crowd and what can be done to lessen the panic of the agents efficiently.

M. Ntika et al. [84] implemented an emotion revision function that updates a given emotion's strength based on the influence of emotional contagion of an agent. This is determined based on the interaction with neighbouring agents and the agent's individual personality traits. Three different models for emotional contagion were also implemented in conjunction with an emotion revision function. The first model introduced contagion strength which determines the strength an agent influences the state of an agent. The second model was based on contagion being affected by an empathy value which then affects the emotion strength. The third model was based on the interaction of an agent with other agents. The agent that possesses the lowest emotional strength will be influenced by the agent with the highest emotional strength [84].

O. Oğuz et al. implemented panic propagation into their crowd simulation by determining awareness regions [108]. An awareness region determined how long an agent will be affected by the incident and switch to its emergency behaviour. The further away the agent was from the incident the longer it takes for it to be affected. Agents who have reached the emergency behaviour each apply a panic value to their neighbouring positions causing any agent who enters that position to be affected [108].

Although emotion propagation provides the ability to realistically spread emotion to other agents, how these studies have implemented emotion propagation can be improved. Instead of creating emotion propagation as an individual component with no links to other modules, it would be more efficient if it was executed within an emotion model or part of a framework that connects emotion propagation to other modules such as decision making, behaviours and emotions themselves.

2.4.3 Discussion

Previous studies have provided many different models in developing personality and emotion into crowd simulation. Personality models have provided ways of mapping personality traits to agent's parameters and vice versa. Some personality models have also provided a different perspective from the usual traits by considering personality as agent characteristics or roles.

The proposed project will implement the OCEAN personality model into the agent's AI and cognitive architecture. The OCEAN model provides five dimensions of personality used to define human personality. The five dimensions will be used to map different personality traits into the virtual agents from data gathered from real people using VR+Q. The OCEAN model will also influence an agent's decisions through its beliefs and towards the agent's emotions based on the five dimensions. Previous emotion models have provided ways of representing different emotions through mapping emotions to certain values, emotional levels, propagation, etc. Some emotion models have provided an open approach to allowing the model to be used in different ways.

The proposed project will implement the OCC emotion model into the virtual agent's AI and cognitive architecture. The OCC model provides 22 basic emotions and hierarchy that splits the emotions into three categories. The data gathered in the VR experiments will be used to develop the parameters of each of the 22 basic emotions and provide a connection to the personality model. The OCC model will also influence and be influenced by the agent's beliefs, desires and decisions based on its emotional state and the situation within the environment.

2.5 Summary

Each chapter discussed an important aspect into creating realistic crowd simulations. This is either by improving an agent's AI using cognitive architecture, personality and emotion or by gathering realistic data and validation. By combining all these aspects together, we can produce realistic agents and simulations. Combining a cognitive architecture with personality and emotions can create realistic agents that think using an architecture based on the human thought process and act based on their personality and emotions. Also gathering data before and after developing the simulation can provide the ability to develop realistic personality and emotions based on real-world data and allow effective validation. However, previous studies have not provided all these aspects into their crowd simulation projects. Table 2.3 provides a comparison list of approaches implemented in previous studies to produce realistic agents.

The first approach used by past studies towards realistic crowd simulation is the cognitive architecture approach [57]. This approach focuses on developing a cognitive architecture that can display realistic decision making. However, it ignores the psychological aspects and collecting real-world data for its development. The second approach is the use of cognitive architecture and personality only approach [62]. This approach does not include emotions that can cause unique dynamic changes to their agents decision making. Also, the use of this approach is not built using data gathered for development or validation.

The cognitive architecture and emotion only approach [66, 67] is similar to the previous approach discussed. However, it ignores personality which creates individuality amongst the virtual agents. Same as the previous method, there is no development or validation using data collected. The cognitive architecture with data gathering approach [63] develops its framework based on data collected by the researcher. However, no psychological aspects such as personality and emotions are not being used to enhance and generate virtual agents to appear or action more realistic. The cognitive architecture and psychological aspects approach [21, 58, 60] implements personality and emotion within the cognitive architecture framework to make virtual agents more realistic. However, no data gathering is implemented making the data used to develop and validate the approach only realistic based on the assumptions of the researchers point of view. The cognitive architecture and emotions with data gathering approach [53–56, 64, 65] collects data for the development of the framework. It can also integrate emotions based on data collected. However, it provides no personality that can create individuality across all their agents. The no personality approach [24] is not a common method. K. Vasudevan et al. [24] implemented a methodology that evaluates evacuation safety against productivity used by various well-known manufacturing layouts. They used virtual reality to gather real-world data of human behaviours through simulated risks. The data was then used to extend the BDI cognitive architecture by adding emotions to model human behaviours under risk in agent-based crowd simulations. The methodology was then validated by implementing an agent based crowd simulation scenario to evaluate evacuation safety in manufacturing facilities. Validation was also implemented by an event based simulation model to evaluate productivity in manufacturing facilities. However, this study did not provide a personality method into their extended BDI architecture.

Personality only approach [90, 110] is a poor approach to developing realistic crowds due to the fact that no cognitive architecture that can generate a realistic decision making process is used. Also, no data is gathered for the development of the personality model used. Psychological aspects approach [17, 23, 37, 85, 87, 93, 101, 102, 105, 107] is another poor method to developing realistic crowds mainly due to no data is gathered for the development of the personality and emotion models used. This makes the approach unrealistic and unable to be compared to the real world as there are no bases for the values used to represent the psychological aspects. Psychological aspects with data gathering approach [27, 56, 59, 86] uses mental data collected only to develop realistic agents. However, to make a true realistic agent the collection of physical and visual data and the integration of a cognitive architecture that can help represent realistic decision making is required. Personality with data gathering approach [20, 89] does provide data collection for mental data. However, it is only for personality and do not collect emotions, physical or mental data for the development of their research.

The emotion only approach [22, 32, 36, 94, 96–98, 103, 104, 108, 109] represents a poor approach to developing realistic crowds. O. Oğuz et al. [108] implemented only emotion into their simulation to simulate virtual crowds in emergency situations that are caused by incidents. They implemented an emotion model of panic propagation in which panic will spread between agents based on their awareness of the danger. However, this approach does not provide a method for either personality or cognitive architectures and has not been developed or validated using any real-world data gathered. Emotion with data gathering approach [9, 80, 106] is not a common approach in crowd simulation even though it does focus on developing emotion into crowd simulation by collecting mental data. However, the mental data is only emotional data and doesn't collect personality, physical or mental data for the development of their research. Emotion and VR with data gathering approach [82] is not a common approach to developing realistic crowd simulations, although it does implement data gathering to develop the researchers emotions by using VR to collect the participant's emotional responses. This approach does not collect personality data to develop the crowd simulation. This is because VR data gathering is unable to collect personality data without some other data gathering method being implemented.

Data gathering only approach [78, 79] focuses on the physical or visual data only to make their agents in crowd simulation more realistic. This approach does not collect mental data or implement a cognitive architecture to develop realistic agents with crowd simulation. VR with data gathering approach [74, 111] uses VR as means to collecting data for the development of the project. However, VR cannot accurately gather mental data, only physical and visual data. This approach also does not include developing realistic decision making using cognitive architectures.

Improvements into the field have been made through the integration of personality and emotions to increase the realism of the agents. Cognitive architectures have also provided a realistic approach to agent thinking and decision making.

However, the methods used to gather data and validate crowd simulation has either not been considered or has only provided limited capabilities into improving the field of research. Also, the integration of VR into crowd simulation is still relatively new and has the potential to improve the data gathering and validation methods.

Studies into improving realistic crowd simulations have provided a significant impact into the field; however, this does not mean the pursuit of developing even better realistic agents, environments, models and simulations should stop. The proposed project will focus on creating realistic crowds through the use of VR as a data gathering and validation method. Real people will be placed into a VR environment and will be required to complete a series of tasks. Real-world data will then be gathered while they are completing their tasks and afterwards through a questionnaire. The data will be used to develop the agent's personality and emotion models which will be implemented into a cognitive architecture. The proposed project will also design a unique framework that generates realistic agents within a crowd and provide a better approach to data gathering and validation.

Table 2.3: Comparison of all approaches in previous studies used to implement realistic crowd simulations.

Approaches	Cognitive Architecture	Personality	Emotion	Data Gathering	VR
Cognitive Architecture Only	Yes	No	No	No	No
Cognitive Architecture and Personality Only	Yes	Yes	No	No	No
Cognitive Architecture and Emotion Only	Yes	No	Yes	No	No
Cognitive Architecture with Data Gathering	Yes	No	No	Yes	No
Cognitive Architecture and Psychological Aspects Only	Yes	Yes	Yes	No	No
Cognitive Architecture and Emotion with Data Gathering	Yes	No	Yes	Yes	No
No Personality Approach	Yes	No	Yes	Yes	Yes
Personality Only	No	Yes	No	No	No
Psychological Aspects Only	No	Yes	Yes	No	No
Psychological Aspects with Data Gathering	No	Yes	Yes	Yes	No
Personality with Data Gathering	No	Yes	No	Yes	No
Emotion Only	No	No	Yes	No	No
Emotion with Data Gathering	No	No	Yes	Yes	No
Emotion and VR with Data Gathering	No	No	Yes	Yes	Yes
Data Gathering Only	No	No	No	Yes	No
VR with Data Gathering	No	No	No	Yes	Yes
Proposed Approach	Yes	Yes	Yes	Yes	Yes

Chapter 3

Overall Agent Based Simulation Framework

This chapter introduces the overall agent based framework proposed in this thesis (see Figure 3.1). The fundamental design for developing an agent based framework consists of three key phases: input, process, and output. The input phase represents where the data is collected by using a data gathering method. The process phase also known as the cognitive architecture model phase is developed using the data collected in the input phase. The process phase also processes the data collected from the input phase when running a cognitive architecture framework. The output phase provides data processed from the agent architecture model phase. This phase also involves the process of evaluating, validating and benchmarking.

Section 3.1 summaries the input phase for gathering data using the VR+Q method. Section 3.2 discusses the process phase which introduces the agent based cognitive architecture framework designed in this study. Lastly, Section 3.3 the output phase discusses the method used to validate the input and process phase.

3.1 Input Phase

The input phase purpose is for researchers to collect data to develop and run the process phase. This phase is important because without real-world data to derive from, the process phase cannot be designed to represent the real world or process real-world outcomes. Also, without the input phase, the output data cannot provide a realistic comparison or validation when evaluated against the real world.

This thesis proposes collecting three types of data (physical, mental and visual) to represent all forms of real-world data. Physical data represent the perception of the body movement of each participant rather than to the mind. Mental data rep-

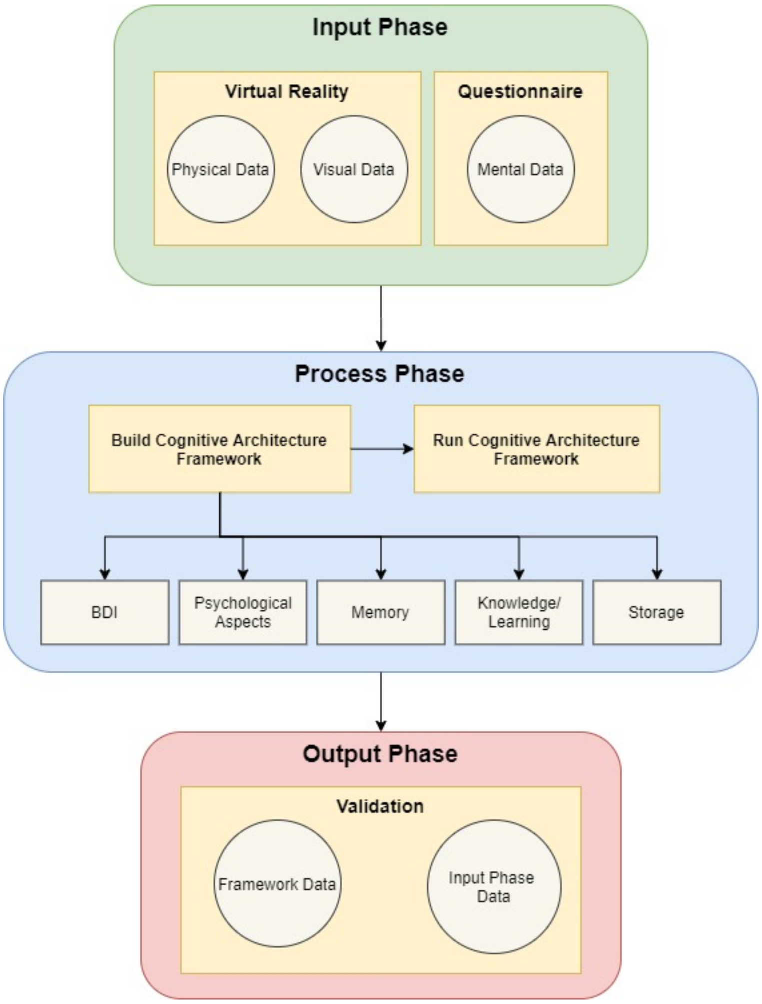


Figure 3.1: Overall agent based framework.

resent the psychological side of each participant such as personality and emotion. Visual data represent data collected based on the perception of the researcher and the participant's point of view.

This is achieved by implementing a hybrid data gathering method of VR+Q. Currently the data gathering methods that are being used in crowd simulation can provide real world data. However, they cannot collect all three types of real-world data (see Table 3.1). This is due to the fact that each method has limitations to them (see Section 2.3 for further detail). For instance, video recordings can collect visual data from the researcher's perspective and physical data using the participant's trajectories inside the video. However, they cannot collect mental data as there is no interaction between the researcher and participant with in video.

Table 3.1: Comparison of data gathering approaches.

	Video	RW Scenario	User Studies	Questionnaires	VR	Proposed VR-Q
Cost effectiveness	Low	Low	Low	High	Medium-High	Medium-High
Time efficiency	Low	Low	Low	Medium-High	Medium-High	Medium-High
Reproduciblity	Low	Low	Medium	High	High	High
Ecological validity	High	High	Medium	Low	Medium-High	Medium-High
Experimental control	Low	Low	Medium	High	High	High
Visual data	High	High	High	Low	High	High
Mental data	Low	Low	Low	High	Low	High
Physical data	High	High	Medium	Low	High	High

VR allows researchers the ability to simulate similar or completely different experiences based on the real world. Even though, VR allows researchers to gather physical and visual data (see Section 2.3) by allowing participants to move through a virtual world. Mental data, however, is unable to be collected through the use of VR. To compensate for this issue a questionnaire is implemented. The questionnaire covers the mental data aspect of the data gathering phase by asking the participants what their personality is and their emotional experience within the VR environment.

In this thesis, the use of a VR headset and motion suit combined is implemented to allow the participant's full control to freely move around and see the virtual environment. The VR headset and motion suit allows the developer the ability to record the participant's trajectories and full body movement into a 3D character. This allows data gathering of the physical and visual data after the participant's have finished participating.

The VR+Q method is implemented inside a virtual university expo environment where the researcher runs a scenario in which participants are asked to explore and find locations within the environment. Once the participants have completed the scenario, they are asked to fill out a simple questionnaire.

In order to evaluate and validate that the VR+Q method can represent real world data, another data gathering method was run for comparison. A real world scenario combined with the questionnaire method was conducted running the same scenario only in a real world environment. The same data was collected by both methods for each of the three data types and was compared, which is further discussed in Chapter 4.

3.2 Process Phase

The process phase is where the development of a cognitive architecture framework based on the input phase is implemented. This phase also implements the framework to gather data for validation in the output phase.

There have been many agent-based models designed using cognitive architectures for crowd simulation however, they have been built for case specific scenarios and environments. This approach makes it difficult to implement the cognitive architecture in other scenarios without making significant changes. Also, the implementation of psychological aspects to improve the overall performance to the agent based model has primarily been in the low-level parameters (path finding, speed, radius, etc.) and not the high-level (behaviours, actions, decision making).

This thesis proposes a generic cognitive architecture framework that can represent real-world crowds in different environments and scenarios. An evolved BDI framework is implemented that incorporates psychological aspect (personality and emotions), storage of information (memory and experiences) and knowledge and learning. Each module within the evolved BDI framework has an important role that allows each agent to make their own unique decisions and output different behaviours and actions. All modules, actions and behaviours are derived and designed using the input phase data collected in the VR+Q method (see Chapter 5).

The core of the framework consists of six modules; sensor system, attention filter, situation assessment, short-term memory, action selection and action execution. The sensor system module allows each agent to gather data from the surrounding environment using 3 different sensors, being visual, audio and touch and to perform internal decisions based on the data. The attention filter module represents the human capacity to focus and process certain information from our surroundings while ignoring others. The attention filter decides whether the sensor system data is noticed or blocked out by the agent. The situation assessment determines the best behaviour suited for the agent to display based on the data noticed through the attention filter. Short-term memory module represents how humans are able to hold a certain amount of information and not manipulate it, within their mind in a readily available and active state for a short period of time. The action selection module represents the decision making process from selecting the best action to perform based on the current processed data. This module provides the agent with the realistic ability to either use current actions it already knows or gain new knowledge and learn a new action. Lastly, the action execution module makes the agent perform the selected action.

The storage section of the framework focuses on receiving and transmitting long term information. The storage section consists of three modules: current strategies, long-term memory and relevant experience. The current strategies stores all the goals and information the agent is currently focusing on such as action, behaviour and sensor data. Long-term memory module represents the indefinite storage of information held by a human being in their deep subconsciousness. The relevant experience module stores all actions, experiences and information related to each action the agent has learnt.

The psychological aspects section focuses on influencing decisions within the core of the framework. The personality module represents static parameter values sent to other modules to influence the agent decision making. The emotion module represents dynamic values that change based on decisions and situations occurring within the environment. The emotion module also influences the agent's decision making process with the core of the framework.

The knowledge/learning section main focus is to provide the agent with a means to learning new actions that can be performed within the simulation (for example, a virtual teacher). The experience system is the mediator between the agent and the learning strategies module. The learning strategies module can be seen as a virtual teacher storing all possible actions that the agent can learn and teaching them the best action based on their current situation.

To add diversity and heterogeneous agents, the modules within the framework were implemented using different methodologies. In particular each modules decision making procedure was implemented using either fuzzy logic or probability. Both methods allow each agent to make decisions differently allowing them to display individuality. The full implementation of the evolved BDI framework is discussed in further detail in Chapter 5.

3.3 Output Phase

The output phase is where data is gathered from the process phase for the evaluation and validation of the entire agent based crowd simulation model. Because of past studies either not conducting or randomly/manually generating values for the input phase; validating past cognitive architecture to the real world has not been possible. This thesis proposes utilising the real-world data collected in the input phase to validate the data collected from the cognitive architecture framework in the output phase (see Chapter 6).

To validate the cognitive architecture framework and whether it can output real-world data, a comparison is conducted against data collected using VR+Q in the input phase. This means that our comparison does not use the VR+Q data collected from the input phase for training our model to be validated. But instead uses it to validate that the cognitive architecture framework and the VR+Q are significantly similar. The same environment and scenario that was used in the input phase is used for the output phase. Also, to ensure the validity of the output phase the same three types of data that were used in the input phase were collected for comparison.

Different parameter variations of speed, personality and emotion were implemented into the agent's cognitive architecture framework. This was to determine if the virtual agents can output similar data to the VR+Q participants. The agent data collected is analysed using two different tests a t-test of equal variance and a chi-square goodness of fit test. The t-test of equal variance validates the proposed hypothesis that the cognitive architecture can output similar real-world data when compared to the VR participants. The chi-square goodness of fit test was conducted to see if any significant differences were exposed between the data collected from the virtual agents and the real world VR participants.

Lastly, to validate the agent based crowd simulation framework's ability to be flexible and adaptable to other environments and scenarios, a case study was implemented. The overall purpose of the case study was to see if any unique behaviours or data would be displayed. That would in turn prove that framework can be flexible and adaptable to other environments and scenarios (see Chapter 7).

Chapter 4

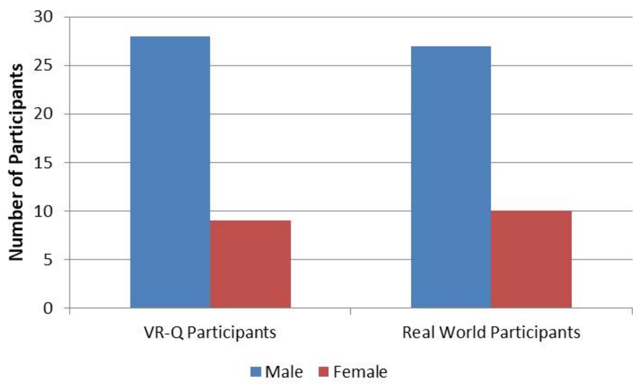
Data Collection

4.1 Participants

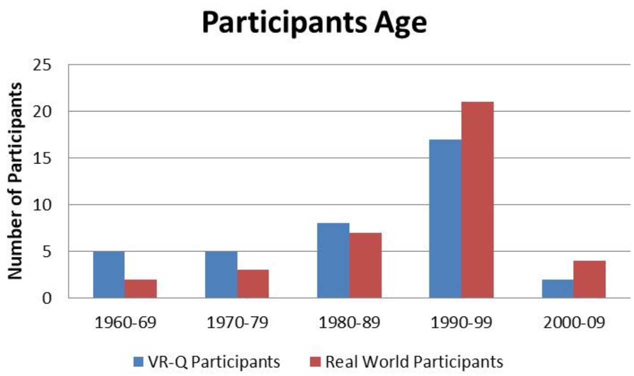
4.1.1 Real World and Virtual Reality

In qualitative studies, it is said that the minimum sample size is 25-30 to reach saturation and redundancy, and studies suggest anywhere between 5 to 50 could be adequate [112–114]. In our study, both VR+Q and real-world experiments were conducted with a total of 37 participants each and 74 in total for both. Both groups are randomly drawn and mutually exclusive. The margin of error for our study at 95% confidence [115] is around 16%. There was no experience (for example experience in VR) or requirements needed to be selected to participate in the experiment. Instead, the participants were volunteers who wanted to be part of the experiment. The participants were all students and staff from James Cook University, Cairns Campus.

Out of the 37 participants from the VR+Q experiment, 28 (75.7%) were male and 9 (24.3%) were female. The age of VR+Q participants was between 17-55 years old with the average age of a participant being 27. While the 37 real-world participants were comprised of 27 (73%) males and 10 (27%) females. The age of the real-world participants was between 18-56 years old with the average age being 28. (see Figure 4.1).



(a)



(b)

Figure 4.1: Participants: (a) gender; (b) age.

4.1.2 Virtual Agent

8 parameter setting variations of virtual agents were implemented for testing. The parameters implemented in all settings were walking speed, which is classified as speed, representing physical data, personality, and emotion modelling mental data (see Table 4.1). Visual data cannot be inputted into the parameters as this data type represents external data while the other two represent internal data.

Table 4.1: Parameter range.

Parameter	Minimum	Maximum
Speed	0.15m/s	0.49m/s
OCEAN Personalities	1	7
OCC Emotions	1	5

The first setting executed all self-set parameters that were collected from the VR+Q data gathering [116]. The second setting executed random parameters ranging from the minimum and maximum values gathered from the VR+Q experiment. The other setting variations were similar to the first two settings with one parameter either changes to self-set or random (see Table 4.2).

Table 4.2: 8 different parameter settings for the virtual agents testing.

	Personality	Emotion	Speed
Setting 1 (S-S-S)	Set	Set	Set
Setting 2 (R-R-R)	Random	Random	Random
Setting 3 (S-S-R)	Set	Set	Random
Setting 4 (S-R-S)	Set	Random	Set
Setting 5 (R-S-S)	Random	Set	Set
Setting 6 (R-R-S)	Random	Random	Set
Setting 7 (R-S-R)	Random	Set	Random
Setting 8 (S-R-R)	Set	Random	Random

Each setting was conducted with 37 agents individually to match the experiments conducted in the real-world scenario and VR scenario [116]. Each setting of 37 was run 3 times to ensure the legitimacy of the results. This resulted in 3 sample size settings of 37 for each test type.

4.2 Scenario

The scenario was designed to be simple but believable that motivates participants to encounter the design tasks we are evaluating [117]. The purpose of the simple scenario is due to the fact that our goal is not to influence or change the participant's responses, but to show they will produce similar responses based on the situation. For instance, we want to see if the participant's emotional response in the real-world scenario can produce similar results in the virtual world scenario.

The virtual agents and the participants for both the VR+Q, real world and simulation tests entered a virtual/real world designed university course expo. The expo consisted of 26 booths each containing different fields of study, 2 entrances/exits, 2 maps stations and an information centre (see Figure 4.2).

Because of low cost effectiveness and time efficiency of real-world scenarios, designing the real world environment identical to the virtual world is very different. However, the scale of both the virtual and real-world environments is identical allowing for no issues when gathering the physical data. Each scenario starts with the participant standing at the bottom left entrance of the course expo. Each participant is given 1 minute to wander freely around the environment, once the minute has passed they were asked to find 3 booths (archaeology, physics and education) one at a time. When the participant has completed finding all 3 booths they were asked to go to one of the 2 exits within the expo and leave. Once the participant reached the exit, the test was completed.


(a)


(b)

Figure 4.2: Experimental environments: (a) real world environment; (b) virtual world environment.

There were two reasons for having the participants wander around for the first minute of the test. The first reason was so they would get use to the equipment that was being used in both data gathering tests. By getting used to the equipment, the expectation was they would feel more comfortable and after a minute they would start reacting more like they would normally if this scenario was happening in real life. The second reason was for them to gain familiarity with the environment. By gaining familiarity with the environment, the expectation was that some of the participants would remember where the 3 booths are while others will not. This would subsequently produce a wider range of data for physical data (such as time and distance).

Each participant was asked to find the same three booths in both experiments. This was to prevent the data comparison of the two methods from being faulty or miss understood. Each of the 3 booths was chosen based on its position in the environment and its position from the previous booth. For instance, the first booth was Archaeology which was at the centre back of the environment, the second was Physics which was positioned at the front right side, and the last one was positioned in the middle left. Each booth was also positioned so that the participants could not see the next booth required without walking to them first.

There were two ways a participant could find each goal, firstly, by walking and looking around and secondly, by using either the maps or the information centre placed within the environment. These maps had detailed information of where each booth was and where the participant's current position was. The maps and information centre's main goal were to see if the participants would use them to find their goals. All decisions made by the participants were freely made with no influence by the researcher. The participants had the freedom to choose their own paths, how they would reach the designated goal by either walking around or using a map and which exit they will go to. At the end of the experiment, each participant was asked to fill out a questionnaire asking questions about their personality and their emotional experience during the experiment. In the VR questionnaire, participants were asked additional questions for better understand of how people feel and respond in VR. Participants were asked about their experience in VR prior to the experiment and after. They were also asked about how they felt and responded in a VR environment. This information was gathered as a means to explaining any significant differences found between the data collected in VR and the real world, but was not used in the research in the end. The consent form for this study can be found in Appendix A.1, the VR questionnaire in Appendix A.2 and the Real world questionnaire in Appendix A.3.

4.3 Equipment

This section discusses the hardware and software used to gather data and develop the agent based cognitive architecture framework.

4.3.1 Hardware Implementation

This section discusses the hardware that was implemented into the project for the data gathering. Two physical hardware devices were used to collect data from the participants: a motion suit and a VR headset.

4.3.1.1 Motion Suit

An inertial sensor based motion suit called Perception Neuron[1] was used in these experiments. Perception neuron is a professional tool designed for video game developers, film makers, visual effects professionals, VR and much more. The perception neuron system uses an embedded data fusion, human body dynamics and physical engine algorithms to generate clean and accurate motion capture. The suit can record motion in three different ways: transmitted through Wi-Fi, directly connected to the computer via USB or by using a built-in micro-SD slot.

The suit works by using interchangeable sensors called Neurons, which are attached to the limbs of the participant's body using Velcro straps. Each neuron can measure its own orientation and acceleration using a gyroscope, a magnetometer and accelerometer. Every connected neuron to the suit transmits all measured

[1] https://neuronmocap.com/

data to a hub which transmits that data to a computer (through Wi-Fi or USB) running Axis Neuron software. The software then in return performs a few complex algorithms, data optimisation and drift corrections and recreates a full human skeleton with 59 bones using the data sent by the Neurons.

4.3.1.2 VR Headset

The Kaiser Baas VR-X headset [2] was used as the wireless virtual head mounted display allowing the user to have total freedom over their movements. The VR-X headset provides an affordable and simple way to experience VR. Powered using a smartphone, for this experiment, the LG G6 [3] was used; the VR-X headset allows the participants to enjoy a fully immersive experience based on their own perception.

4.3.2 Software Implementation

This section discusses the software that was implemented into the project for the data gathering and development of the agent based cognitive architecture framework. Three different software were utilised in this project: Unity3D, RAIN and mobile streaming.

4.3.2.1 Unity3d

Unity3d [4] is a cross-platform game engine developed by Unity Technologies. The Unity3d game engine can support more than 25 different platforms. The game engine is able to be used to create 3D, 2D, VR, augmented reality games, simulations and other experiences. The Unity3d engine has been adopted by other industries such as film, architecture, engineering, construction and automotive.

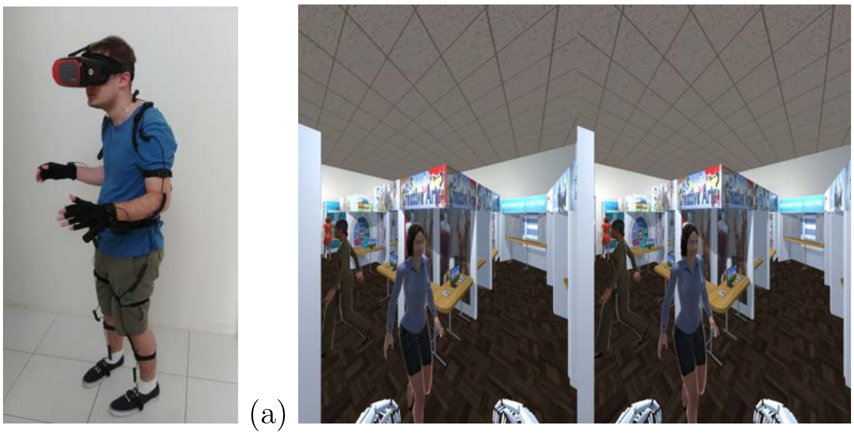
4.3.2.2 AI Software RAIN

RAIN [5] is an AI engine developed by Rival Theory. Rival Theory started as an AI company working in interactive entertainment and simulation. RAIN has been used by over 100,000 studios and developers worldwide to create sophisticated interactive characters based on real and fictional people. RAIN is a free fully featured AI system that includes built in path finding, sensor systems and behaviour tree editor. RAIN is fully compatible with Unity3d making it easy to develop an agent based crowd simulation.

[2]https://www.kaiserbaas.com/products/vr-x-headset
[3]https://www.lg.com/au/smartphones/lg-LGH870K-g6-smartphone
[4]https://unity.com/
[5]http://www.rivaltheory.com/?ref=Welcome.AI

4.3.2.3 Mobile Streaming

The environment was streamed from the computer to the smartphone using Trinus VR [6]. Trinus VR provides an easy and affordable VR solution that allows the user to stream rendered high quality PC content to a smartphone. The only issue when streaming from PC to a smartphone is the battery life of the phone. But this issue is easily resolved by attaching a portable power bank to the smartphone. Figure 4.3 displays a participant wearing the VR-X headset and motion suit and a visual perspective of the virtual environment.



(a) (b)

Figure 4.3: VR setup and visual perspective: (a) Participant wearing the VR headset and motion suit; (b) A visual perspective of the virtual environment from the participant's point of view.

4.4 Data Types Collected

Using the motion suit, VR headset and questionnaire, collecting all three data types (physical, mental and visual) was achieved with ease. All data collected from the VR+Q and real-world experiments is used in the comparison to prove that VR+Q method can equally gather real-world data. The data collected within each data type were selected for comparison due to their ability in creating agent-based models.

4.4.1 Physical Data

Physical data was collected in the form of distance, time and speed by using the motion suit ability to record and transmit the participant's movements. The

[6]https://www.trinusvirtualreality.com/

position of the participant was collected every one second to accurately calculate the distance. Distance is a solid measure to compare the two data gathering methods and the agent based model. This is because it allows us to determine whether the participants and virtual agents move the same number of spaces in a virtual environment to a real one. The total time it takes a participant to finish the entire scenario was collected throughout the experiment. In addition, speed was computed using the data collected from distance and time. As same as distance and time, speed allows us to compare whether the participants from the VR experiment move at the speed and the real-world participants. This data can also be used to compare whether virtual agents output similar results to the VR participants.

The virtual agents physical data was collected employing the same method that was used in collecting the distance, time and speed from the real world and VR+Q participants. Each agent's position was collected every one second and the total time of completing the scenario was collected throughout the simulation. The speed of the agents was also collected using distance and time.

4.4.2 Mental Data

Mental data were collected through the questionnaire in both methods. The data collected were both the participant's personality and what his/her emotions were during the experiment. The agent's mental data were collected directly from its personality and emotion modules. Both the OCEAN model and the OCC model were selected as a means to comparing the two methods. This is because both are well known psychological models used in previous research and can be used to develop agent-based models [118].

4.4.2.1 Personality

The OCEAN personality model [119] was used to determine the participant's personality. To measure the participant's personality using the OCEAN model, the ten item personality measure (TIPI) method [120] was used. TIPI is best used for researchers who have limited time to collect data and their primary topic of interest is not personality. It also provides a similar means of collecting personality data for researchers who are not experts in the psychological field.

The TIPI method uses 10 traits (5 positive and 5 negative traits) each consisting of two descriptors in which the participants are asked to rate between 1 (disagree strongly) and 7 (agree strongly) using a 7-point Likert scale (see Figure 4.4) within a questionnaire. Each of the 10 traits are then measured to one of the 5 personality traits within the OCEAN model using Equation 4.1.

3) Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

I see myself as:

1. ____ Extroverted, enthusiastic.
2. ____ Critical, quarrelsome.
3. ____ Dependable, self-disciplined
4. ____ Anxious, easily upset
5. ____ Open to new experiences, complex
6. ____ Reserved, quiet
7. ____ Sympathetic, warm.
8. ____ Disorganized, careless
9. ____ Calm, emotionally stable.
10. ____ Conventional, uncreative

Figure 4.4: TIPI method question.

$$OCEAN\ Personality\ Trait = Positive\ Trait + \frac{(8 - Negative\ Trait)}{2}. \quad (4.1)$$

TIPI scale measurements (Note: "R" denotes reverse-scored items): Extraversion: 1, 6R; Agreeableness: 2R, 7; Conscientiousness; 3, 8R; Neuroticism: 4R, 9; Openness to Experiences: 5, 10R. The virtual agent's personality values were collected directly from the agent's personality module. The agent's personality module runs the OCEAN personality model as static values (this is further discussed in Chapter 5).

4.4.2.2 Emotion

After the participants finished the scenario, using the questionnaire participants were asked to rate their average emotional state based on their entire experience inside the environment. The emotions were gathered by asking the participants to rate between 1 (none) and 5 (extreme amount) their emotional intensity using a 5-point Likert scale from 40 different emotions. The main aim of collecting the emotional data from both methods in the same manner is to see if the participant's emotional state produces similar results to the real world, when placed inside a virtual world. These 40 emotions represented 20 positive emotions and 20 negative emotions. Based on previous research [121] in emotions, these 40 emotions are clearly valenced in nature and can also be seen as easy terms for people to understand. These emotions are then mapped to the OCC model [122] which is then used to compare between the two data gathering methods. The OCC model is a hierarchy that classifies 22 emotional types. These emotions are represented based on different psychological situations such as emotions that focus on events, actions and objects. The reason we map the 40 emotions to the OCC model is due to understanding and implementation factors. These 40 emotions are simple for people to understand and are valid psychological emotions, however implementing them into an agent based framework without an emotion model design or validation from past studies is not practical. On the other hand, the OCC modelling has been validated and implemented into multiple simulations [21, 94], however, asking people to rate how they felt based on these 22 emotions can cause some misunderstandings. For instance asking the participants to rate their emotional intensity to the emotion HappyFor, which is an emotion towards others, would be illogical when they are the only person in the environment. By combining the 40 emotions and the OCC model we solve both methods weaknesses. Since there being no explicit method for emotion mapping, a hybrid style in which the 40 emotions were mapped using the Parrott's hierarchy framework [123] is used as a basis. Based off of the Parrot's framework, a primary emotion can contain a secondary and tertiary emotion. In this research, the OCC emotions were represented as the primary emotions and the 40 emotions from the questionnaire were mapped into them as if they were secondary emotions (see Figure 4.3). Not all 40 emotions were able to be mapped to the OCC primary emotions. This was because there was no connection between some of the 40 emotions and the OCC emotions through either definition or Parrott's hierarchy framework.

Table 4.3: Hybrid emotion mapping based of Parrott's hierarchy framework.

OCC Primary Emotions	**Secondary and Tertiary Emotions**				
Joy	Joyful	Cheerful	Happy	Excited	thrilled
Distress	Distress	Anxious	Worried	Nervous	Upset
Happy-For	Happy	Delighted	Joyful	Elated	cheerful
Resentment	Angry	Moody	Irritated	Annoyed	
Gloating	Delighted	Elated	Thrilled		
Pity	Disappointed	Ashamed			
Hope	Confident	Peaceful	Inspired		
Fear	Fearful	Nervous	Anxious	Distressed	afraid
Satisfaction	Delighted	Happy	Gratified	Thrilled	joyful
Fears-Confirmed	Fearful	Frightened	Distressed	Worried	afraid
Relief	Peaceful	Gratified			
Disappointment	Disappointed	Upset	Distressed	Annoyed	
Pride	Proud	Confident	Gratified	Delighted	Happy
Shame	Ashamed	Guilty	Disappointed	Distressed	
Admiration	Inspired	Worthy	Interested	Delighted	
Reproach	Disappointed	Annoyed			
Gratification	Thrilled	Happy	Gratified	Joyful	delighted
Remorse	Guilty	Ashamed	Down		
Gratitude	Gratified	Proud	Delighted	happy	
Anger	Angry	Irritated	Annoyed	Moody	Upset
Love	Affection	Passionate	Interested		
Hate	Angry	Moody	Annoyed		

To accurately compare the virtual agent emotions to the VR+Q participant emotions, the data had to be gathered in a different way. Unlike the VR+Q participants who were asked to give their average emotional response in the form of 40 emotions which were then mapped to the OCC emotion model, the virtual agents runs the OCC emotion model within their emotion module (for further information see Chapter 5).

With the agent emotions dynamically changing throughout the simulation, it was decided that the emotional data needed to be collected throughout the simulation. The value of each OCC emotion was collected every 10 seconds to ensure that each emotional value had enough time to dynamically change. After the simulation is conducted an average value is calculated for each OCC emotion using the data collected. By collecting each emotion value throughout the simulation, an overall average of each emotion is able to be calculated. This in turn, represents the same average emotion state collected and mapped for participants as the agent's average emotional state is based on its entire experience within the environment. The reason we gather emotional data from the participants differently to the agent was due to the fact that our goal was not to influence or change the participants' responses. If we chose to ask the participants emotional questions throughout the scenario, it would make gathering physical and visual data harder and unrealistic as each participant would be forced to stop and answer questions. We also do not consider facial expressions for emotional data as we are not looking at improving the agent's facial responses but the agent's decision making responses.

4.4.3 Visual Data

The five types of visual data were collected using the researcher's point of view to examine the external behaviour of the participant. This means that all data collected in this section is based entirely on the researcher's visual assessment of the participant and events occurring in the environment. First, recording how many left *vs.* right turns the participant made throughout the experiment. The purpose of this was to compare whether the VR+Q participant executes the same number of turns as the real-world participants. This data can also be used to represent whether people turn left more than right and vice versa. Second, both experiments presented the participants with two options when starting and that was either to walk straight or turn left. This data was collected also to see if VR changes the participant's movements. Third, the number of times a participant would use a map or the information centre was collected. This data was collected to see if the participants would recognise that there was help setup in the environment to find the goals and see if the VR+Q experiment would produce similar results to the real world experiment. Fourth, both experiments presented the participants two options at the end of the scenario to exit the environment and that was the exit they started the scenario at located in the South-West corner or the exit located in the North-East corner. This data was collected to see if the participants in the VR+Q method would behave and make the same decisions as the participants in the real-world method. Last, unique behaviours were collected from the researcher's point of view. Unique behaviours are motions or actions participants that stood out but happened rarely among all the participants. All observations of the unique behaviours are qualitative data and were observed and validated by the author of this thesis.

The agent's visual data were collected in a similar way as the VR+Q and real-world methods. Using the positional data collected every one second from the physical data allowed the ability to visually assess the agent's left and right turns for comparison. Running each simulation allowed the opportunity to manually record each unique behaviour observed, exit the agent used at the end and whether the agent would use the map or information centre to help them. However, due to developing realistic navigation was not within the scope of the project, gathering whether the agent started the scenario by walking straight or left was considered unimportant and was not collected.

Chapter 5

AI Architecture

The proposed agent framework is a modified and refined version of BDI [124], and it is depicted in Figure 5.1. Details of each component are explained in subsequent subsections. The framework is composed of four main parts: 1) main cognitive module composed of sensor system, attention filter, situation assessment, short term memory, action selection and action execution; 2) psychological aspects module including personality traits and emotional state; 3) knowledge/learning module dealing with experience system and learning strategies; and 4) storage module managing current strategy, long term memory and relevant experience. Details of each module is explained in subsequent subsections.

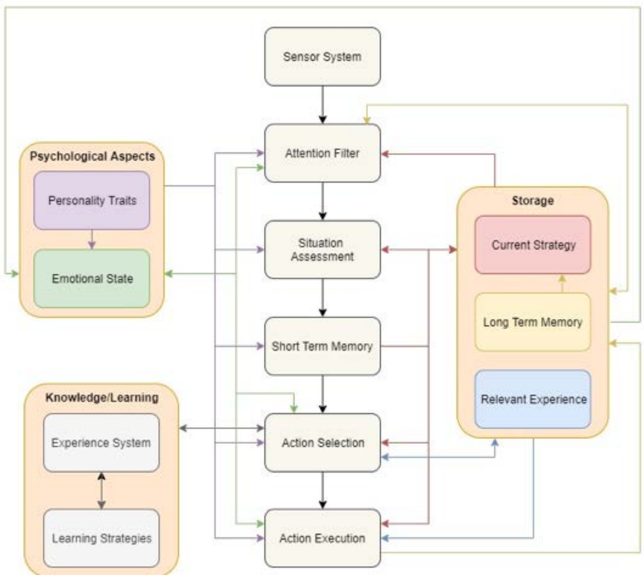


Figure 5.1: Proposed cognitive architecture framework for agent based crowd simulations.

5.1 Sensor System

The framework starts with determining whether information from the world will affect or influence the agent. To achieve this, a Sensor System and an Attention Filter are implemented. The Sensor System gathers information from the virtual world by simulating real human sensors (for example sight, hearing, touch and memory), see Figure 5.2 for details. The Sensor System is represented utilising three different types of sensors. The first sensor is a visual sensor that allows the agent to see their surroundings within the environment. The second sensor is an audio sensor which allows the agent to hear sounds from nearby agents and the environment. Using the RAIN AI engine, a visual and audio sensor is implemented representing the agent eyes and ear. These visual and audio sensors provide the agent with the ability to detect all virtual objects within their field of view and hearing range. The third sensor is a touch sensor which is only active if the agent collides with an object within the environment or with another agent. This sensor is integrated using the Unity3D game engines built-in collider components. The collider component can define and detect the shape of an object for the purposes of physical collisions.

Each sensor has its own range and angle providing the agent with a sense of realism to its perception and hearing. These three sensors provide data from the environment (such as fellow agents, objects and sound) are collected and sent to the Attention Filter for processing. The information collected from the sensors is then filtered through the Attention Filter.

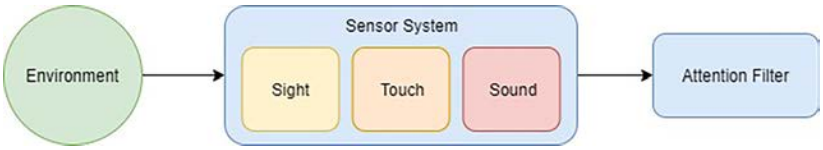


Figure 5.2: An overall structure of the Sensor System module.

5.2 Attention Filter

The Attention Filter is tasked with gathering all the data transmitted from the Sensor System and determines whether the agent does or does not notice it. The Attention Filter provides a realistic approach to how real people tend to focus and process certain information they see or hear while ignoring or not processing everything else [125]. The Attention Filter was developed based on visual (sensor data) and mental data (personality and emotions). The sensor data sent is filtered by cycling through each piece of data and calculating a probability factor. The probability of not being filtered out is determined based on the agent's current goals, personality and emotional state. Figure 5.3 describes details of the Attention Filter.

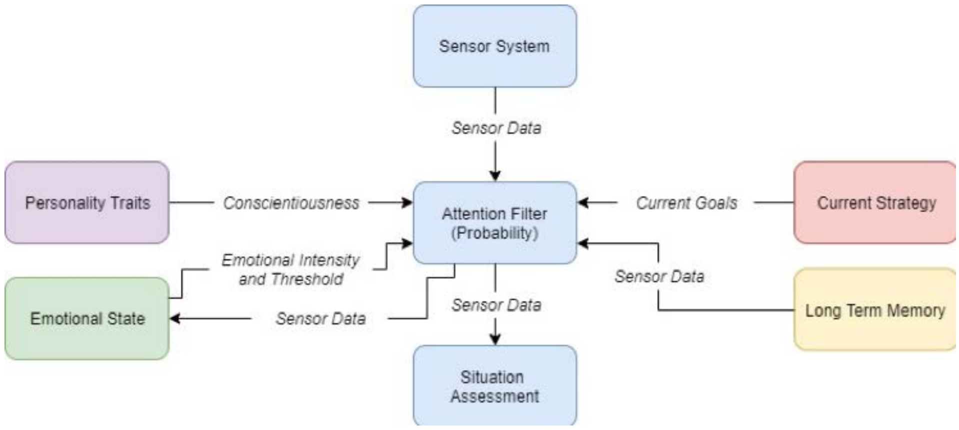


Figure 5.3: An overall flow of the Attention Filter module.

The probability is calculated in three phases. The first phase determines the starting probability value by using the agent's conscientiousness value. The conscientiousness value is one of the five personalities from the OCEAN personality model [119]. Conscientiousness is classified as a person's self-discipline, impulse control, organisational skills, and dependability [19, 126]. This makes this personality trait perfect for the Attention Filter as this personality trait involves being focused, careful and the ability to pay attention to details. The second phase determines whether the data probability value increases or decreases based on its importance to the agent. For example, if the agent's sensor detects a fire, the importance would be high. While a piece of dirt on the floor would be given a low level of importance. This module primarily focuses on whether the data is related to agent's goals, but is also able to be used to determine if it is important to their lives. The third phase increases or decreases the probability value using the agent's current emotional state, which is discussed in Section 5.9 in detail. If any of the agent's emotions is over their threshold the probability is altered based on whether it is a positive or negative emotion. Once all modules are completed a value is randomly generated. If the value is within the probability value range, the Attention Filter allows the data to pass through to the Situation Assessment module. If the value is not within range the data, then it is stopped and forgotten.

5.3 Situation Assessment

The Situation Assessment focuses on determining what behaviour should be performed based on each piece of data sent from the Attention Filter module (see Figure 5.4). To accomplish this, the implementation of an MFS is provided for the

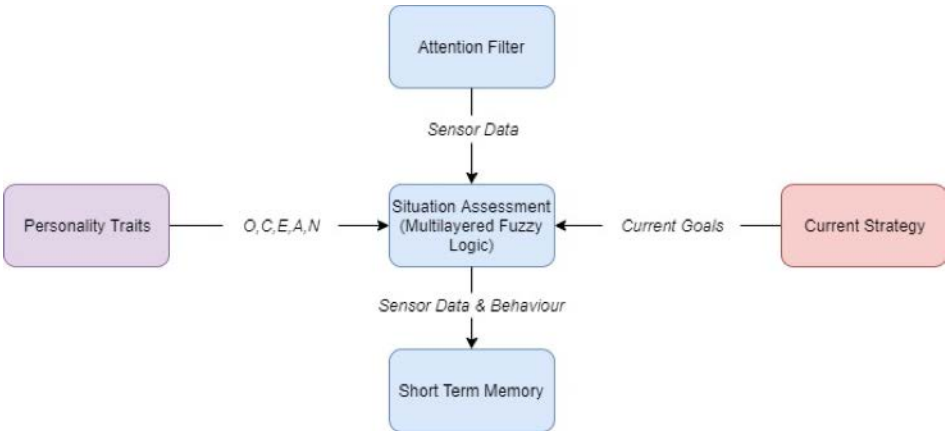


Figure 5.4: An overall flow of the Situation Assessment module.

decision making process. A MFS is a system that runs multiple fuzzy systems one after another until it selects the best suited behaviour. Each fuzzy system contains its own set of fuzzy rules and parameters to make its decisions. By implementing an MFS to the decision making process it allows researchers and developers to integrate an endless amount of fuzzy systems which will produce an infinite number of behavioural outcomes.

The MFS run in this project uses four fuzzy systems: Goal Orientated, Movement Based, Audio Based, and Object Based. First, GOFS focuses on behaviours related to the agent's goal. These behaviours are: Seek, Explore and Ignore (will be further explained below in the behaviour description). GOFS implements fuzzy rules to determine if the data sent is related to the agent's goal and what behaviour is the best suited (see Equation 5.1). The data's relation to the agent's goal is described using three fuzzy sets: High, Medium and Low [127]. For a given set X of goal oriented behaviours and *data* denoted by d, the agent's behaviour is decided as:

$$GOFS\ Behaviour\ =\ max(x_i, d),\ \forall x_i \in X, \tag{5.1}$$

where $max(.,.)$ returns the maximum relatedness between the two.

Second, MBFS focuses on behaviours related to how an agent reacts to its current speed. These movement based behaviours are: Impatience, Wait and Ignore (will be further explained below in behaviour description). MBFS implements fuzzy rules to determine the behaviour the agent feels based on the movement speed and the agent's personality traits conscientiousness, extraversion and agreeableness [19]. The movement speed is described using three fuzzy rules: Fast, Normal and Slow. The three personality traits of the agent are described using three fuzzy rules: High, Medium and Low. For a given set Y of movement based behaviours and *data* denoted by d, the agent's movement behaviour is decided as:

$$\begin{aligned} MBFS\ Behaviour \ &= \ max[\mu y_i(d), \mu c_i(C), \mu e_i(E), \mu a_i(A)], \\ &\forall y_i \in Y,\ \forall c_i \in C,\ \forall e_i \in E,\ \forall a_i \in A, \end{aligned} \tag{5.2}$$

where $max[.,.]$ returns the maximum relatedness between two, μ is a function that checks the equality, C is for conscientiousness, E is for extraversion whilst A is for agreeableness.

Third, ABFS focuses on behaviours related to data that has come from the Attention Filter that contains audio. These behaviours are: Panic, Communicate and Ignore. ABFS fuzzy rules are the behaviours of the agent based on the audio type and the agent's personality traits conscientiousness, extraversion and neuroticism [19]. The audio type is described as using four fuzzy rules: Null, Talking, Scream and Others. The three personality traits of the agent are described using three fuzzy rules: High, Medium and Low. For a given set Y of audio based behaviours and *data* denoted by d, the agent's movement behaviour is decided as:

$$\begin{aligned} ABFS\ Behaviour \ &= \ max[\mu y_i(d), \mu c_i(C), \mu n_i(N), \\ &\forall y_i \in Y,\ \forall c_i \in C,\ \forall n_i \in N, \end{aligned} \tag{5.3}$$

where $max[.,.]$ returns the maximum relatedness between two, μ is a function that checks the equality, C is for conscientiousness; and N is for Neuroticism.

Last, OBFS is the last fuzzy system and focuses on the type of object the data is, and what behaviour is suited to it. OBFS behaviours are: Seek, Explore and Ignore. OBFS fuzzy rules are the behaviours related to what type of object the data is, agent personality trait extraversion and the object's relation to the agent's goal. The type of object is described as four fuzzy rules: Null, Agent, Booth, and Audio. The agent personality is described using three fuzzy rules: High, Medium and Low. The object's relation to the goal is described using three fuzzy rules: High, Medium and Low. For a given set Y of object based behaviours and *data* denoted by d, the agent's object behaviour is described as:

$$\begin{aligned} OBFS\ Behaviour \ &= \ max[\mu y_i(d), \mu e_i(E), \mu g_i(G), \\ &\forall y_i \in Y,\ \forall e_i \in E,\ \forall g_i \in G, \end{aligned} \tag{5.4}$$

where $max[.,.]$ returns the maximum relatedness between two, μ is a function that checks the equality, E is for extraversion, whilst G is for the object Goal Relatedness.

Once all data is cycled through the Situation Assessment module, the behaviours selected and data related to each of the behaviours are transmitted to the Short Term Memory module. The Situation Assessment was developed using all three data types. Physical data were represented by the speed in which the agent was moving, mental data is represented using personality and emotions, and visual was represented by the data sent from the Attention Filter. The agent's behaviours were selected based on visual data collected in the data gathering phase.

5.3.1 Behaviour Description

There is a total of seven behaviours used amongst the MFS, and they are: Seek, Explore, Wait, Impatience, Panic, Communicate, and Ignore. They are explained as below:

- Seek: is the focus on finding the sensor data or goal;
- Explore: is the ability to look around the environment freely without any obligation;
- Wait: when the agent is unable to move fast enough around the environment due to congestion or other reasons they will choose to patiently wait;
- Impatience: if the agent is not moving fast enough because of congestion or other reasons they will choose to push through the congestion;
- Panic: depending on the situation the agent will panic based on the situation and the agent personality;
- Communicate: depending on the situation the agent will decide to talk to another agent to gather information or share information;
- Ignore: forget the data sent from the Attention Filter.

5.4 Short Term Memory

The Short Term Memory module is tasked with storing and organising all data sent from Situation Assessment, based on priority (see Figure 5.5). This module represents short term memory as the data is only stored here for a limited time. STM is the ability to hold a limited amount of information within the mind for a

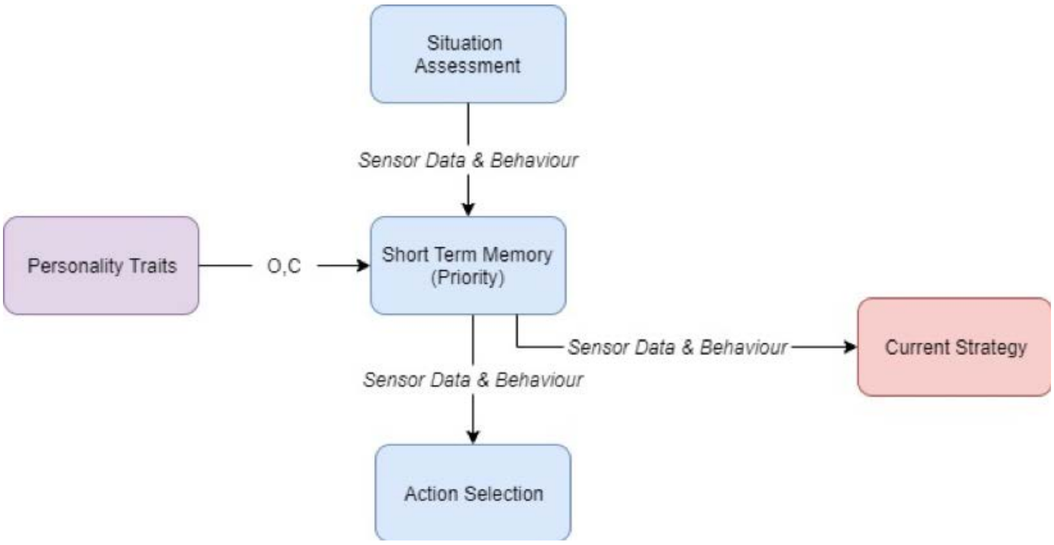


Figure 5.5: An overall flow of the Short Term Memory module.

short period of time. STM is designed to store the visual data (Attention Filter data) and be influenced by the mental data (personality only) [128, 129]. Once the MFS has selected an appropriate behaviour, it is sent along with the data from the Attention Filter to the STM. All the data sent is added to a priority list representing STM. This module focuses on two key aspects of STM: they are limited capacity and limited time. According to [130], people possess the capacity to store up to seven items at a time on average. This is represented by giving the priority list a limited size which is calculated using two OCEAN personality factors from the agent: openness and conscientiousness (see Equation 5.5). If the priority list reaches to the full capacity, the first behaviour and sensor data in the list are removed making room for more recent data.

$$Priority\ Capacity = 7 \times ((O + C)/14), \tag{5.5}$$

where O stands for openness whilst C stands for conscientiousness.

According to [130], STM is very fragile and can only last for a certain amount of time. They claim the maximum time that information can be retained is between 15-30 seconds. Based on this, each piece of data in the priority list is given a time limit of 30 seconds. Once the time limit is up, the data is forgotten. However, [130] also states the information can be retained over the 30 seconds mark within the STM if the information is repeated. This has also been implemented by resetting the timer back to 30 seconds every time the exact same data is sent from the Situation Assessment module to the STM within the allocated time frame. To determine what data from the priority list should be past to the next section of the framework, a priority value of 1 is given to each line of data. The priority value can be increased in two ways: first if the data sent from the Situation Assessment is identical to the data currently within the priority list, the data priority value is increased by a value 1. However if only the behaviour data sent by the sensor data is the same then a value of 0.5 is given. The second way a priority value can increase is by being related to an agent's goal. If any data within the priority list are similar to the agent's goal, the data's priority value is doubled. This is completed to ensure the agent prioritises its goal over everything else, however this will not always happen. For instance, if data related to the agent's goal has a value of 4 and is then doubled to 8, it can still be overwritten by data not related to the agent's goal that has a value higher than 8. Last, the STM organises the priority list based on the priority values and transmits the data with the highest priority value to the Current Strategy to be set as the main priority for the agent. The system then moves on to the next phase of the framework the Action Selection module.

5.5 Action Selection

The Action Selection module provides the agent with the ability to select the best action based on the behaviour and data sent from the Short Term Memory module (see Figure 5.6).

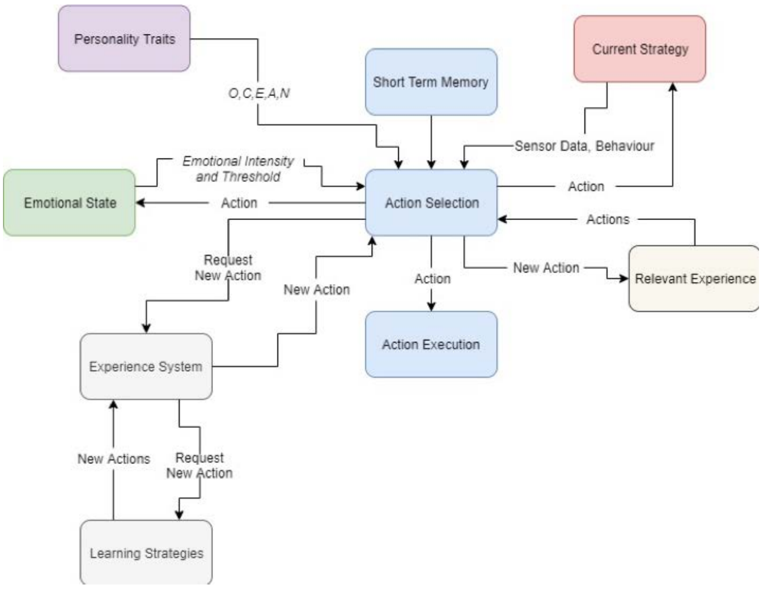


Figure 5.6: An overall flow of the Action Selection module.

The Action Selection is influenced by visual data (behaviour) and mental data (personality and emotion), while it also outputs physical data (action).

The Action Selection starts by collecting the main priority data from Current Strategy, and then it checks to see if the agent already knows an action related to the data. This is implemented by using the main priority data to search the Relevant Experience module. If an action is found, it is added to a list of possible actions it can use. The Action Selection then decides whether to learn a new action or use the action the agent already knows. This is decided by two factors: first is to check if the agent has no actions related to the data, and the second is based on the agent's OCEAN personality factor, openness. The agent's openness personality value is used as a probability value. A random value is generated and if the random value is within the probability range than the agent wants to learn a new action. Otherwise, the agent will use the current action it has.

If the agent decides to learn a new action, it sends a request to the Experience System (see Section 5.8). The Action Selection will then receive a new action and check to see if it already exists in Relevant Experience. If the agent doesn't know the new action then it is added to Relevant Experience and the main priority in Current Strategy. If the agent already knows the action, the action is only added to Current Strategy. If the agent decides not to learn a new action and rather to use actions it already knows, then it is calculated using probability. Each action related to the data is given a probability value of 0. The action probability value is calculated based on the agent's experience with the action, the agent's personality, and emotional state. The agent's experience in an action increases the probability of being selected. While agent's personality can increase or decrease the probability, each action has its own personality requirements and is compared to the agent's personality to calculate a differential which is then used in the action probability. Just like the Attention Filter, the action's probability of success is influenced by the agent's current emotional state. If any of the agent's emotions is over its threshold, the action probability is either increased or decreased based on whether it is a positive or negative emotion. A random value is then generated and the action with the closest probability value is selected to be performed. The action is then added to the main priority in the Current Strategies module. The framework then moves on to the next module the Action Execution module.

5.6 Action Execution

The Action Execution module is responsible for accessing the agent's lower level processes (such as navigation and movement), and performing the selected action. This section also determines whether the action performed is successful by using probability. The probability factor is determined based on the agent's personality and current experience (from the Relevant Experience module) with the action.

It also performs the selected action, and experience is given to the agent based on the action successfulness. The action execution focuses on influencing through agent's physical data (actions) and mental data (personality and emotion). There are six actions that the agent can perform as below:

- Wander: the agent moves around the environment going to random locations;
- Go to Target: the agent goes directly to a targeted location stored in Current Strategy;
- Seek Information: the agent will go to places where information can be gathered about the environment (such as maps and information centres);
- Wait: if the area the agent is in is congested and cannot move, the agent will stop and wait for a certain period of time before moving on;
- Push Through: if the area is highly congested, the agent will attempt to push through the crowd to get to its destination;
- Run Away: the agent will flee the area for safety.

Depending on the action being performed, the agent's personality can influence the success or how long the action is performed. For example, the amount of time an agent will stop and wait is determined based on the agent's agreeableness personality value. Agreeableness represents how kind and patient the agent will wait. Also, depending on the action the agent's experience in that particular action can also determine its success in performing it. For example, the action Seek Information requires the agent to look at a map and find its goal, however, if its experience is to low then it might not see its goal on the map. Some actions such as Wander are only successful if the agent's goal is found while it is wandering around. While some are always successful as it does not require experience (for example the action Wait). Once an action is completed, the action is given an increase to its experience based on whether it is successful or not. The agent's success with the action is also sent to the Emotional State to influence the agent's emotions (see Section 5.9.2 for further detail). Once this is all completed, Action Execution sends a request to the agent's Current Strategy to move the main priority data and action to the agent's Long Term Memory. This then allows the Short Term Memory to select a new main priority to be sent to Current Strategy.

5.7 Storage

The Storage module consists of three parts: Relevant Experience, Current Strategy and Long Term Memory. Each part is explained as follows:

5.7.1 Relevant Experience

Relevant Experience stores all the actions that the agent has learnt and the amount of experience it has in performing them. Each action contains additional information that can be accessed by other modules in the framework when requested. The additional data are behaviours and personality traits related to each action, the agent's total experience in performing the particular action and the number of attempts and successes. Relevant Experience can also check to see if an action exists by either looking for an action with a similar name or by behaviour. Actions and information related to the action can be sent to Action Selection and Action Execution when requested. Lastly, values such as actions, experience and successful attempts can be increased when results from Action Execution are received. Relevant Experience was influenced and designed using physical data (actions and experience), mental data (personality only) and visual data (behaviours).

5.7.2 Current Strategy

Current Strategy is where all the current information that the agent is focused on is stored such as the agent's current behaviour, action, and sensor data. Current Strategy also stores and changes the agent's goals based on the current situation. Current Strategy was designed based on physical (action) and visual data (behaviours). The main purpose of Current Strategy is to receive agent's main priorities such as behaviour, action, and sensor data and store it. Current Strategy also sends this data when another module of the framework requests it. Lastly, this module stores the agent's goals and has the ability to send, remove, and update them when needed.

5.7.3 Long Term Memory

LTM is where information and knowledge are held indefinitely. LTM is a large storage device that contains all the data from Current Strategy (behaviour, sensor, and action data) that has been completed. LTM is influenced by mental data (personality only) and was designed to store physical (action) and visual data (sensor data and behaviours). LTM can be accessed by other areas of the framework however, based on studies by [131], LTM can only be accessed 60% of the time.

5.8 Knowledge/Learning

The Knowledge/Learning module manages two sub-modules: The mediator module Experience Systems and the frameworks external module Learning Strategies.

This module primary job is to store new actions and teach them to the agent when requested.

5.8.1 Experience System

Experience System is the mediator between Action Selection and the external section of the framework Learning Strategies. This module is built based on all three data types: physical (actions), mental (personality), and visual (behaviours). The purpose of Experience System is to find the best new action from all data related to send to Action Selection. This is achieved by first receiving a request for a new action from Action Selection containing information such as current agent behaviour and sensor data. Experience System will then send all relevant information to Learning Strategies asking for all actions best suited for this situation.

The system then waits to see if more information is needed in the form of the agent's personality. Once Learning Strategies has sent the best possible actions back to Experience System, it is forwarded on to Action Selection for final decision making. If actions are sent back from Learning Strategies, then Experience System uses a probability based value to determine the best action. The probability starting value is calculated using the actions best suited personality and the agent's personality. A random value is then generated and the action with the closest probability is selected. By implementing a random probability system to learn new actions, we are giving the agent a chance to relearn actions they already know but do not use often or are not skilled at. If no actions are sent back from Learning Strategies, a null value is sent to Action Selection indicating there is no new action available.

5.8.2 Learning Strategies

Learning Strategy stores all the possible actions that can be learnt by the agent, and the requirements related to those actions within the scenario. This section is an external section that cannot access information about the agent. It can only request or receive information from the agent through Experience System. Being that this module is built as an external system, it is not influenced by any data type. However, this module was implemented using the three data types: physical (actions), mental (personality), and visual (behaviours). This section works when a request for a list of actions is sent from Experience System. Learning Strategies is a system that contains a list of all possible actions that can be performed within a simulation. The Learning Strategies module scans through all actions and the data related to them, and finds all the best actions. Each action selected is stored in a separate list to be sent to Experience System. Actions have three parameters used to find the best actions: behaviour, sensor data and personality traits. These parameters are compared to the information sent from Experience System and allow Learning Strategies to narrow down the best suited action.

5.9 Psychological Aspects

Psychological Aspects manages two sub-modules: Personality Trait and Emotion State.

5.9.1 Personality Trait

Personality Trait generates the agent's personality traits using the OCEAN model: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. This module is designed to influence the low and high level of the framework using the personality data collected. Each personality trait can be set manually or randomly generated between the range of 1.0 (representing a weak trait) and 7.0 (representing a strong trait). Personality Trait can also receive requests for a single trait or all traits, and send them to the requested destination. Personality Trait influences multiple sections of the framework such as Attention Filter, Situation Assessment, Short Term Memory, Action Selection, Action Execution, Experience System, and Emotional State.

5.9.2 Emotional State

Emotional State generates the agent's emotions using the OCC model [92]. The Emotional State module can send and receive information from Attention Filter, Action Selection, Action Execution, Relevant Experience, LTM, and Current Strategy. This is either to influence a section based on the agent's current emotional values, or to increase the agent's emotional values intensity based on a situation or outcome. Emotional State also maintains the agent's emotional threshold, which can put more influence on decisions in other sections. Lastly, Emotional State maintains all 22 emotions from the OCC model by using an emotional decay to decrease the emotion's intensity after an allotted time.

We increase the agent's emotional state by combing the OCC model process with fuzzy logic. The OCC model is a popular method that provides a hierarchy that classifies 22 different emotion types [92]. The OCC model hierarchy contains three branches: they are consequences of events (for instance Joy, Pity etc.), actions of agents (Pride, Reproach etc.), and aspects of objects (Love, Hate etc.). When the emotional state receives information, it is processed through all three OCC branches.

The information sent first goes through the branch, consequences of events. Consequences of events evaluate the goal based emotions by whether the information is desirable or not. Consequences of events break down into three subbranches: well-being, prospect based and fortune of others. The well-being branch determines how much the information sent influences the agent's emotion, Joy or Distress. Using the table in [92], we compute this using three fuzzy logic systems: desirability, expectation, and appraisal of well-being. Desirability fuzzy logic uses fuzzy rules to determine if the information sent is related to the agent's goal, and whether it is *Desirable* or *Undesirable*. Expectation fuzzy logic determines whether the agent is *Pleased* or *Displeased* with the information related to their goals and the agent's Neuroticism personality. Expectation fuzzy logic focuses on the expectations of one's self from an emotional perspective and not of other people. The Neuroticism was selected as it focuses on ones self while a personality trait like Agreeableness focuses on social harmony with others and not with one's self. Lastly, once the desirability and agent expectations of the information are determined, we then perform an appraisal of the agent's well-being emotions (see Table 5.1).

Based on our results from the real world and VR tests, it is found that our positive emotions seem to be increasing at a higher rate than the negative emotions. Also past studies into implementing the OCC model show that emotions are calculated differently [132]. For this subbranch the desirability was multiplied by the agent's expectations to determine the increase in intensity for the selected emotion.

The prospect based branch evaluates the agent's emotions based on the current prospect of whether something will or will not occur. This section influences the emotions of Hope, Fear, Satisfaction, Fears-Confirmed, Relief, and Disappointment. At this point in time, the agent's feeling about the information is just a prospect of it being pleased or displeased. The information now needs to be confirmed that it is what they want. To achieve this, the agent must be within a certain range of the information otherwise it is considered unconfirmed. Once within the range, the agent will confirm the information has not changed by either Confirming the information is correct or Disconfirming it.

If the event is out of range, the agent perceives it as unconfirmed. Only two emotions are able to be appraised by an unconfirmed event, and they are Hope and Fear. Hope and Fear are calculated as the same as Joy and Distress by multiplying the desirability by the agent's expectations. However, there is a chance of the information being confirmed or disconfirmed, so the rate of these emotions being triggered is less than Joy and Distress. If the agent is within the range, it checks to see the information is still goal related. Fuzzy logic was used to check if the information's previous goal relation value matches the new one and if it

Table 5.1: Emotion fuzzy rule set.

Emotion	Fuzzy Rule
Joy	IF(Desirability is Desirable) AND (Expectation is Pleased) THEN Emotion is Joy
Distress	IF (Desirability is Undesirable) AND (Expectation is Displeased) THEN Emotion is Distress
Hope	IF (Desirability is Desirable) AND (Expectation is Pleased) THEN Emotion is Hope
Fear	IF (Desirability is Undesirable) AND (Expectation is Displeased) THEN Emotion is Fear
Satisfaction	IF (Desirability is Desirable) AND (Expectation is Pleased) AND (Confirmation is Confirmed) THEN Emotion is Satisfaction
Fear-Confirmed	IF (Desirability is Undesirable) AND (Expectation is Displeased) AND (Confirmation is Confirmed) THEN Emotion is Fear-Confirmed
Disappointment	IF (Desirability is Desirable) AND (Expectation is Displeased) AND (Confirmation is Disconfirmed) THEN Emotion is Disappointment

does then it is confirmed otherwise it is disconfirmed. The agent then re-evaluates its Expectations. After that the appraisal of one of four emotions (Satisfaction, Fears-Confirmed, Relief, and Disappointment) based on the outcome is conducted.

The fortune of other branch relates to how the agent feels about another agent successfully or failing to achieve its goal. This is computed using the three fuzzy logic systems: desirability, expectation and appraisal for others. The first step implemented was to check the desirability of other agent achievement on whether the information that was sent was desirable or undesirable. The agent then determines whether it is pleased or displeased with the other agent's desirability by running the expectation fuzzy logic that uses the information related to the other agent's goals and the agent's Agreeableness personality. The results are then appraised to one of four emotions: Happy-for, Resentment, Gloating or Pity (see

Table 5.1). The chosen emotion intensity is then increased using the calculation in Table 5.2. Each calculation in Table 5.2 is a formula designed for this project based on the OCC model.

Once an emotion has been intensified across all sub-branches within consequences of events, the system moves on to the next main branch actions of the agent. This branch only runs if the information sent is related to an action being performed. Actions of agent appraise the agent's actions, and how much influence the outcome affects the agent's emotions.

Table 5.2: Calculations for the increase of emotion intensity.

Emotion	Intensity Calculation
Joy	((1 - Desirability)* expectations) / 2
Distress	(Desirability * expectations)
Hope	((1 - Desirability)* expectations) / 2
Fear	(Desirability * expectations)
Satisfaction	(Hope * (1 - Desirability))
Fear-Confirmed	(Fear * Desirability)
Disappointment	(Fear * (1 - Desirability))
Relief	(Hope * Desirability)
Happy-For	(Hope * (1 - Desirability))
Resentment	(Fear * Desirability)
Pity	(Fear * (1 - Desirability))
Gloating	(Hope * Desirability)
Pride	+ Praiseworthiness
Shame	+ Praiseworthiness
Admiration	+ Praiseworthiness
Reproach	+ Praiseworthiness
Love	+ Attitude
Hate	+ Attitude
Gratification	(Admiration + Joy) /2
Remorse	(Shame + Distress) /2
Gratitude	(Pride + Joy) /2
Anger	(Reproach + Distress) /2

First, was the need to determine if the action was performed by the agent itself or the other agent. For either outcome, the agent determines the action's praiseworthiness by whether the agent approves or disapproves the results of an action performed. This is computed using a fuzzy logic system that runs fuzzy rules: Neuroticism personality, action, and action outcome. Once the agent knows whether it approves or disapproves the results of the action, it then appraises the results to one of pride, shame, admiration, and approach. The selected emotion is then intensified using the calculations in Table 5.2. The last main branch, aspect of object, is the attitude that the agent feels towards an object. This attitude can either Like or Dislike. This is determined by the appealingness (goal related) of the object and familiarity (memory) of the object. Once the agent determines the attitude towards the object, the results are appraised to either Love or Hate based on the agent's attitude and the object's appealingness. The emotion appraised is then increased in intensity seen in Table 5.2. Some of the main branches combine to form a group of compound emotions, namely emotions concerning consequences of events caused by actions of agents. There is a total of four compound emotions: Gratification, Remorse, Gratitude, and Anger. These emotions are calculated based on other emotions (see Table 5.2).

5.9.2.1 Emotional Decay

The implementation of emotional decay to decrease the agent's emotional state. Emotional decay represents the decrease of emotion intensity with time. This is implemented using the equation for emotional decays [83], and run it every 20 seconds (see Equation. 5.6). Emotional thresholds are placed on each of the 22 emotions. Emotional thresholds are considered breaking points in which overpower our rational thoughts and significantly influences out decisions. This was implemented using the threshold equation [83] combined with the agent's personality Neuroticism to determine its emotional threshold. When an emotional state exceeds its threshold, it then influences the agent's decision making and empathy.

$$e_t = e_{t-1} - \beta \ e_{t-1}. \tag{5.6}$$

At each time step t, the value of an emotion e is decreased. β determines the speed of the emotional decay and how it is proportional to neuroticism.

5.9.2.2 Emotional Empathy

Emotional empathy represents the cognitive and emotional reaction of an agent received from another. Based on past studies [83], empathy was implemented when an emotion intensity passes its threshold. Any agents within a certain distance from the emotional agent are then influenced with a dose of that emotion. A combination of personality and emotion is used to calculate the dose of empathy [83] (see Equation. 5.7) that will be spread to other agents.

$$\epsilon_j = 0.34\Psi_j^O + 0.17\Psi_j^C + 0.13\Psi_j^E + 0.3\Psi_j^A + 0.02\Psi_j^N. \tag{5.7}$$

Based on Durupinar et al. [83] the correlation values empathy ϵ will take a value between 0 and 1 then compute it for the agent j.

5.10 Algorithm

An algorithmic procedure of the proposed cognitive architecture framework for agent-based simulations is shown below Algorithm 1. Please refer to details explained for each procedure in this section.

Algorithm 1 Cognitive Architecture Framework for Agent based Simulations

Input: Sensor Data (SD), Behaviour List (BL), Current Action (CA), Current Behaviour (CB), and Current Sensor Data (CSD);
Output: Sensor Data (SD, SDi), Behaviour List (BL, BLi), Action (A), Current Action (CA), Current Behaviour (CB), Current Sensor Data (CSD), and Action Success (AS);

```
procedure SENSOR SYSTEM
    Collect SD from Agent sensors;
    if the number of SD > 0 then
        Send SD to Attention Filter procedure;

procedure ATTENTION FILTER
    Receive SD;
    Check LTM for Goal Related Memories (GM);
    if GM exists then
        Add GM to SD;
    for each SDi do
        Calculate the Probability (P) of Agent notices SDi;
▷ Using Personality, Emotion and Goals (Current Strategy)
        Generate Random Value (Rand);
        if Rand < P then
            Keep SDi;
        else
            Remove SDi;
    Send SD to Emotional Start module;
▷ Emotional Start module sets SD to the agent's emotional intensity;
    Send SD to Situation Assessment procedure;

procedure SITUATION ASSESSMENT
    Receive SD;
    for each SDi do
        Compute B from SDi;
▷ Using Multilayered Fuzzy Logic, Agent Personality, and Goals (Current Strategy)
        Run Goal Fuzzy Logic Layer;
▷ Finds the best behaviour related to the agent's goals
        if B is found then
            Add B to BL;
            Break;
        Run Movement Fuzzy Logic Layer;
▷ Finds best behaviour related to agent's movements
        if B is found then
            Add B to BL;
            Break;
        Run Audio Fuzzy Logic Layer;
▷ Finds the best behaviour related what the agent hears
        if B is found then
            Add B to BL;
            Break;
        Run Object Fuzzy Logic Layer;
▷ Finds the best behaviour related what the agent is seeing
        if B is found then
            Add B to BL;
            Break;
    Send BL and SD to Short Term Memory procedure;
procedure SHORT TERM MEMORY
    Receive BL and SD;
    for each SDi do
        if SDi and BLi exist in Short Term Memory List (SML) then
            Increase priority of SMLi;
        else
            Add SDi and BLi to SML;
        Find highest priority in SML;
        Send highest priority SMLi (SDi,BLi)
            to Current Strategy module;
▷ Current Strategy module sets Di and BLi from SMi to CSD and CB;

procedure ACTION SELECTION
    Get CSD and CB from Current Strategy module;
    Get all known Actions (A) from Relevant Experience;
    for each Ai do
        if Ai is related to CSD and CB then
            Add Ai to Related Actions (RA);
    Check if Agent learns new action;
    if RA == 0 then
        Learn new A from Experience System;
    else
        Calculate probability of learning new action using
            Agent's Personality (O);
        Generate Rand;
        if Rand < P then
            Learn new A from Experience System;
        else
            Select an A from RA;
    Send A to Current Strategy module;
▷ Current Strategy sets A as current action
    Send A to Emotional Start module;
▷ Emotional Start module influences the agent's emotional intensity with A

procedure ACTION EXECUTION
    Get Current Action (CA) from Current Strategy;
    Perform CA;
        Compute CA Success Probability (ASP)
            using Action Experience (AE) and Personality;
    Generate Rand;
    if Rand < ASP then
        Perform Action Success (AS);
    else
        Fail to perform Action Success (AS);
    Once CA is performed
        Send AS to Emotional Start module;
        Send AS to Relevant Experience;
        Send CA,CSD,CB to Long Term Memory;
        Remove CA,CSD,CB from Current Strategy;
```

Chapter 6

Experimental Results

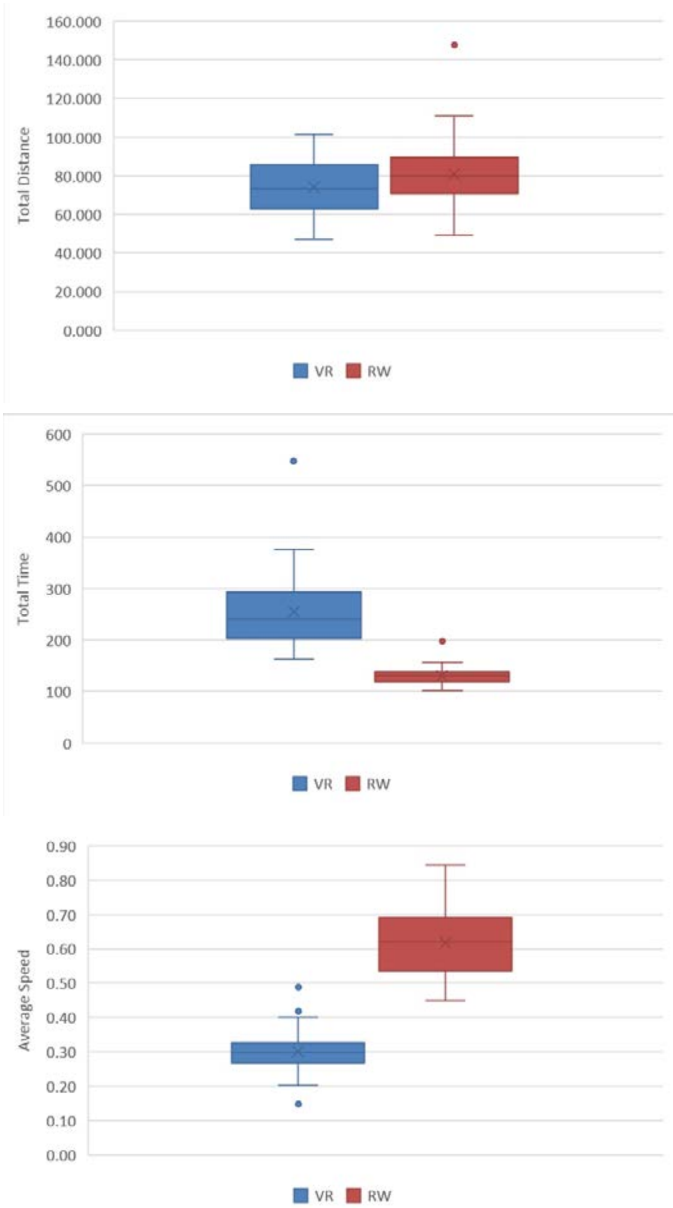
6.1 Data Gathering Results

This section reports data gathering results on three different types between the VR+Q method and the real-world method. In this study, the Chi-square Goodness of Fit Test [133] is used as a significance test to compare the two data collection methods. Chi-square Goodness of Fit Test was conducted in this experiment as it provides a non-parametric test in finding out if an observed value produces any significant differences from the expected value. In this experiment our observed value is the VR+Q participant's data and we want to see if there is no significant difference when compared to the expected value which is the real-world participant's data. We display the Chi-square Goodness of Fit results using a distribution graph, which provides a clear way of showing whether there are any significant differences (p-value) between two data samples (x^2) and the degree of freedom.

6.1.1 Physical Data Analysis

The results of the physical data are displayed in Figure 6.1. The total average distance travelled from the two data gathering methods reveals that the VR participants (74.11m) moved at a similar distance to the real-world participants (80.72m). This shows that the VR+Q method can produce similar distances travelled with an 8.19% offset. Please note that this is within the margin of error for our study which is 16% as discussed in Section 4.1.1. It can be assumed that one of the reasons for this is because the VR environment was developed to the same measurements as the real-world environment. By doing this, it controls the participant's movement to only the space within the environment. This will, in turn, cause the distance travelled between the two methods to be very similar.

This also demonstrates the capability of our method to capture approximate real world travel distance for agent-based simulations.



(a)

(b)

(c)

Figure 6.1: Physical data comparison: (a) total distance (y-axis: meter); (b) total time (y-axis: second) (c) average speed (y-axis: m/s).

The average time taken to complete the task in the given scenario was nearly double. The VR+Q participants took on average 255 seconds to complete the scenario while the real-world participants on an average of 130.7 seconds. This difference in time could be caused by the VR+Q participants moving around the environment with a VR headset on. The VR+Q participants, not knowing where they are walking in the real world could have caused them to move slower than the real-world participants. This is consistent with previous studies [134] that demonstrated distances appear to be compressed in VR environments thus it takes longer time to complete a distance-related task in VR environments. This is also validated by another previous study [135] that demonstrated that people tend to take more steps walking to reach their goal when within a VR environment. This difference in steps significantly affects and increases the amount of time it takes for a person to reach their goal within a VR environment. Also, cybersicknesss and motion sickness could represent possible reasons for the inefficiency of task completion [136].

Similar to the average time, the average speed (distance/time) taken by the VR+Q participants is nearly half of the real-world participants. Chi-square Goodness of Fit Test with the three physical data (distance, time and speed) under study indicates that the real world-data and the VR+Q data are significantly different where p-value with degree of freedom = 2, approximates to 0 (see Figure 6.2). Therefore, these average time and speed physical data measured by the VR+Q method could not be directly used as input for agent-based simulations but rather requires an adjustment factor to consider this difference. Implementing an adjustment factor helps us avoid losing time by having to halve the size of the environment and re-running all the VR+Q tests. Instead it allows us to adjust the current physical data collected so that a more realistic value is outputted.

An adjusted agent data value is computed as below:

$$AATV = UATV \times \frac{RWTV}{VRTV}, \tag{6.1}$$

where $AATV$ represents Adjusted Agent Time Value, $RWTV$ stands for Real World Time Value, $UATV$ for Unadjusted Agent Time Value, and $VRTV$ means VR Time Value. For instance, let us assume $RWTV$ is given 130.766 seconds and $VRTV$ is given 255.005 whilst $UATV$ is given 267.418. As we discussed above, there is a significant difference between $RWTV$ and $VRTV$. A ratio of these two is used as an adjustment factor to moderate the auto-generated agent value ($UATV$). This will reflect the difference in time completion between two spaces as evidenced in past studies [134–136]. After the adjustment, $AATV$ becomes 137.131 which is relatively similar to $RWTV$ (130.766). Equation 6.1 mitigates the time difference and makes the physical data collected through the VR+Q method more realistic and usable for agent-based simulations. Another Chi-square Goodness of Fit Test was implemented for the physical data which included the adjustment factor into the VR+Q physical value. With the adjustment factor added to the physical data, the real-world data and the VR+Q data are now not that significantly different where p-value with degree of freedom = 2, approximates to 0.803 (see Figure 6.2).

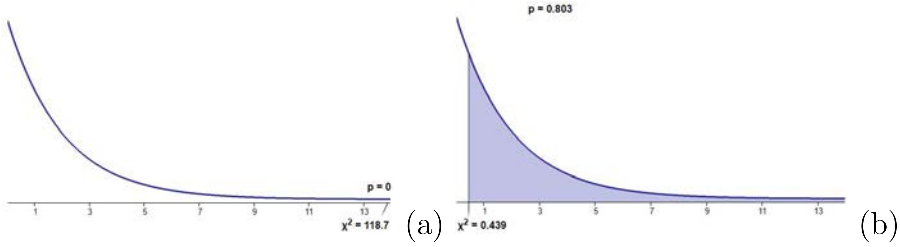


Figure 6.2: Physical data Chi-square Goodness of Fit Test comparison: (a) before adjustment factor; (b) after adjustment.

6.1.2 Mental Data Analysis

The results of the data collected based on the overall average of all participants' personality are compared in Table 6.1. Using the questionnaire to ask the participants to rate their personality, we were able to map using the TIPI method to the OCEAN model. The personality results showed the VR+Q can provide similar results to the real world method. This was expected as both methods questionnaire asks the same personality question. The average personality offset found between the real-world participants, and the VR+Q participants was only 0.21.

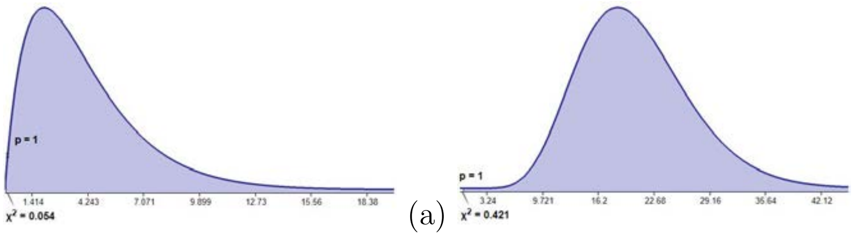
Table 6.1: Average personality comparison (values between 1-7).

	Real World Participants	Virtual Reality Participants
Openness	5.76	5.53
Conscientiousness	4.73	5.07
Extraversion	3.93	4.11
Agreeableness	4.72	4.65
Neuroticism	4.85	5.09

The results of the data collected based on the overall average of all participants emotions are compared in Table 6.2. Using the questionnaire to ask the participants what their average emotions were from 40 different emotions, we were able to map these emotions, using the hybrid model, into the OCC model. Using the OCC emotions for each participant, an overall average of all 37 participants was calculated and compared. The results revealed the VR+Q method did produce similar emotions values to the real world. First, what can be seen is that both the real world and VR+Q participants experienced more positive emotions than negative emotions within the environment. Second, the results are so similar, the average offset between the real world and VR+Q emotion is less than 0.16. The statistical significance test results in p-value with degree of freedom = 4 for personality becomes 0.999 whilst p-value with degree of freedom = 21 for emotion becomes 1. This indicates that the VR+Q data is extremely similar to the real-world data (see Figure 6.3). Therefore, mental data (personality and emotion) collected by the VR+Q method could be directly used for agent-based simulations to represent real-world data.

Table 6.2: Average emotion comparison.

	Real World Participants	Virtual Reality Participants
Joy	3.18	3.07
Distress	1.23	1.50
Happy-For	3.08	2.94
Resentment	1.19	1.19
Gloating	2.82	2.57
Pity	1.19	1.35
Hope	3.37	3.16
Fear	1.31	1.57
Satisfaction	3.09	2.96
Fears-Confirmed	1.14	1.24
Relief	3.19	2.86
Disappointment	1.14	1.28
Pride	2.76	2.57
Shame	1.11	1.35
Admiration	3.01	2.91
Reproach	1.19	1.35
Gratification	2.92	2.78
Remorse	1.03	1.24
Gratitude	2.95	2.72
Anger	1.19	1.19
Love	2.93	2.83
Hate	1.20	1.30



(a) (b)

Figure 6.3: Mental data Chi-square Goodness of Fit Test comparison: (a) personality; (b) emotion.

6.1.3 Visual Data Analysis

The results of the visual data collected from all participants are compared in Figure 6.4. During the real world experiment, only 8 participants looked for help, by using the maps or information centre, while the VR+Q experiment had 12 participants. It was also found that the VR+Q experiment showed that the participants would use the maps, 37.8% of the time, more than the information centre, which was 16.2% of the time. While the real-world experiment showed that they were equally used at 21.6% of the time. Based on these results we can assume that the VR+Q participants required more assistance in finding the target goals. The data collected from the real world reveal that people tend to turn left more than right when walking. The participants from the real world would turn left an average of 6.67 times and an average of 6.29 times turning right during the experiment. Even though the VR+Q participants did not provide similar averages to the real world, it showed that even in a virtual world people would turn left (average of 7.35 times) more than right (average of 4.70 times). In the real world experiment, participants were given the option at the start to either turn left or walk straight when entering the environment. The data collected reveals that 86.5% of the participants would start by walking straight rather then turning left. In the VR+Q experiment, the participants were given the same option and it was found that 78.4% of participants would prefer to walk straight on. Based on these results, it shows that there is no significant difference between how participants start the experiment. This validates that real world data can be collected from the VR+Q method as VR is not changing how participants are responding or reacting.

Towards the end of the experiment, participants were asked to pick one of the two exits and go to it. Based on the real world experiment, 59.5% of the participants chose to go back to the exit in which they started at, while 40.5% of the participants went to the furthest exit on the opposite side of the environment. While the VR+Q experiment showed different averages but similar results. A total of 83.8% of VR+Q participants would go to the same exit that they started at, while 16.2% would go to the exit on the other side of the environment. In both experiments, the participants who went to the furthest exit were asked why they chose to go to that exit instead of the closest one. The same response was given in both experiments; they believe that was what they were meant to do. Even though they were given the option to pick which exit, they thought that the furthest exit was the correct one. The data show most participants from both experiments would choose to go to the closest exit rather than the furthest. The statistical test shows that p-value becomes 0.108 when degree of freedom = 7. Thus we accept the null hypothesis stating there is no significant difference between the two groups (see Figure 6.5). This again supports the VR+Q approach could provide real-world data for agent-based simulations.

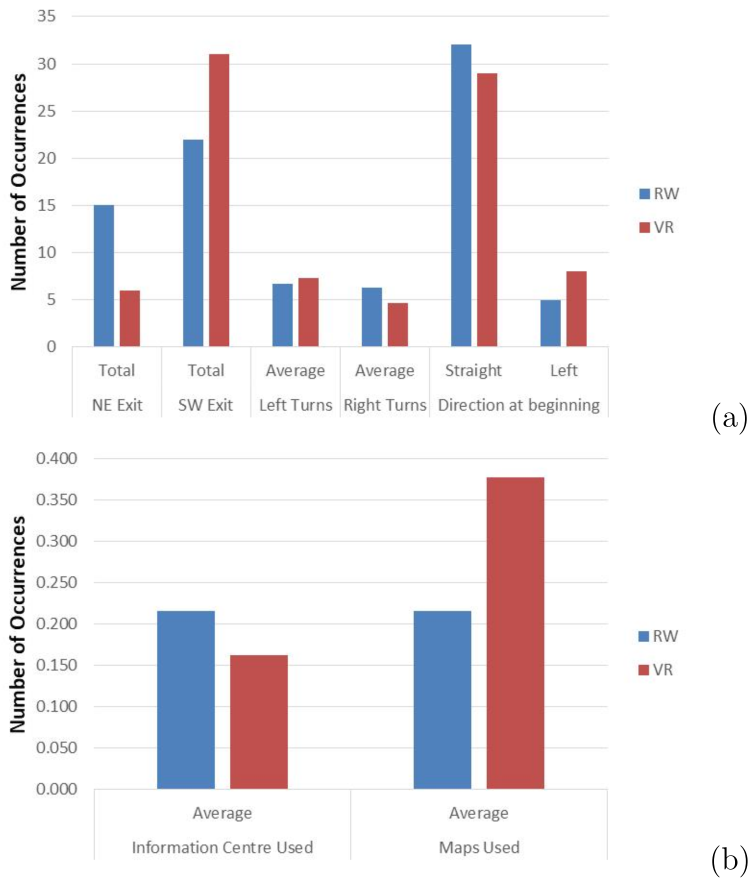


Figure 6.4: Visual data comparison (y-axis: the number of occurrences): (a) visual data; (b) information centres and maps used.

During both experiments, it was revealed that no matter whether the participants were in VR or the real world, some of them would display the same unique behaviours. For instance, participants in both experiments, when asked to find one of the goals they would stop and look around them before heading off. This behaviour tells us that the participants either believed that the goal was nearby or they just wanted to make sure it wasn't so they don't have to go back there. Another unique behaviour found in both experiments was the tendency of the participants back tracking. Back tracking is when somebody walks down a certain path and then decides to turn around and retrace his/her steps. There are two causes for this: one is due to him/her thinking he/she missed something. The other is he/she remembered where the goal was so he/she changed direction to get there. The last behaviour observed in both experiments was the participant's looking left and right while walking. Majority of the participants produced this behaviour as it can be considered a common behaviour.

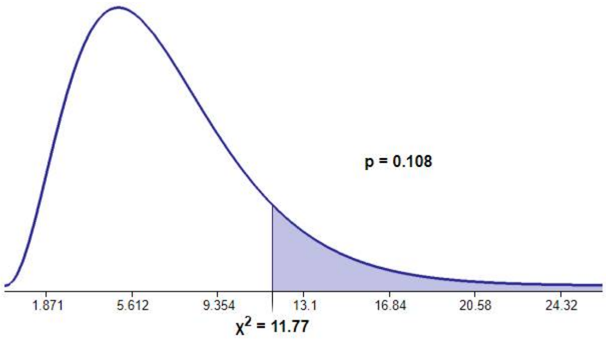


Figure 6.5: Visual data Chi-square Goodness of Fit Test.

6.1.4 Overall Data Analysis

To ensure that VR+Q method can produce real-world data a Chi-square Goodness of Fit Test was conducted. The statistical test combined all three types of data together to determine whether the VR+Q method can provide similar results to the real-world method (see Figure 6.6). The results revealed there was no significant difference between the VR+Q and real-world methods with p-value=1 when degree of freedom = 37. This proves the VR+Q method can output data similar to the real world for the development and validation of agent-based crowd simulations.

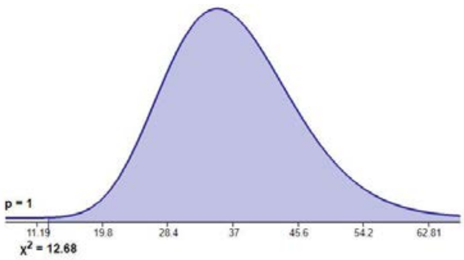
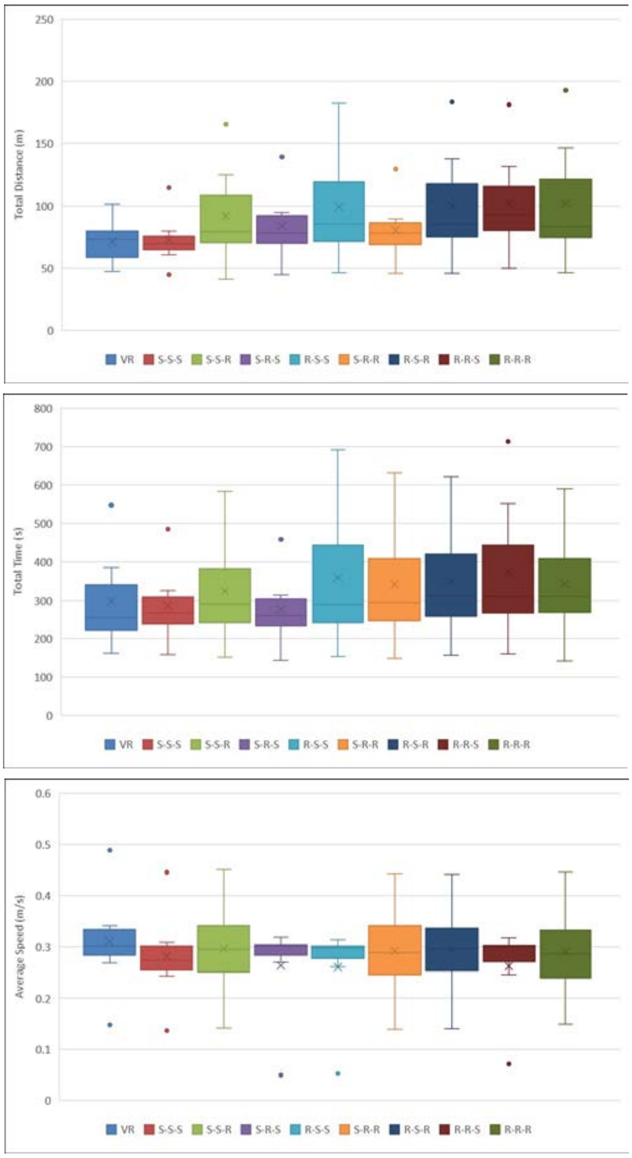


Figure 6.6: All data combined Chi-square Goodness of Fit Test.

6.2 AI Results

This section reports data gathering results on three different types between different variations of the AI cognitive architecture and the VR+Q method. In this study, a t-test of equal variance is conducted to compare the difference between the AI parameter variations and the VR+Q data. The parameter variations (Speed, Personality and Emotion) that are compared were collected from the VR+Q data input stage. The purpose of the t-test is not to compare the outputs from the AI to the systems parameter variations. We are generating the outputs of our systems using the parameter values from VR+Q input stage. We display the t-test results using the standard statistical analysis method, tables, when comparing the Mean, Standard Deviation and p-value. This is due to its simplicity and provides a clear understanding for anybody to read. A Chi-square Goodness of Fit Test [133] is also used as a significance test to compare the different data sets.

6.2.1 Physical Data Analysis



(a) (b) (c)

Figure 6.7: t-test on physical data: (a) Average total distance; (b) Average time; (c) Average speed.

A two sample equal variance t-test [137] was conducted on the physical data which includes distance, time and speed from both tests and compared them to the VR+Q physical data results (see Figure 6.7). Normality of data distribution is assumed in population. The t-test of equal variance was selected because of its ability to analyse any significant differences between the means of two data samples which can either validate or disprove our hypothesis. The hypothesis is that the all set parameter setting agents (S-S-S) will produce closer results to the VR+Q setting than all other variations of the parameter settings. This is due to the fact that it is believed by setting the agents parameters using the individual VR+Q participants data, it will output similar results. It is also hypothesised that if the results are similar to the VR+Q data, then it proves the framework is capable of providing realistic data. All t-tests are conducted without the adjustment factor.

The distance results showed that the S-S-S (see Table 4.2 for definition) parameter agents (Mean (M)= 71.19; Standard Deviation (SD)=15.05) showed the least significant difference to the VR+Q participants (M=74.11; SD=15.53) with p-value = 0.155 with 95% confidence. This has proven the first hypothesis is true that all set parameter agents do provide similar results over the other variation parameter agents when compared to the VR+Q participants. Also based on the S-S-S parameter agent results, we can state that the second hypothesis is also valid. The next parameter variation to show the least significant difference was the S-R-R parameter agents (M= 78.373; SD=19.85) with p-value = 0.118, closely followed by S-R-S (M=78.431; SD=17.82) with p-value = 0.095. The parameter variation with the most significant difference was the R-R-S parameter agents (M=92.691; SD=28.23) with p-value = 0.0001. All distance results related to other agent parameter variations can be seen in Figure 6.7 and Table 6.3.

Table 6.3: Two sample t-test of equal variance total average distance comparison with 95% confidence.

Parameter Setting	Mean	SD	p-value
VR+Q	74.113	15.53	N/A
S-S-S	71.189	15.05	0.155
S-S-R	79.430	20.31	0.073
S-R-S	78.431	17.82	0.095
R-S-S	85.586	27.42	0.008
S-R-R	78.373	19.85	0.118
R-S-R	85.336	24.55	0.005
R-R-S	92.691	28.23	0.0001
R-R-R	83.422	23.18	0.012

What can also be seen is the order of which set parameter (derived from individual VR+Q data) has more influence over the agent's decision making based on the distance results. The most influential parameter towards the agent's distance is personality, second being emotion and lastly speed. This is a valid outcome based on past studies which have shown that personality can provide an impact on people physical attributes and activities such as speed and walking distance [138–140]. This is also showing that the mental data implemented from each VR+Q participant is influencing the agent's actions and behaviours to a significant extent.

The time results showed there was no significant difference, p-value $= 0.168$ with 95% confidence, between the S-S-S parameter agents (M=267.4; SD=65.29) and the VR+Q participants (M=255; SD=74.08). However, S-R-S produced the least significant difference (M=260.2; SD=59.25) when compared to the VR+Q participants with p-value $= 0.331$.

However, the first hypothesis still is proven to be true as it still provides similar results to the VR+Q participants over the other 6 parameter variations. Also, based on the S-S-S parameter agent results, we can state that the second hypothesis is also valid. The parameter variation with the most significant difference to the VR+Q data is R-S-R (M=311.8; SD=103.42) with p-value $= 0.001$. For all parameter variations total time results, see Figure 6.7 and Table 6.4. What was also seen is the order of which each set parameter (derived from individual VR+Q data) has more influence over the time it takes for the agents to complete the scenario. The most influential parameter towards the agent's time is speed and then split evenly is personality and emotion. This is showing that the physical data implemented from each VR+Q participant is influencing the agent's ability to complete each action, which is decided by its cognitive architecture decision making modules.

Table 6.4: Two sample t-test of equal variance total average time comparison with 95% confidence.

Parameter Setting	Mean	SD	p-value
VR+Q	255.005	75.13	N/A
S-S-S	267.418	65.59	0.168
S-S-R	291.062	105.59	0.028
S-R-S	260.252	59.25	0.331
R-S-S	288.868	97.64	0.027
S-R-R	294.044	100.23	0.015
R-S-R	311.860	103.42	0.001
R-R-S	310.851	99.92	0.001
R-R-R	310.648	99.89	0.001

The speed results showed there was no significant difference across all parameter variations when compared to the VR+Q participants. However, S-R-S parameter agents (M=0.301; SD=0,1) did produce the least significant difference to the VR+Q participants (M=0.291; SD=0.06) with a p-value=0.428. Followed closely by R-R-S parameter agents (M=0.298; SD=0.01) with a p-value=0.423 and S-S-R parameter agents (M=0.273; SD=0.09) with a p-value=0.346. Even though S-S-S parameter agents (M=0.266; SD=0.05) with a p-value = 0.004 with 95% confidence produced the most significant difference to the VR+Q participants speed data, it is a very small difference. The range of both the VR+Q participants and the S-S-S parameter agents speed is shaped very similar (see Figure 6.1 and Table 6.5), showing the S-S-S parameter agents are able to provide a similar minimum to maximum speed ratio. This small difference keeps our first hypothesis true that the set parameter agents do provide similar results to the VR+Q participants. Also based on all the parameter agent variations, it can also be stated that the second hypothesis is also valid.

Table 6.5: Two sample t-test of equal variance average speed comparison with 95% confidence.

Parameter Setting	Mean	SD	p-value
VR+Q	0.291	0.06	N/A
S-S-S	0.266	0.05	0.004
S-S-R	0.273	0.09	0.346
S-R-S	0.301	0.01	0.428
R-S-S	0.296	0.01	0.299
S-R-R	0.267	0.09	0.236
R-S-R	0.274	0.09	0.263
R-R-S	0.298	0.01	0.423
R-R-R	0.269	0.09	0.170

What was also seen was the order of which each set parameter (derived from individual VR+Q data) had more influence over the speed it takes for the agents to complete the scenario. The most influential parameter towards the agent's speed was the speed parameter, second the agent's emotions and lastly personality. This is showing that the physical data implemented from each VR+Q participant is influencing the agents ability to quickly complete the scenario. Also, based on the range from all the data collected for distance, time and speed using random parameter setting; it can be considered as a larger variety of real-world participants when being compared to S-S-S parameter agents. This is due to S-S-S parameter agents being based entirely on the VR+Q participants data. This means the proposed agent based cognitive architecture framework possesses the potential to produce and compare to a larger group of real-world people in the future.

A Chi-square Goodness of Fit Test using all three physical data (distance, time and speed) to provide further proof that the S-S-S parameter agent can produce real-world data over all other parameter variations. Before implementing the Chi-square Goodness of Fit Test, the physical data requires an adjustment factor in order to minimise the physical movement gap between the real world and the VR world caused by cybersickness, motion sickness or perception difference [116, 134–136]. Past studies [134–136] have proven there is a significant difference between real-world physical data and virtual world physical data. An adjustment factor provides a ratio between the real world and virtual world to moderate the auto-generated agent data and allows the data to be more realistic.

The statistical significance test resulted (see Figure 6.8) in the p-value with the degree of freedom = 2 for the physical data. The parameter variation that was the most significantly similar to the VR+Q participants was the S-R-S parameter agents with p-value of 0.848 and S-S-S parameter agents with p-value of 0.803. This indicates that the physical data collected by the S-S-S and S-R-S parameter agents is significantly similar to the real-world data and can be used to represent real-world data. Whilst the other parameter variations agent such as R-R-R with p-value of 0.023 and R-R-S with p-value of 0.003 were all significantly different from the real world with 95% confidence.

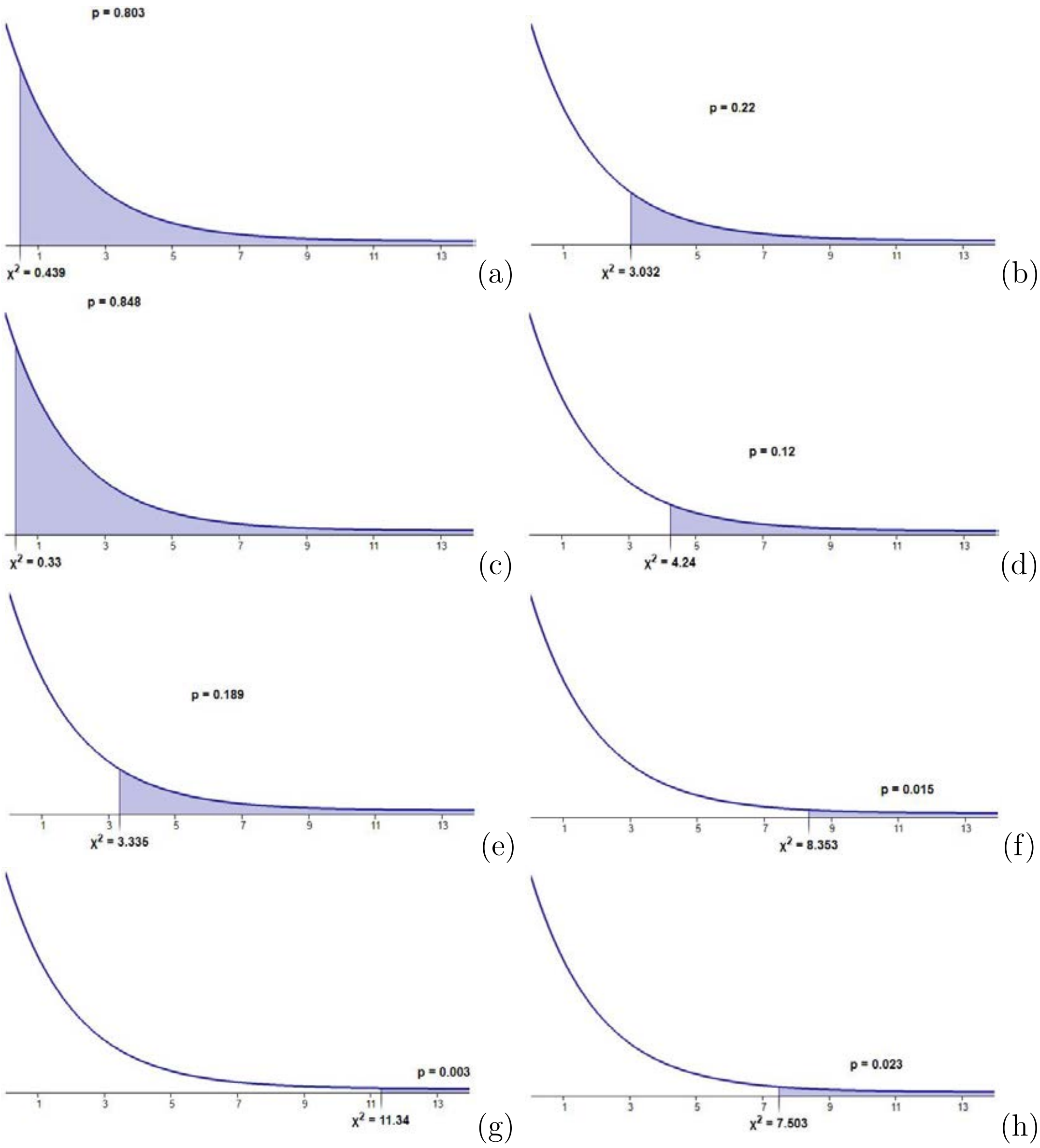


Figure 6.8: Physical data Chi-square Goodness of Fit Test: (a) S-S-S; (b) S-S-R; (c) S-R-S; (d) R-S-S; (e) S-R-R; (f) R-S-R; (g) R-R-S; (h) R-R-R.

6.2.2 Mental Data Analysis

The results of the mental data collected based on the overall average of all agents and VR+Q participants' personality are compared in Figure 6.9. The results showed that setting the parameters will produce better results to real world data over random parameters. However, what we can also assess from the random parameters alone is it produces a larger range of results that can be used to compare a larger sample size of real-world data.

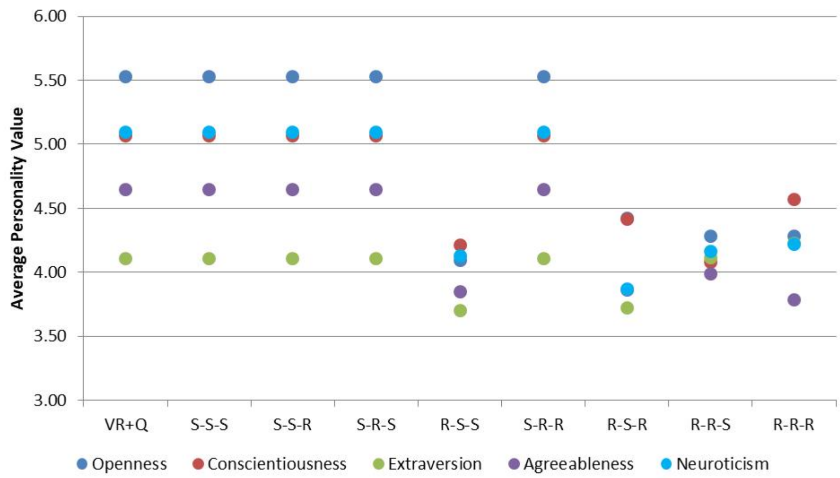


Figure 6.9: A comparison of OCEAN personality (y-axis represents the average personality value across all agents).

The results of the data collected based on the overall average of both the agent's emotions and VR-Q participants are compared in Table 6.6. Even though emotions that are influenced by other agents have been implemented, these emotions (Happy-for, Resentment, Gloating, Pity, Admiration, Reproach) are not tested. The reason for this is by replicating the same conditions from the VR+Q method; the participants were unable to interact or influence other agents. Therefore, we cannot compare these outcomes without further study into participants' interactions with others. The results reveal the S-S-S parameter agents can produce the most similar emotional results to the VR+Q participants amongst all parameter variations. While the R-R-R and R-R-S parameter agents produce more unpredictable results. What can also be revealed is that agents whose emotion parameter setting are set produce similar emotional results to the VR+Q participants; more so than agents with random emotion settings.

Lastly, it was revealed that all the parameter variations agents experienced more positive emotions than negative which coincides with the VR+Q participants results collected [116]. This proves that real world emotional data can be outputted from the virtual agents as it has shown to produce similar emotional responses to the VR+Q participants.

Table 6.6: A comparison of emotion data.

	VR+Q	S-S-S	S-S-R	S-R-S	R-S-S	S-R-R	R-S-R	R-R-S	R-R-R
Joy	3.07	3.07	2.91	3.00	2.61	2.97	2.70	2.55	2.65
Distress	1.50	1.50	1.46	1.67	1.45	1.73	1.43	1.56	1.61
Happy-For	2.94	1.20	1.19	1.21	1.19	1.19	1.18	1.17	1.18
Resentment	1.19	1.02	1.01	1.20	1.03	1.20	1.02	1.17	1.19
Gloating	2.57	1.16	1.15	1.21	1.14	1.21	1.14	1.18	1.16
Pity	1.35	1.04	1.05	1.19	1.04	1.20	1.04	1.20	1.16
Hope	3.16	2.60	2.46	2.51	2.27	2.48	2.34	2.15	2.27
Fear	1.57	1.38	1.36	1.54	1.33	1.52	1.33	1.46	1.49
Satisfaction	2.96	2.27	2.17	2.18	1.82	2.21	1.79	1.84	1.90
Fears-Confirmed	1.24	1.11	1.10	1.33	1.14	1.29	1.15	1.30	1.35
Relief	2.86	2.26	2.11	2.16	2.02	2.17	2.13	1.94	2.06
Disappointment	1.28	1.17	1.14	1.36	1.29	1.31	1.30	1.40	1.43
Pride	2.57	2.56	2.58	2.67	2.47	2.64	2.26	2.35	2.45
Shame	1.35	1.31	1.26	1.47	1.30	1.41	1.33	1.47	1.44
Admiration	2.91	1.19	1.19	1.21	1.19	1.18	1.17	1.17	1.17
Reproach	1.35	1.05	1.04	1.20	1.04	1.20	1.04	1.16	1.17
Gratification	2.78	2.13	2.03	2.09	1.90	2.07	1.94	1.87	1.92
Remorse	1.24	1.40	1.35	1.56	1.36	1.57	1.37	1.52	1.53
Gratitude	2.72	2.82	2.74	2.83	2.54	2.81	2.49	2.46	2.56
Anger	1.19	1.26	1.24	1.43	1.23	1.46	1.23	1.37	1.39
Love	2.83	2.67	2.50	2.54	2.35	2.59	2.45	2.25	2.44
Hate	1.30	1.14	1.15	1.32	1.14	1.30	1.15	1.31	1.32

A Chi-square Goodness of Fit Test was conducted for the mental data (personality and emotion). The statistical significance test in which the p-value with the degree of freedom = 21 for the emotions (see Figure 6.10), revealed all parameter variations of the test showed significantly similar to the real-world data with p-value=1. However, the closest to agent parameter variation to the real world is the S-S-S parameter agents with the lowest x^2-value=3.801. The furthest agent parameter variation when compared to the real world was R-R-S parameter agents with the highest x^2-value=4.845. This indicates that the emotion data from all variations of set and random parameter agents are significantly similar to the real-world data with 99% confidence and can be used from crowd simulations to represent real-world data.

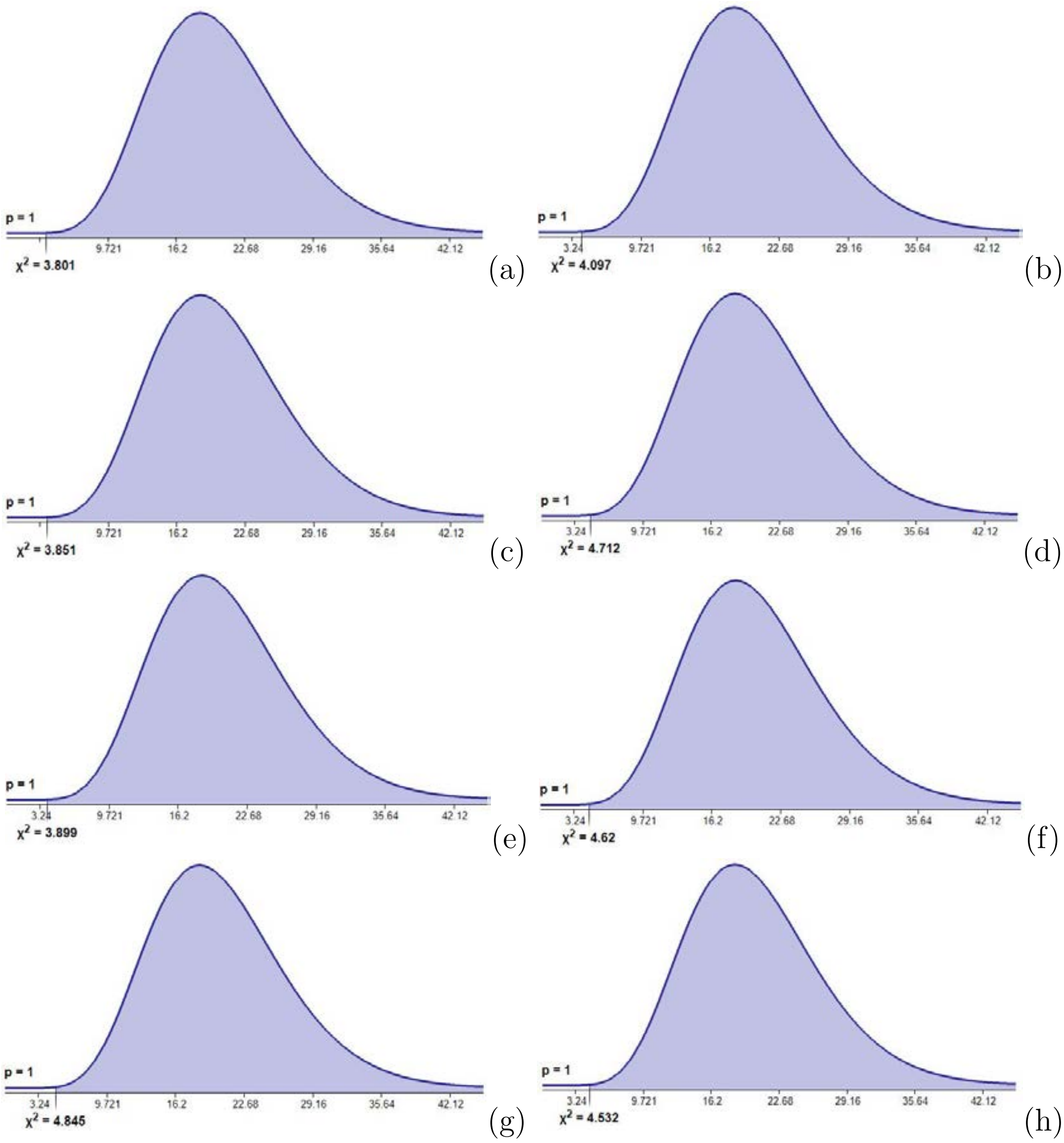


Figure 6.10: Emotion data Chi-square goodness of fit test: (a) S-S-S; (b) S-S-R; (c) S-R-S; (d) R-S-S; (e) S-R-R; (f) R-S-R; (g) R-R-S; (h) R-R-R.

The personality statistical significance test (see Figure 6.11) in which the p-value with the degree of freedom = 4 for all set parameter variation agents setting becomes 1; whilst the random parameter variation agents setting becomes 0.9. These results show that set parameter variation agents will produce identical results to the real world through the framework.

While the random parameter variation agents will produce similar results to the real world. Therefore, the mental data (personality and emotion) collected from the agents in all test types has shown this framework is capable of producing real-world data for agent-based crowd simulations.

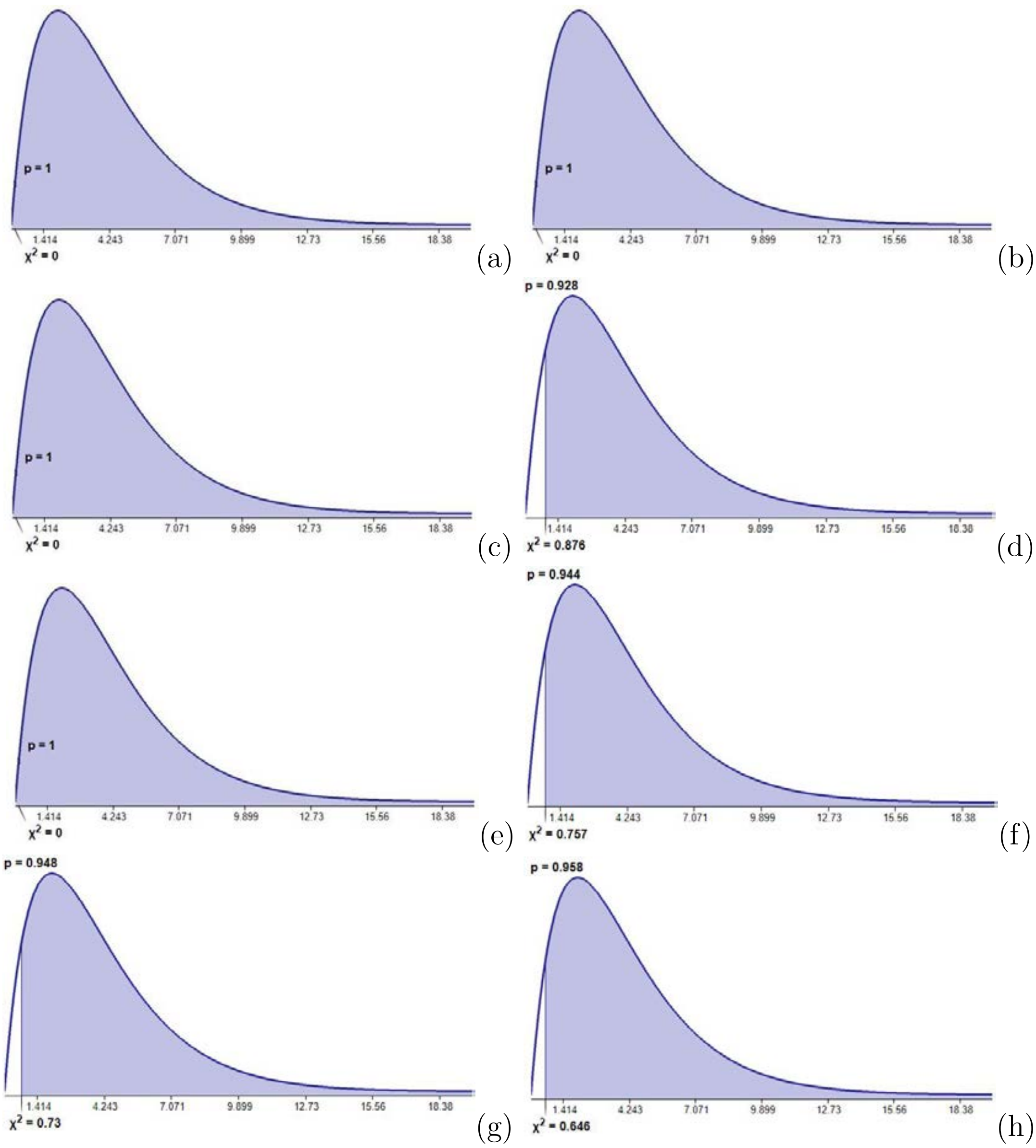


Figure 6.11: Personality data Chi-square goodness of fit test: (a) S-S-S; (b) S-S-R; (c) S-R-S; (d) R-S-S; (e) S-R-R; (f) R-S-R; (g) R-R-S; (h) R-R-R.

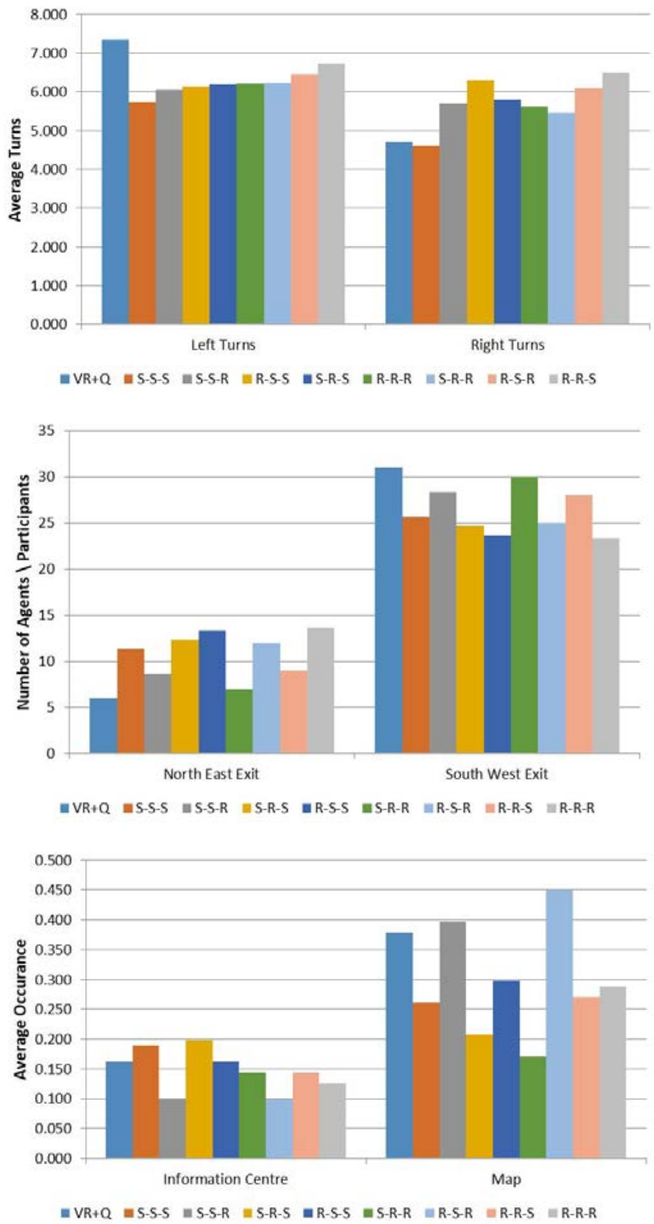
6.2.3 Visual Data Analysis

The results from the visual data collected from the agents are compared in Figure 6.12. During the VR+Q experiment, only 12 participants looked for help by using the maps and information centre. It was also revealed that for each 37 samples looking for help that R-S-R parameter produced the same results with 12. S-S-S parameter agents, on the other hand produced similar results with an average of 11.66 agents and the same with S-S-R parameter agents producing an average of 12.66 agents looking for help. Some close results were produced by R-S-S with an average of 10.33 and S-R-S with an average of 10. While S-R-R parameter agent with an average of 9.67, R-R-R parameter agents with 9.33 and R-R-S parameter agents with an average of 8.66 produced the least similar results for looking for help when compared to the VR+Q participants.

However, when it came down to the overall percentage in which the agents would use the maps or information centre individually the results are different (see Figure 6.12). The VR+Q experiment showed the participants would use the maps 37.8% of the time and the information centre 16.2% of the time. The agent parameter variation with the most similar chance of using the maps was S-S-R with 39.6%. This was closely followed by R-S-R (45%), R-S-S (29.7%), R-R-R (28.8%), R-R-S (27%) and S-S-S (26.1%). While the agent parameter variation with the lowest similarity was S-R-S (20.7%) and S-R-R (17.1%). The agent parameter variation with the most similar chance of using the information centre was R-S-S with an identical 16.2%. This was closely followed by S-R-R (14.4%), R-R-S (14.4%), S-S-S (18.9%), R-R-R (12.6%) and S-R-S (20.7%). While the agent parameter variation with the lowest similarity was S-S-R (39.6%) and R-S-R (45%).

The data collected in the input phase revealed that people tend to turn left more than right when walking. The VR+Q participants showed this with an average of 7.35 times for left turns and average of 4.70 times for right turns. Even though all set and random parameter variations of the virtual agents did not provide similar averages to the VR+Q participants; it did show that even they would turn left more than right on average (see Figure 6.12). What was also revealed was the S-S-S parameter agents displayed a similar average for right turns (average of 4.60 times) to the VR+Q participants. While R-R-S parameter agents showed a similar average for left turns (average of 6.73 times). These results provide validation that the agent based framework can produce similar behaviours to people in the real world.

During all agent's experiments, no matter whether the agent's parameters were set or random, some of them would display similar behaviours to the VR+Q participants. A behaviour shown in both the agent and VR+Q experiment was the tendency to back track. It was revealed that the agent tended to do this quite



(a)
(b)
(c)

Figure 6.12: A comparison of visual data collected (x-axis represents the number of instances). (a) Left vs Right Turns; (b) Exits Used; (c) Average use of Maps and Information Centre.

often.

Similar to the end of the VR+Q experiment, the agents were asked to find one of the two exits and go to exit. Based on the results from the VR+Q experiment, 83.8% of the participants would go to the same exit that they started with while 16.2% would go to the exit on the other side of the environment. It was also observed in both the agent and VR+Q experiments were participants would look left and right while walking. In the VR+Q experiment, most participants produced this behaviour making it a common occurrence. This behaviour was given as an option to the agents to implement based on their personality and probability. It was found that the majority of the agents across all parameter variations would produce this behaviour.

It was revealed that all the parameter variation agents would produce different averages to the VR+Q data but similar results (see Figure 6.12). A total of 69.4% of S-S-S parameter agents would go to the same exit they started at while 30.6% would go to the other exit. While R-R-R parameter agents would go back to the exit, they started 76.6% of the time while 23.4% would go to the other exit. The closest variation to show similar results to the VR+Q participants were S-R-R parameter agents with 81.1% would go back to the same exit they started at and 18.9% would go to the other exit.

A Chi-square Goodness of Fit Test using all visual data collected to provide validation, the agent-based framework can output real world data by showing there is no significant difference (see Figure 6.13). The statistical significance test shows us that majority of the agent parameter variations can produce similar results to the real world. Proving the hypothesis that this framework can produce real-world data in agent-based crowd simulations. For instance, the S-S-S parameter agents p-value becomes 0.868 with the degree of freedom = 5. The most similar parameter variation found to real-world data was S-R-S with p-value=0.972 and p-value=0.988.

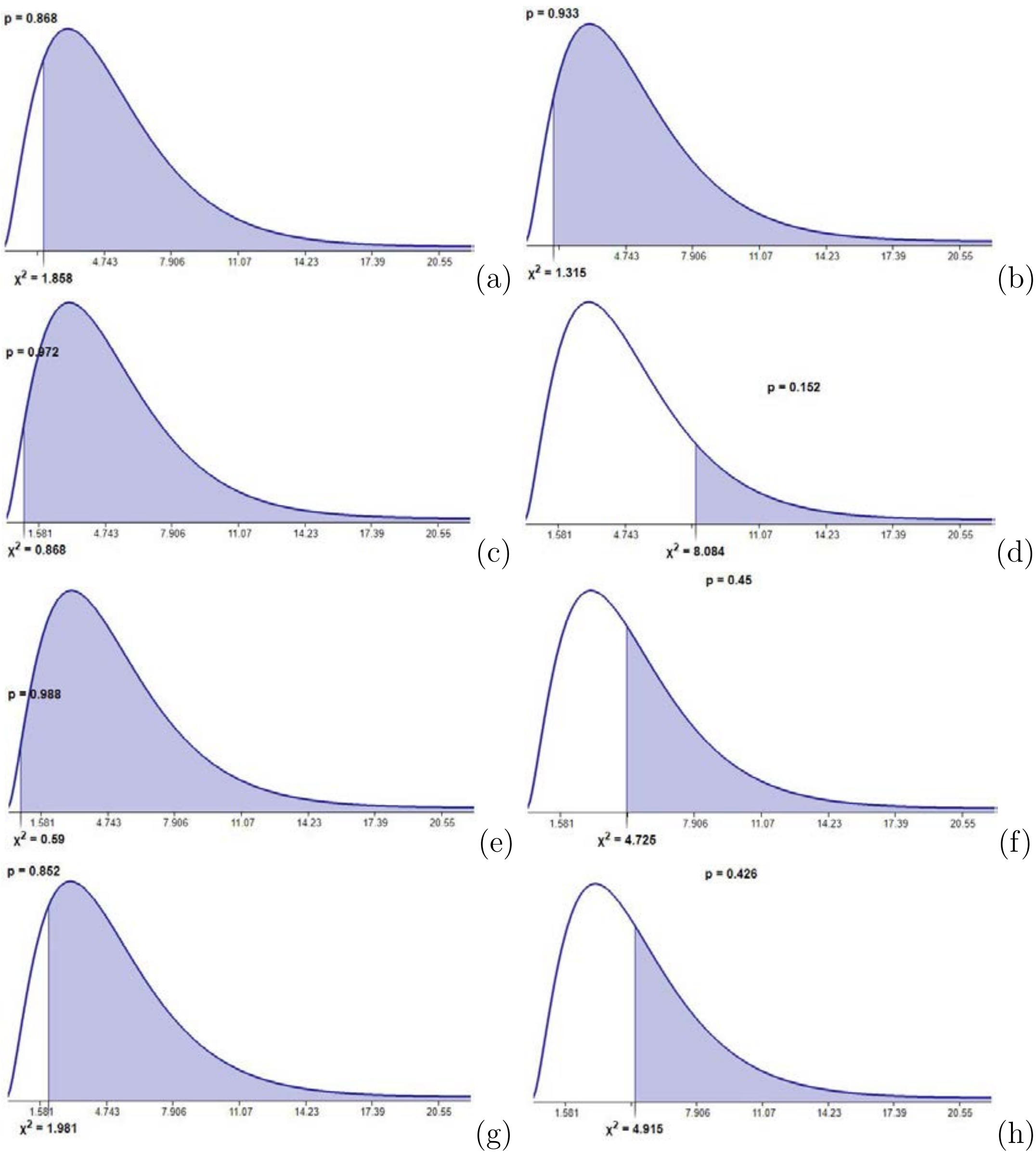


Figure 6.13: Visual data Chi-square Goodness of Fit Test: (a) S-S-S; (b) S-S-R; (c) S-R-S; (d) R-S-S; (e) S-R-R; (f) R-S-R; (g) R-R-S; (h) R-R-R.

6.2.4 Overall Data Analysis

To ensure the overall agent based cognitive architecture can produce real-world data within crowd simulation, a Chi-square Goodness of Fit Test was conducted. The statistical test combined all three types of data together to determine whether any of the agent parameter variation method can provide similar results to the real-world method by using the agent based cognitive architecture framework (see Figure 6.14). The results revealed there is no significant difference between any of the agent parameter variations and the real world with half of them having a p-value=1 when degree of freedom = 35. This proves the framework is capable of outputting data similar to the real world for the development and validation of agent-based crowd simulations.

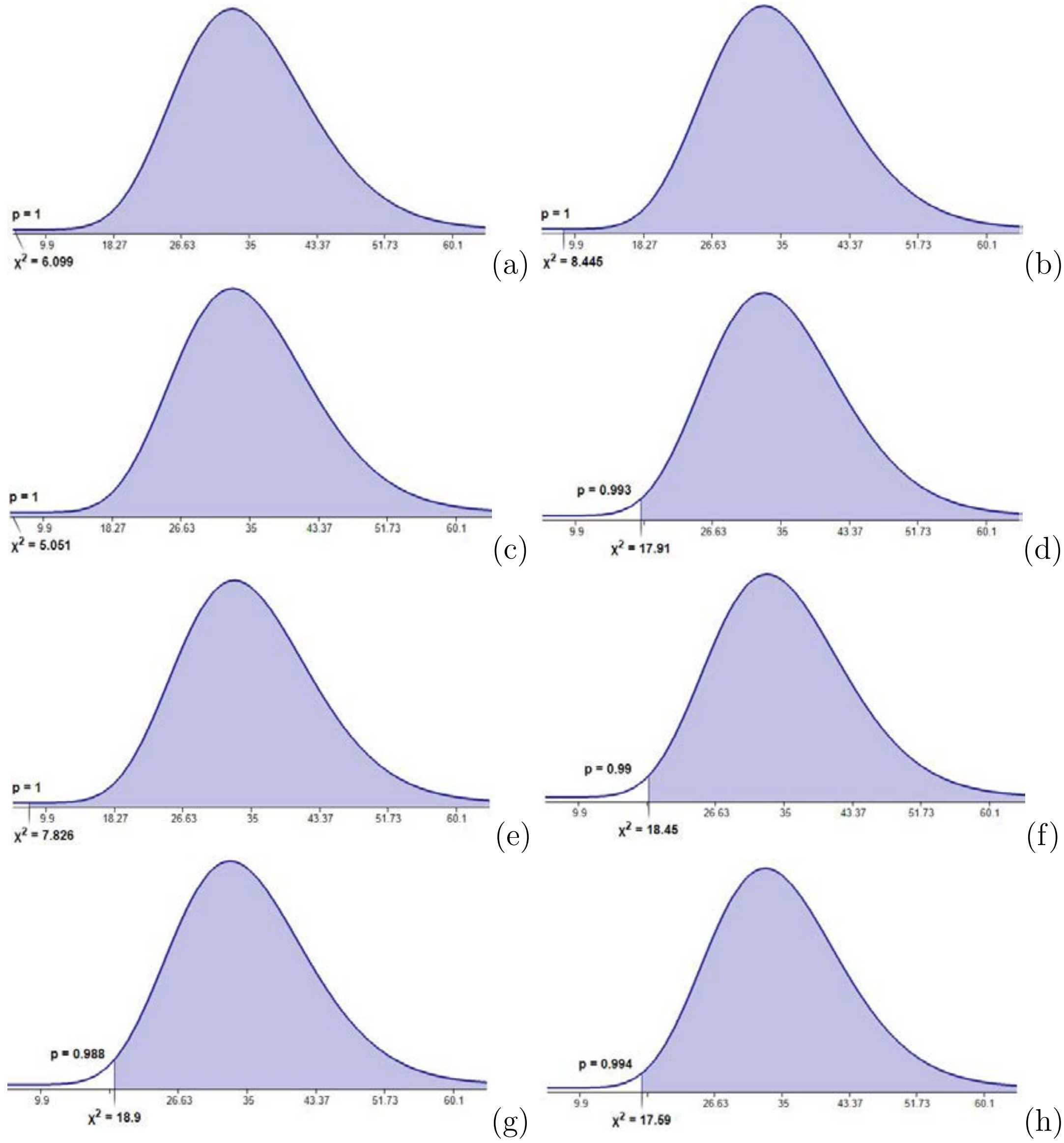


Figure 6.14: All data combined Chi-square Goodness of Fit Test: (a) S-S-S; (b) S-S-R; (c) S-R-S; (d) R-S-S; (e) S-R-R; (f) R-S-R; (g) R-R-S; (h) R-R-R.

Chapter 7

Case Study

The purpose of this case study is to show the flexibility and adaptability of the framework in a different environment and scenario. To prove the flexibility and adaptability of the framework, the analysis of all three data types is conducted to see if any unique patterns or behaviours were displayed. If any behaviours or patterns are revealed, this will validate whether the framework possesses the potential to be used in different scenarios and environments. The other purpose for this case study is to collect new data that may or may not have been gathered in the previous phase and analyse any real-world behaviours.

7.1 Virtual Agent

For the case scenario, 4 parameter setting variations of virtual agents were implemented for testing (see Table 7.1). The parameters implemented were the same as in the previous tests which were speed, personality and emotion. However, an additional higher functioning parameter was used in the case study, and that is LTM. In the previous experiments the goal was to prove that the framework can output real world data by having virtual agents run the same scenario, and environment using data collected in the input phase using the VR+Q method. Due to this using LTM as a parameter was not possible as the participants from the VR+Q method did not possess any prior knowledge of the environment meaning, the agents would also possess no knowledge when they started. However, in this case study, LTM can be incorporated as a high-level parameter as the goal is to output new data and real-world behaviours.

The speed, personality and emotions were represented using the same physical and mental data collected in the input phase of the project (see Figure 4.1). While LTM would be represented in two distinct ways: No knowledge or Full knowledge. These two distinct parameter variations of LTM represents the amount of information stored within the virtual agents LTM at the start of the simulation (See Section 5.7.3 for further information on LTM).Virtual agents with no knowledge are representing real-world people who have never been in the environment before and are instead having to learn about the environment from the start. However, as time goes on and more information is learnt the virtual agents with no knowledge evolve into agents with some knowledge, but for simplicity we will be calling them agents with no knowledge. Full knowledge agents, on the other hand, are agents who have all the locations of the environment in their LTM. This represents real-world people who have entered an environment where they have spent an extensive amount of time. For example, students who have been at the same school for years (Full knowledge) would know where all the buildings are. While a new student (No knowledge) would be learning their surroundings from scratch. The purpose of using this high-level parameter is to see if any new or different data or behaviours are displayed throughout the case study.

Table 7.1: 4 different parameter settings for the virtual agents in the case study.

	Personality	Emotion	Speed	LTM
Setting 1 (S-S-S)	Set	Set	Set	No knowledge
Setting 2 (R-R-R)	Random	Random	Random	No knowledge
Setting 3 (S-S-S)	Set	Set	Set	Full knowledge
Setting 4 (R-R-R)	Random	Random	Random	Full knowledge

To represent a true crowd simulation case study, each parameter setting variation was conducted using 3 different size crowds. The 3 sizes were 37, 111 and 185 agents all running at the same time.

7.2 Scenario

The case study scenario was designed to be simple yet believable that allows the virtual agents to encounter the design tasks that are being evaluated. The case study scenario designed is a split between a search and evacuation scenario. The virtual agents entered a virtual environment built to represent James Cook University, Cairns Campus (see Figure 7.1). The environment did not include the entire campus only the centre of the university. This area of the university was selected as it is the most populated locations used by students. The environment consisted of 7 large buildings, 4 small buildings, and 4 evacuation assembly points.

The scenario starts with each agent spawning in at the same location; the car park. From there they are immediately tasked with finding 3 buildings (A1, B1 and E1) all at the same time in any order. When the virtual agents have found all

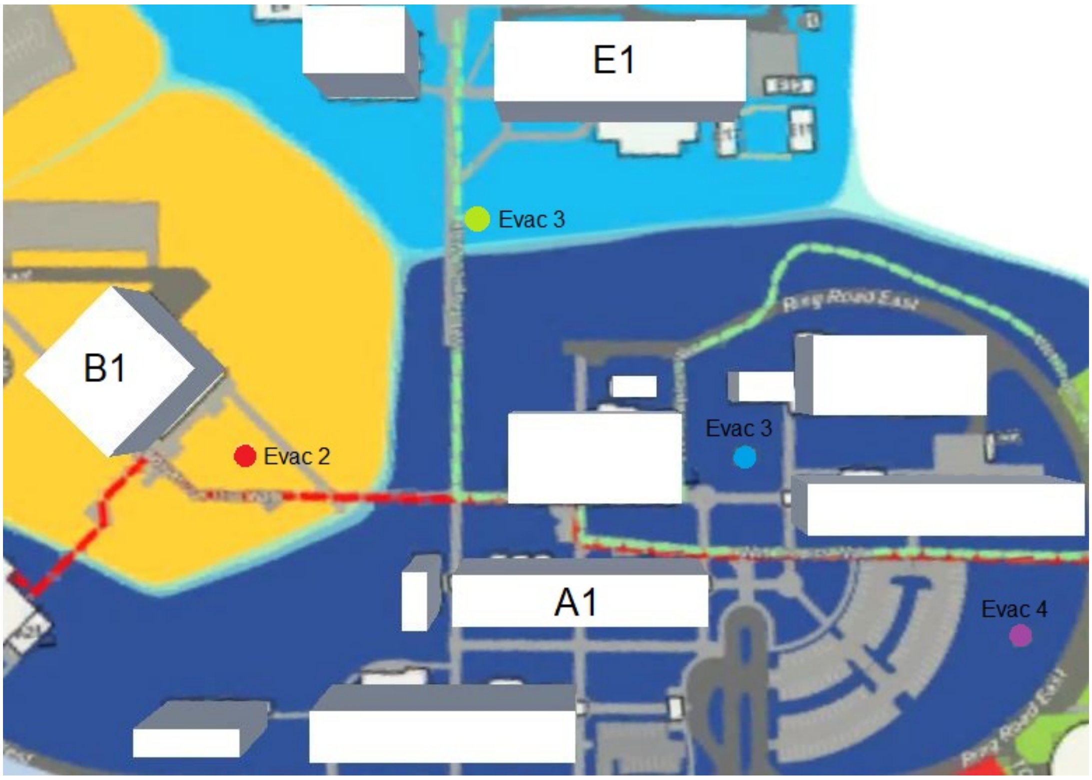


Figure 7.1: Experimental environment: James Cook University, Cairns Campus.

3 buildings,they were tasked with urgently finding the closest evacuation assembly point as if there was an emergency. Once all the agents had reached an evacuation assembly point, the case study was completed.

There were three reasons for having the virtual agents find the 3 buildings first. The first reason was to see the difference in the data collected from agents with no knowledge against ones with full knowledge. This allows us to see whether having familiarity of the environment provides people with an advantage over people who do not. The second reason was to make the agents split up and by doing so would it produce any unique behavioural patterns. The third reason was to see whether splitting the agents up across the environment would affect the location in which the agents evacuate too.

The 3 buildings chosen as the goals represent 3 important locations at the university: A1 Chancellery building; B1 Library; and E1 main Health and Science Building. These locations also had a reasonable distance from each other. For instance, A1 is in the centre of the environment, B1 is the furthest on the left and E1 is furthest centre north.

The 4 evacuation assembly points are located in the same real-world location at James Cook University. 3 of the 4 evacuation points are located near the 3 buildings that the agents need to find. While the last evacuation point is located nowhere near any of the buildings. These 4 points were selected to see if the virtual agents would only go to an evacuation point closest to one of their goals. Another reason was to see if any unique patterns or behaviour could be seen from within the data collected.

Two versions of the environment were conducted for the case study: low fidelity paths and high fidelity paths. Low fidelity paths allowed the virtual agents to walk through anywhere they liked (except through the buildings) such as rivers and trees located at the university in the real world. While a High fidelity path only allowed the virtual agent to move through walk paths and open fields located at the university in the real world.

7.3 Data Types Collected

7.3.1 Physical Data

Physical data were collected in the form of distance, time and speed using the same method that was used in the previous phase of the project (see Section 4.4.1). Each agent's position was collected every one second and the total time of completing the scenario was collected throughout the simulation. The speed of the agents was also collected using distance and time. Two versions of the distance, time and speed were collected: first overall data and second evacuation data only. The overall data analyses the average of all accumulated data throughout the entire case study. While evacuation data only analyses the average of all data collected from the point in which the agents are instructed to evacuate the environment.

7.3.2 Mental Data

Both the OCEAN model and the OCC model were used as a means to comparing the data collected from the agent within the case study. As in the previous phase of the project (see Section 4.4.2.1) the virtual agents' personalities are collected directly from the personality module. The agent's personality module still runs the OCEAN personality model as static values (discussed in Chapter 5). The emotion data is collected in the same manner as the previous phase of the project (see 4.4.2.2) and was collected throughout the simulation. The value for each OCC emotion of collecting every 10 seconds to ensure there was a dynamic change occurring. The agent's mental data was only collected for analysis of the overall case study and not for the evacuation phase. This was due to two reasons, firstly, the personality data will not change due to the values being static. Secondly, with the emotional data the purpose of this project was not to forcefully stimulate the emotional values in anyway, but to allow them to naturally change throughout the case study by the agent's decision making. This means there would be no significant emotional change setup for the evacuation phase to be analysed (although this is a possible test that can be conducted in the future with this framework).

7.3.3 Visual Data

Unlike in the other two data gathering types (physical and mental), the visual data collected for this case study is not the same as the previous phase of the project. Only 2 types of visual data are collected for this case study: evacuation locations and unique crowd and individual behaviours. Collecting each virtual agents evacuation location was to see if any unique patterns or behaviours appeared from a crowd perspective. For example, if a majority of the agents go to the same evacuation location, this could mean that agents are either following the same pattern or maybe it is because the evacuation location close by. The purpose of the unique crowd and individual behaviours was to see if any non-social interaction between the virtual agents are seen and if any can be seen as representing a real-world phenomenon and why.

7.4 Results

This section reports data gathering results on three different types between the different agent parameter variations implemented in this case study.

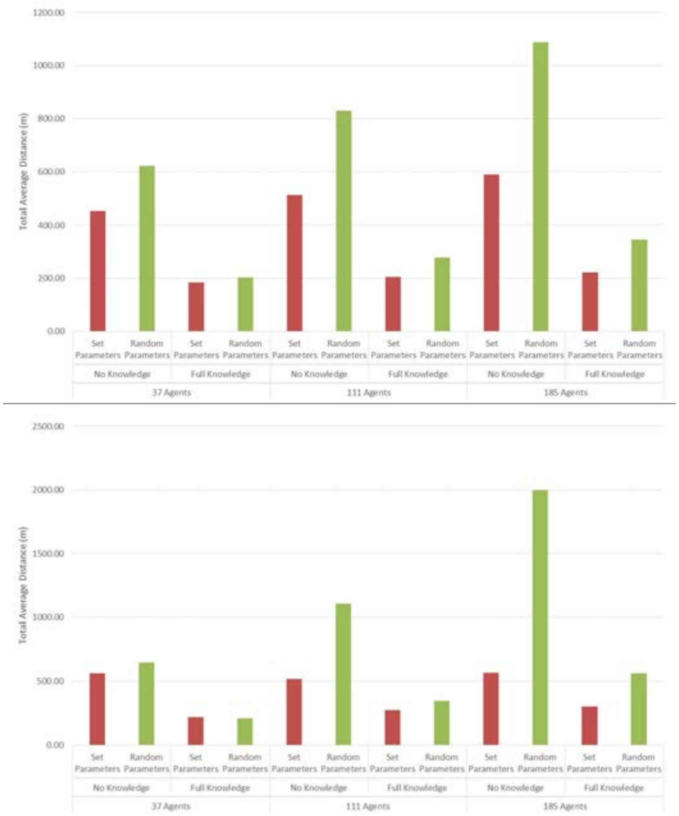
7.4.1 Physical Data

Physical data were collected through distance, time and speed and through two versions: overall data and evacuation data only.

7.4.1.1 Overall Physical Data

The overall distance results revealed four unique patterns (see Figure 7.2). First is that as more virtual agents are added to the case study, the total average distance increases in a linear path, no matter what the parameter variation or fidelity was being run. This reveals that as more people attend the university, the average distance travelled will increase. The second unique pattern is that set parameter agents are travelling less distances than random parameter agents. This is valid from the previous phase of research (see Section 6.2.1) as random parameter agents will display a wider range of data representing a larger group of real-world people. The third unique pattern revealed was agents with full knowledge of the environment would travel less distances to finish the scenario. This can easily represent how new people to the university (such as new students, visitors, etc) tend to travel further distances learning their surroundings. While people who already have an understanding of the university (such as current students and staff) already know where to go and the best path to get there.

The fourth pattern revealed that high fidelity paths tended to increase the distance travelled by the virtual agents. This is expected because of the fact that low fidelity allows that agents to take direct paths to their target location without considering environmental or real-world objects as interference. But at the same time the average distance travelled by the virtual agents is very high. A past study has shown high fidelity can cause either equal to or worse data results when compared to low fidelity [141].

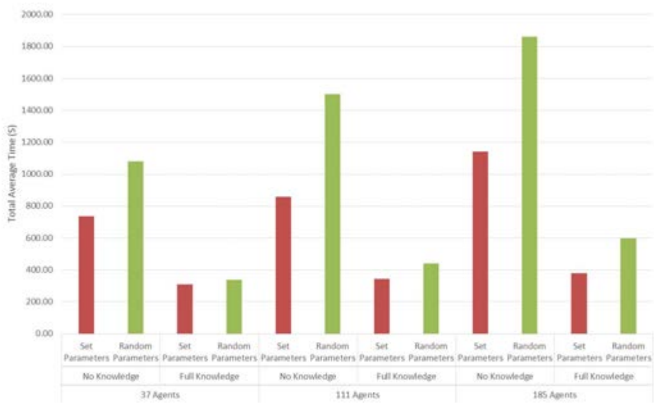


(a)

(b)

Figure 7.2: Case study physical overall average distance analysis: (a) Low Fidelity; (b) High Fidelity.

The overall time travelled results revealed the same four unique patterns seen from average distance (see Figure 7.3). First is that as more virtual agents are added to the case study, the total time to complete the entire scenario would increase to form a linear progression no matter what the parameter variation or fidelity is being run. This reveals that as more people attend the university the average time spent will increase. The second unique pattern is that set parameter agents are spending less time to complete the scenario than random parameter agents. The third unique pattern revealed is that agents with full knowledge of the environment would take less time to travel around the university to finish the scenario than agents with no knowledge. This is demonstrating a realistic outcome about how real world people who know the university are able to reduce the time travelled by knowing the shortest or best path to their goal. While new people to the university will spend most of their time wandering learning about the university as they look for their goal.



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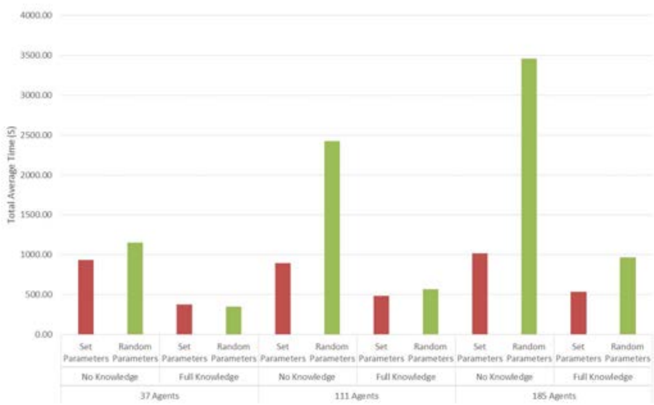

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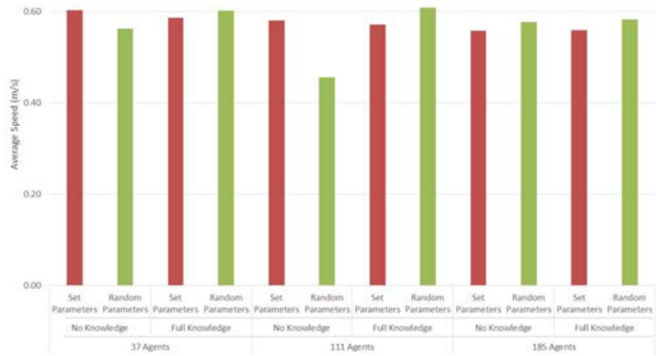
Figure 7.3: Case study physical overall average time analysis: (a) Low Fidelity; (b) High Fidelity.

Lastly the forth pattern revealed was that high fidelity paths tend to increase the time travelled by the virtual agents. This is expected because of the fact that low fidelity shortens the time travelled by allowing agents to take direct paths through locations that normally cannot be accessible such as environmental objects (rivers, rainforest, etc.) or real world object.

The overall speed results revealed a single unique pattern (see Figure 7.4). This was that there was no significant difference between each parameter variation or fidelity being run. This is a similar outcome found in the previous phase of the project (see Section 6.2.1). However, as more agents are being added to the crowd a slight decrease in the average speed is starting to show.



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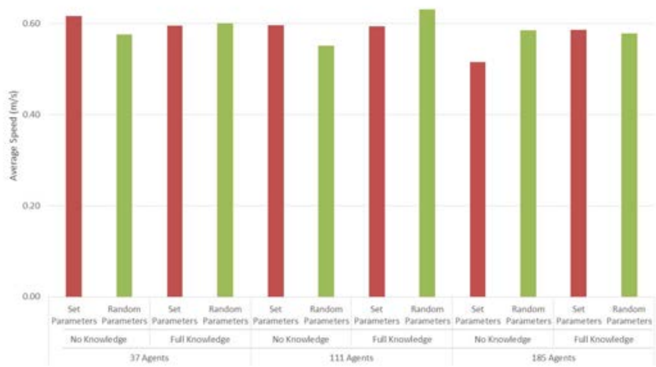
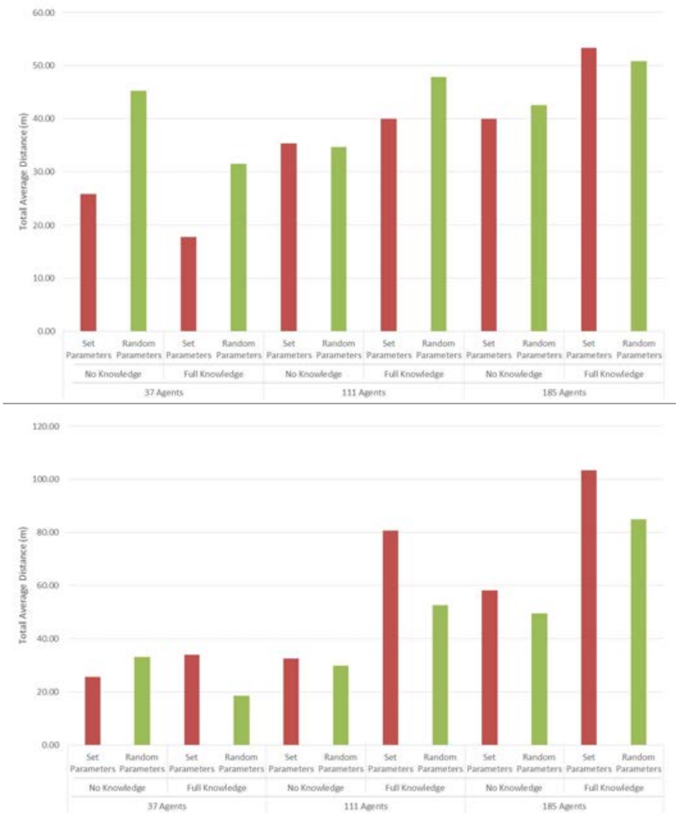


(b)

Figure 7.4: Case study physical overall average speed analysis: (a) Low Fidelity; (b) High Fidelity.

7.4.1.2 Evacuation Physical Data

The average evacuation distance results revealed some different patterns (see Figure 7.5) to what was seen from the overall distance data. Firstly, what was revealed was that as more agents were added to the scenario, the average distance would increase in both low and high fidelity. Secondly, the set and random parameter agents average distance travelled from their last goal to the evacuation point did not show any linear progression, instead the average distance displayed a fluctuating outcome. This was due to a unique circumstance that coincides with the visual data results (see Section 7.4.3) in which some of the virtual agents tended to go to evacuation points further from where they started. This was caused by two occurrences: first was due to a large crowd blocking an agent's field of view stopping them from seeing the evacuation point nearby, forcing them to go to another evacuation point. The second was certain agents chose to go to an evacuation point that they already know exists instead of searching for one nearby. What is learnt from these two occurrences can help improve the universities evacuation plan by ensuring the evacuation points are able to be seen within large crowds and by ensuring that all new students and staff are informed with knowing where all evacuation locations are through out the university.



(a)
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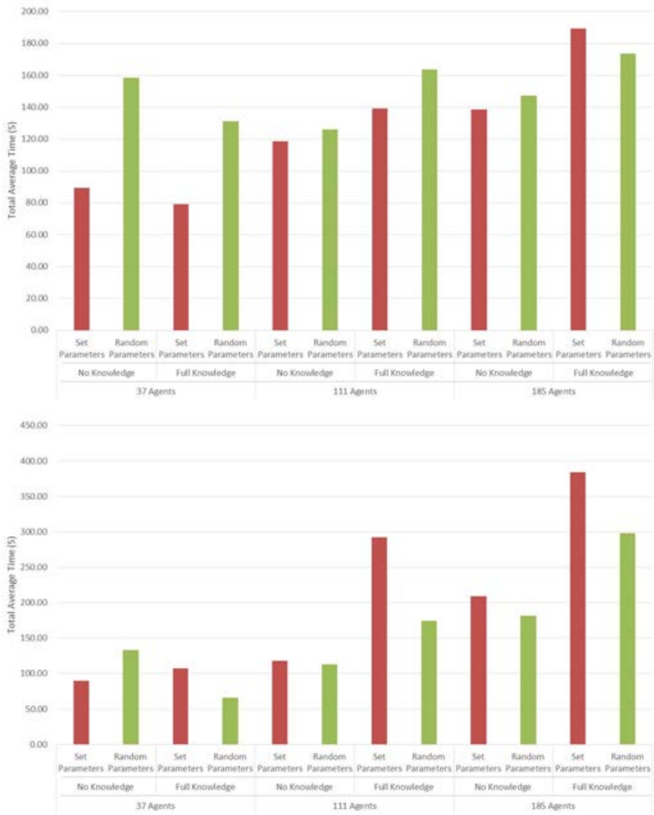
Figure 7.5: Case study physical evacuation average distance analysis: (a) Low Fidelity; (b) High Fidelity.

Lastly, high fidelity simulations showed to produce lower distances travelled to evacuate than low fidelity in most cases. This is due to the fact that low fidelity allows agents to walk in areas that real people cannot. This increase the chances of an agent walking further away from the evacuation point and preventing the agent from noticing them. While high fidelity is forcing the agents to follow the same paths that are in the real world. This increases the chances of the agents noticing the evacuation points as they are always near a path.



(a)

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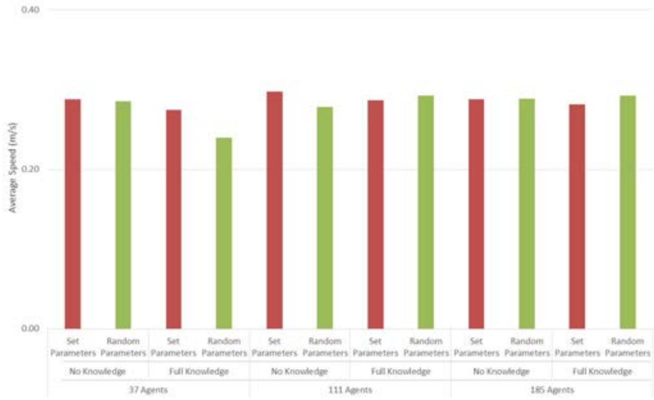
Figure 7.6: Case study physical evacuation average time analysis: (a) Low Fidelity; (b) High Fidelity.

The average time for all the agents to evacuate exhibited the same patterns as the average evacuation distance (see Figure 7.6). First, as more agents were added to the crowd the average time would increase in both low and high fidelity. Second, the difference between the set and random parameter agents average time travelled to evacuate also showed a fluctuating outcome instead of a linear progression. Last, high fidelity showed to also simulate less time was travelled to evacuate than the low fidelity due to the same reason discussed above.

The evacuation speed results revealed the same unique pattern (see Figure 7.7) seen from the overall data results. This was that there is no significant difference between each parameter variation or fidelity being run. However, as more agents are being added to the crowd, a slight decrease in the average speed is starting to show.



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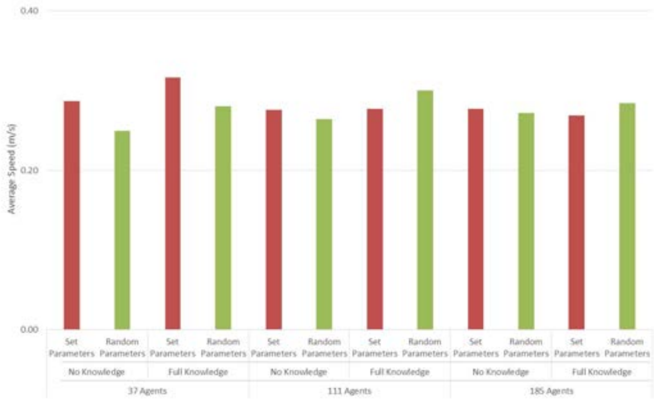
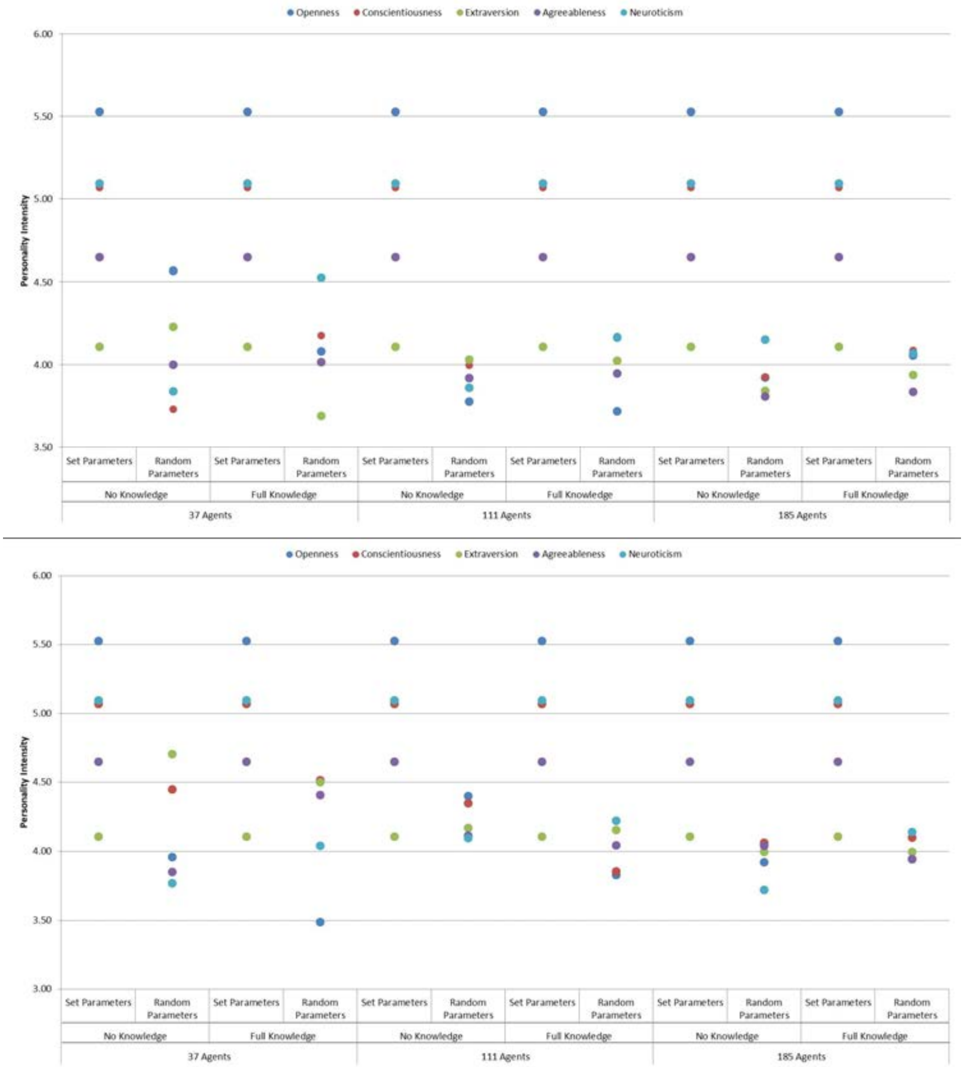


(b)

Figure 7.7: Case study physical evacuation average speed analysis: (a) Low Fidelity; (b) High Fidelity.

7.4.2 Mental Data

The mental data collected and analysed was the average personality and emotions for the entire case study scenario. The personality data results (see Figure 7.8) showed that setting the agent parameters will produce a more stable and identical result over random parameters. This is due to using the personality data collected in Section 6.1 is representing real-world personality data. However, what is also being shown are the random parameters can produce a larger range of results representing more variations of people from the real world.



(a)

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Figure 7.8: Case study personality data analysis: (a) Low Fidelity; (b) High Fidelity; (c) Average Speed.

The emotion data results (see Table 7.2 and Table 7.3) revealed that set parameter agents would show to have a more positive emotional response throughout the scenario than the random parameter agents. From a real-world perspective, what is being revealed are random parameter agents are displaying a wider range of emotional response for a larger group of people. While set parameter agents are displaying an emotional response for a selected range of people.

The data also revealed that agents with knowledge displayed a higher positive response to the scenario over the agents with no knowledge. Using a real-world perspective, the results are expected as people who have full knowledge of the environment would have an easier time finding and completing the requested tasks. This, in turn, would produce a higher increase in positive stimuli. While people who are having to find and complete the tasks without any knowledge of the environment display less positive stimuli as it would take longer for these agents to find each location.

Agents in both low fidelity and high fidelity simulations showed to have similar emotional responses when within all crowd sizes. However, as more agents were added some emotional responses started to show slight differences. High fidelity agents started to show slightly higher emotional responses to the low fidelity agents. This is a valid outcome due to virtual agents within the high fidelity simulation paths being more congested making it easier for emotional empathy to spread. While the low fidelity simulations path is more open allowing agents to avoid each other causing less spread of emotional empathy. Emotion empathy is the spread of emotions within a small space allowing other people to directly feel the emotions that another person is feeling and imitate them [83]. See Section 5.9.2.2 for how emotional empathy has been implemented and how they are spread.

Table 7.2: Low Fidelity emotion data comparison.

	Set 37 No Knowledge	Random 37 No Knowledge	Set 37 With Knowledge	Random 37 With Knowledge	Set 111 No Knowledge	Random 111 No Knowledge	Set 111 With Knowledge	Random 111 With Knowledge	Set 185 No Knowledge	Random 185 No Knowledge	Set 185 With Knowledge	Random 185 With Knowledge
Joy	1.59	1.38	2.36	1.85	1.96	1.60	2.71	2.02	2.41	1.87	2.85	2.19
Distress	1.20	1.20	1.30	1.28	1.28	1.27	1.48	1.34	1.44	1.35	1.56	1.43
Happy-For	1.05	1.04	1.08	1.08	1.04	1.04	1.08	1.08	1.03	1.02	1.07	1.08
Resentment	1.00	1.04	1.01	1.09	1.00	1.03	1.01	1.08	1.00	1.03	1.01	1.08
Gloating	1.04	1.03	1.07	1.10	1.03	1.03	1.07	1.07	1.03	1.03	1.06	1.08
Pity	1.01	1.03	1.02	1.11	1.01	1.04	1.02	1.07	1.01	1.02	1.01	1.07
Hope	1.52	1.35	2.18	1.78	1.82	1.54	2.58	1.92	2.26	1.82	2.70	2.10
Fear	1.18	1.19	1.26	1.25	1.25	1.26	1.41	1.31	1.38	1.32	1.47	1.38
Satisfaction	1.14	1.09	1.43	1.24	1.24	1.09	1.59	1.25	1.41	1.15	1.65	1.31
Fears-Confirmed	1.02	1.07	1.04	1.10	1.03	1.05	1.05	1.12	1.04	1.05	1.06	1.12
Relief	1.16	1.10	1.43	1.30	1.27	1.13	1.58	1.36	1.45	1.21	1.68	1.43
Disappointment	1.02	1.09	1.05	1.14	1.04	1.07	1.07	1.16	1.06	1.08	1.07	1.17
Pride	2.49	2.09	1.41	1.52	2.45	1.99	1.50	1.47	2.48	2.27	1.56	1.54
Shame	1.53	1.37	1.12	1.18	1.50	1.47	1.14	1.21	1.52	1.40	1.13	1.21
Admiration	1.05	1.04	1.08	1.11	1.04	1.03	1.08	1.08	1.03	1.03	1.07	1.07
Reproach	1.01	1.05	1.02	1.10	1.01	1.03	1.02	1.08	1.01	1.02	1.01	1.07
Gratification	1.32	1.21	1.72	1.48	1.48	1.31	1.87	1.54	1.72	1.46	1.94	1.62
Remorse	1.36	1.28	1.20	1.22	1.38	1.37	1.29	1.27	1.47	1.37	1.32	1.31
Gratitude	2.04	1.73	1.88	1.69	2.20	1.79	2.10	1.74	2.45	2.08	2.19	1.86
Anger	1.10	1.12	1.15	1.19	1.14	1.15	1.23	1.20	1.21	1.18	1.26	1.24
Love	1.34	1.24	2.19	1.74	1.58	1.34	2.41	1.92	1.92	1.53	2.54	2.05
Hate	1.10	1.10	1.10	1.16	1.19	1.14	1.07	1.11	1.27	1.17	1.08	1.10

Table 7.3: High Fidelity emotion data comparison.

	Set 37 No Knowledge	Random 37 No Knowledge	Set 37 With Knowledge	Random 37 With Knowledge	Set 111 No Knowledge	Random 111 No Knowledge	Set 111 With Knowledge	Random 111 With Knowledge	Set 185 No Knowledge	Random 185 No Knowledge	Set 185 With Knowledge	Random 185 With Knowledge
Joy	1.63	1.58	2.39	1.95	2.23	1.88	2.91	2.20	2.77	2.07	3.13	2.35
Distress	1.22	1.23	1.32	1.32	1.36	1.32	1.67	1.35	1.60	1.43	1.92	1.56
Happy-For	1.04	1.04	1.07	1.08	1.04	1.02	1.06	1.06	1.03	1.02	1.05	1.05
Resentment	1.00	1.05	1.01	1.08	1.00	1.03	1.00	1.06	1.00	1.02	1.00	1.05
Gloating	1.03	1.04	1.06	1.09	1.03	1.03	1.05	1.07	1.02	1.02	1.04	1.05
Pity	1.01	1.03	1.01	1.09	1.01	1.02	1.01	1.08	1.01	1.02	1.01	1.06
Hope	1.52	1.47	2.14	1.83	2.01	1.75	2.71	2.05	2.52	1.95	2.94	2.23
Fear	1.19	1.21	1.25	1.27	1.30	1.29	1.52	1.30	1.48	1.38	1.74	1.47
Satisfaction	1.21	1.14	1.60	1.24	1.41	1.20	1.96	1.37	1.73	1.21	2.18	1.54
Fears-Confirmed	1.03	1.08	1.06	1.14	1.05	1.07	1.10	1.11	1.08	1.07	1.14	1.15
Relief	1.22	1.24	1.66	1.42	1.46	1.28	2.03	1.53	1.81	1.38	2.28	1.69
Disappointment	1.04	1.12	1.09	1.17	1.06	1.10	1.12	1.15	1.10	1.12	1.18	1.21
Pride	2.53	1.88	1.38	1.34	2.47	2.18	1.62	1.45	2.50	1.97	1.71	1.60
Shame	1.58	1.50	1.12	1.17	1.52	1.42	1.21	1.20	1.52	1.46	1.24	1.24
Admiration	1.04	1.04	1.07	1.09	1.04	1.03	1.06	1.06	1.03	1.02	1.05	1.05
Reproach	1.01	1.05	1.01	1.07	1.01	1.03	1.01	1.07	1.01	1.02	1.01	1.06
Gratification	1.33	1.31	1.73	1.53	1.61	1.44	1.99	1.62	1.89	1.54	2.12	1.71
Remorse	1.40	1.36	1.22	1.24	1.43	1.37	1.42	1.27	1.55	1.44	1.55	1.39
Gratitude	2.08	1.73	1.89	1.65	2.34	2.02	2.27	1.82	2.63	2.02	2.45	1.99
Anger	1.11	1.14	1.16	1.19	1.17	1.17	1.32	1.20	1.29	1.22	1.43	1.29
Love	1.32	1.28	2.15	1.86	1.74	1.47	2.54	1.97	2.18	1.66	2.77	2.21
Hate	1.12	1.12	1.08	1.16	1.28	1.20	1.15	1.13	1.39	1.25	1.16	1.12

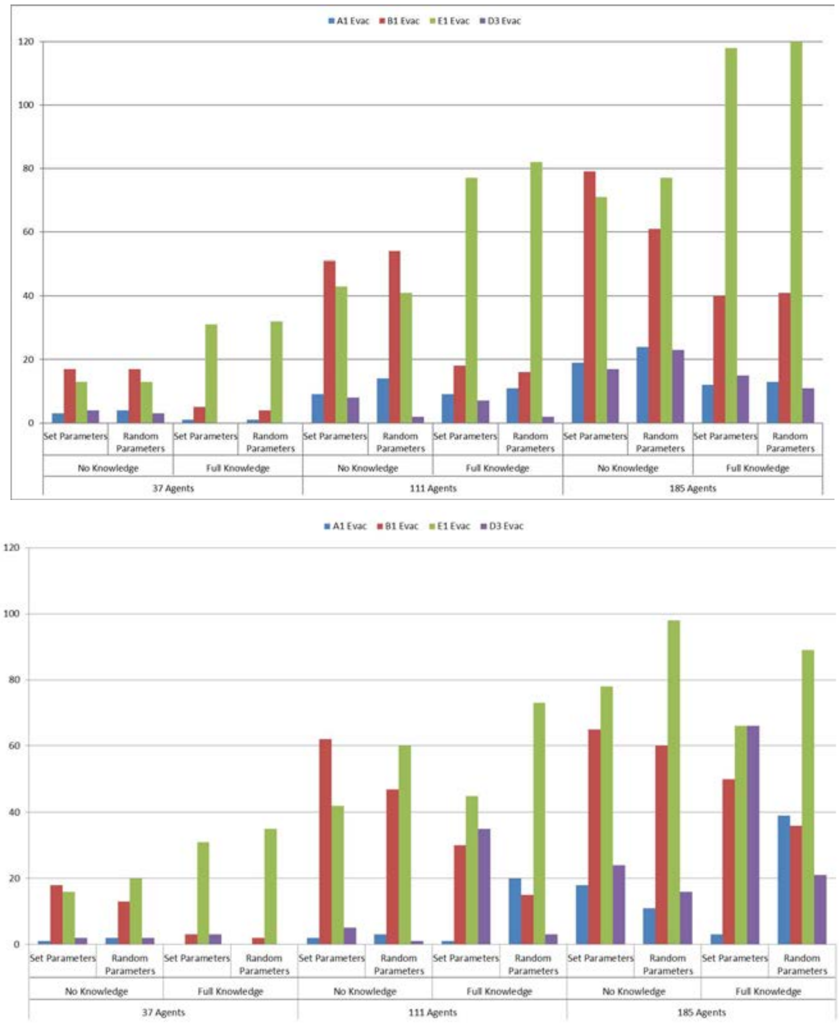
7.4.3 Visual Data

The two types of visual data collected and analysed from the case study were agent evacuation point (see Figure 7.9) and unique crowd and individual behaviours. The agent evacuation points revealed that set and random parameter agents with no knowledge most common evacuation location was near buildings B1 and E1. While set and random parameter agents with full knowledge most common evacuation location was near building E1. Based on what was observed, the main reason for this data was due to the order of goals completed. Agents with no knowledge were found to complete each of the three goals for the scenario in many different orders. This is due to the agents possessing no prior knowledge of the exact location of each goal and having to find them by wandering through the environment. However, what was noticeable was that due to the goal, building A1, being the closest to the starting point, the car park, majority of the agents would go and complete that goal first. This explains why B1 and E1 were the most common evacuation locations.

Agents with full knowledge of the environment displayed a different pattern to complete all three goals. Instead of completing each goal randomly, majority of the agents would complete each goal in the order that they were listed (A1, B1 and E1). This, in turn, explains why the most common evacuation point for the agents was E1. However, this does not explain why some agents chose to go to other evacuation points. Two reasons were discovered during the observation of the case study. The first was that due to completing the goals in the same exact order, the agents started to create crowded locations near the E1 evacuation point. This caused some agents to miss seeing the evacuation point and either search for or go to another evacuation point that the agent knows. The second reason was that based on some agents' personality values, some random parameter agents were unable to access their long term memory. This made it difficult for them to remember where all their goals and evacuation locations were. This situation shows a realistic behaviour of real people in which they forget or subconsciously have trouble remembering locations and end up having to aimlessly wander around until they either remember or find it by accident.

During the case study in low and high fidelity paths, some unique individual and crowd behaviours were displayed that represent real-world behaviours (see Figure 7.10). The first unique behaviour observed was a dispersal behaviour from agents with no knowledge. In order for agents with no knowledge of the environment to complete the scenario, they had to wander around until they found one of their goals. This produced a dispersal behaviour amongst the agents showing individuality by taking different paths to find each goal.

Another unique behaviour observed was a queuing behaviour from agents with full knowledge of the environment. This behaviour was formed because of the fact



(a)

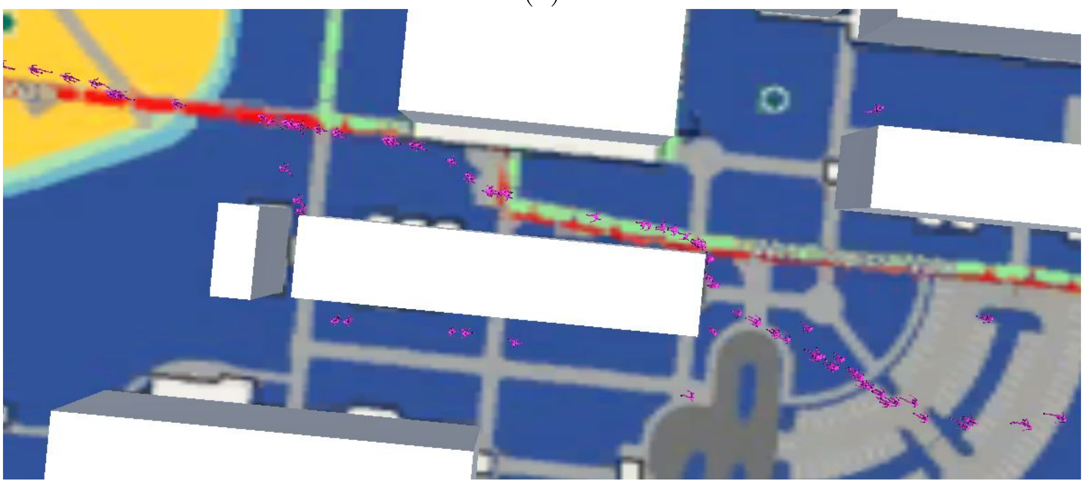
(b)

Figure 7.9: Case study visual analysis: (a) Low Fidelity; (b) High Fidelity.

that majority of the agents would complete the scenario goals in the same order. But due to each agent's speed being different they would not arrive at each goal at the same time. This caused the formation of a queue towards each goal. This behaviour is a perfect representation of a normal real world crowd behaviour. For example if you asked a group of students at school to go to another building, they would all walk a similar path. However, each student would move at different speeds. This would make all the students form a queue or line.

The final unique behaviour observed during the case study was non social grouping, which was seen from agents with full knowledge. This was because majority of the agents completing the scenario goals in the same order and the emergence of the queuing behaviour, agents with similar speed tended to group up without any social capabilities. This behaviour provides a promising prospect that this framework has the capability of implementing social interaction and social grouping in the near future.

(a)



(b)

Figure 7.10: Case study unique behaviours: (a) Crowds dispersing; (b) Crowds queuing and grouping.

Chapter 8

Conclusion

Research in making virtual agents realistic to human beings is important for crowd simulation. To achieve this modelling agents each with their own movement, goals, collision avoidance and ability to adapt to different environments, situations and scenarios through a decision making process is needed. To develop such realistic agent-based models it is important to gather real-world data first.

In this thesis, we have discussed that the current data gathering methods used for agent-based crowd simulations do not collect all three data types (physical, mental and visual). This issue was addressed by combining VR and questionnaire to form a hybrid method called VR+Q. The VR+Q method has shown it is capable of collecting all three data types. We also discuss the VR+Q method would be able to collect real-world data from these three data types. This is proven by running a simple scenario in both the real world and VR and comparing the results are similar. The purpose of the simple scenario is due to the fact that our goal is not to influence or change the participant's responses but to show similar responses will be produced based on the situation. It has shown that it can produce real-world data in the form of these data types. Based on the comparison of the data collected from both the real world and VR+Q experiment, the VR+Q method did produce realistic mental and visual data for developing agent-based simulations.

The mental data collected (personality and emotion) from both experiments have revealed no significant difference. This has proven that the mental data collected from the VR+Q experiment can be implemented into agent-based model to develop realistic agents. The visual data showed that even though the results between the VR+Q and real world experiment were slightly different, it did show that the participants' way of thinking and habits did not change. The participants from both experiments displayed similar behaviours, and the data did produce the same outcome (e.g. participants from both experiments prefer to turn left more than right). Overall, the visual data collected can be implemented into agent-based simulations for developing agent models and validation. The physical data did show that the distance a participant walks in VR is no different in the real world. However, there was significant difference found between the VR+Q participants' speed and time to the real-world participants. The reason for this difference is consistent with past studies [134–136]. To solve this, we introduce an adjustment factor to mitigate this difference. A statistical Chi-square Goodness of Fit Test showed that with an adjustment factor in place, the VR+Q data is extremely similar to the real-world data, which demonstrate the robustness and usability of our proposed method for realistic agent-based simulations.

The VR+Q method allowed us to achieve our contributions in regards to data gathering in agent-based crowd simulations. First, by identifying a set of important data gathering features (such as cost effectiveness, time efficiency, reproducibility, physical data, mental data, visual data, etc.) that are required for selecting the best data gathering method. Second, by proposing an ecologically valid and time/cost efficient method that can capture physical, mental and visual data for agent-based simulations. Third, providing an experimental process and the results that demonstrate the robustness of the proposed method with a comparison to a real-world data gathering approach. Fourth, the implementation of an adjustment factor for physical data in order to mitigate the real world space and the virtual world space. Lastly, the statistical significant test to prove the validity of data collected by our proposed method.

This research also aimed to use a data driven approach to develop and validate a generic agent based crowd simulation framework that can output real-world results. This issue has been addressed by utilising the data collected from the VR+Q method to develop an agent based crowd simulation framework using all three data types. The VR+Q data was also used to validate the output data from the framework to compare whether the framework can produce real-world data. Using the VR+Q method to collect all three data types, the analysed data was used to develop an agent based framework. The framework incorporates all three data types into the higher (module design) and lower level (parameters) functionality. We also incorporated fuzzy logic, probability, priority queue and memory to improve the diversity of the framework and the output data.

The framework was implemented into the same scenario and environment the VR+Q experiment was conducted in. We ran 8 different agent parameter variation types to show the framework can produce realistic results to the VR+Q data. The parameters that were influenced were mental (personality and emotions) and physical (speed). The hypothesis was that agents with all set parameters would produce better results to all the other parameter variation agents when compared to the VR+Q data. Based on the comparison, this was proved mostly correct through physical, mental and visual data.

The physical data showed that all set parameter agent data displayed no significant difference in distance when compared to the VR+Q data. All set parameter agents also showed to have one of the least significant differences amongst the parameter variations in time when compared to VR+Q data. While majority of the other parameter variation agents showed significant difference in distance and time. The mental data collected revealed no significant difference between the all set parameter agents and the VR+Q mental data. Whilst some other parameter variation agents did show significant difference proving our hypothesis. The visual data did show that even though the results between the VR+Q and all the different parameter variation were slightly different; it did show the agents did produce similar thinking and movement to the VR+Q participants.

A statistical Chi-square Goodness of Fit Test with an adjustment factor in place to validate the framework's ability to output real-world data. The all set parameter agents data has been proven to be similar to the real-world data where p-value with degree of freedom $= 35$ for all data becomes 1. This demonstrates the robustness and usability of our framework for developing realistic agent-based simulations.

Lastly, this research aimed in providing an agent-based crowd simulation framework that can be used in many different scenarios and environments. A case study was conducted to validate the framework flexibility and adaptability to different scenarios and environments. The framework was implemented in an evacuation scenario within a university. The overall goal was to see if any unique patterns or behaviours would be displayed from the three types of data collected, therefore proving the framework is flexible and adaptable. The physical data revealed some unique patterns that could be explained by the previous phase of the research. The mental data revealed some unique patterns when it came to emotions. The visual data showed unique behaviours performed by the agents as individuals and as a crowd. The visual data also showed a unique pattern when it came down to which evacuation location the agents went. Overall the unique patterns and behaviours outputted by the framework validating the frameworks ability to be flexible and adaptable.

In relation to the development of the agent-based crowd simulation framework we were able to achieve the following contributions; first, we developed a flexible agent based simulation model that systematically incorporated that collected physical, mental and visual data from the VR+Q method. Second the model's performance was evaluated, validated and benchmarked which allowed it to show its robustness and the effectiveness of our framework. Third, we developed an agent based simulation framework that can conduct realistic crowd simulations and encompass the input phase, the agent architecture model phase (also known as the process phase) and the output validation phase. Lastly, this agent-based simulation framework is generic enough to be implemented and adapted to different scenarios and environments.

8.1 Future Work

Even though we successfully achieved our research goals and contributions there are still some limitations to the framework. For instance we have not implemented nationalities, culture or gender which can be considered important to developing realistic agents. These could help improve the realism of crowd simulation, the individuality of each agent and the output of data from the agent based model. We also don't consider social interactions between agents, other than emotion empathy which has limited the number of OCC emotions that were able to be assessed correctly. In this section we mention several areas where future work can be undertaken due to the current limitations of the project, as listed below:

1. The implementation of individual characteristics into the agent based framework. In the future, more mental data can be collected on people individual characteristics such as gender, likes, dislike, hobbies and interests. Currently, we do not look at the data from an individual characteristic perspective but instead as a crowd. However, past studies [142, 143] have already been conducted that show individual characteristics such as gender and personality can influence the way we navigate and make decisions. Further studies into individual characteristics will further improve the diversity of the agent-based models decision making and emotions. Lastly, combining individual characteristics and personality can also produce more variety of individual agents.

2. The study and implementation of different cultures and nationalities into the agent based framework. In future developments further mental data can be collected on people nationality and cultural traits. This data can further create more diverse individual agents through their decision making and emotional responses. The collection of people's nationality and culture can also be used as a benchmark as a comparison for validating realistic agents.

3. Further study into more types of data that can be collected under the VR+Q and three data types. More data gathering tests can gather more in-depth data which would help further develop the agent based crowd simulation framework. More in-depth data such as reasoning's behind their decisions and behaviours could help improve the decision making process.

4. Further refine analysis of the data collected. At this stage, the data has been analysed as a whole to represent crowd behaviours. In future work,

the analysis of the data can be further refined by breaking down the data into smaller groups using different variables such as individual behaviours, personality, emotion, gender, age and VR experience. By breaking the data into small groups researchers will be able to use the data collected from individual microscopic simulations.

5. Further development into the framework's knowledge and learning module. Researching more into how to teach an agent a new action could help improve the framework's dynamic. Also adding learning behaviours could provide more unique decision making.

6. The study and implementation of social interaction. One of the most important next steps of the framework is the integration of social interaction and communication. To achieve this research into how people interact, react to each other within an environment, and communicate is needed. The data gathered can then be integrated into the framework to develop social interaction which will create even more realistic agents and will display more unique behaviours.

7. The study and implementation of different stimuli to emotions. Study into how different objects and events occurring can influence different emotions at different rates can help create a more realistic agent. This can help improve the emotional intensity for each emotion in the framework and how it can affect each emotion at different times. It can also help change the influence the emotions have on the frameworks decision making processes.

8. Improve emotional intensity to emotions related to other people. This study focus was not on social interaction, so the emotions related to other people were not implemented effectively. Study into emotions related to other people can help towards social interactions and improving the realism of the decision making processes.

9. Further development into the influence of personality traits for the agent based framework. Researching how other personality traits, that have not been implemented, affect a person's decision and behaviours can help improve the modules within the framework. By implementing other personality traits into modules such as Attention Filter and Situation Assessment we can improve the framework's ability to make realistic decisions and behaviours.

10. Further study and implementation into how psychological aspects (personality and emotion) can influence and affect STM and LTM. By further studying personality and adding emotions into both STM and LTM it will improve the realism of the agents and how they access their memories.

11. Further testing of various degrees of knowledge. In the case study we test two degrees of knowledge (No knowledge and Full knowledge) and analyse the results from them. However, this can be taken further by adding a third degree of knowledge called Some knowledge. Some knowledge would represent how people each have a different amount of knowledge stored within their LTM. The framework already has the capacity and flexibility to run this test in the future.

12. More case studies using different environments and scenarios. This will provide more validation towards the framework's ability to be flexible and adaptable.

References

[1] Paul Davidsson. “Agent based social simulation: A computer science view”. In: *Journal of artificial societies and social simulation* 5.1 (2002).

[2] Steven F Railsback, Steven L Lytinen, and Stephen K Jackson. “Agent-based simulation platforms: Review and development recommendations”. In: *Simulation* 82.9 (2006), pp. 609–623.

[3] Sujeong Kim, Stephen J. Guy, Dinesh Manocha, and Ming C. Lin. “Interactive Simulation of Dynamic Crowd Behaviors Using General Adaptation Syndrome Theory”. In: *Proceedings of the ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games*. I3D ’12. Costa Mesa, California: ACM, 2012, pp. 55–62. ISBN: 978-1-4503-1194-6.

[4] Ming C. Lin and Dinesh Manocha. “Virtual cityscapes: recent advances in crowd modeling and traffic simulation”. In: *Frontiers of Computer Science in China* 4.3 (Sept. 2010), pp. 405–416.

[5] William John Teahan. *Artificial Intelligence–Agent Behaviour*. BookBoon, 2010.

[6] Peiyao Zhang, Nan Li, Zhongming Jiang, Dongping Fang, and Chimay J. Anumba. “An agent-based modeling approach for understanding the effect of worker-management interactions on construction workers’ safety-related behaviors”. In: *Automation in Construction* 97 (2019), pp. 29–43. ISSN: 0926-5805.

[7] Robin B Matthews, Nigel G Gilbert, Alan Roach, J Gary Polhill, and Nick M Gotts. “Agent-based land-use models: a review of applications”. In: *Landscape Ecology* 22.10 (2007), pp. 1447–1459.

[8] Ameya Shendarkar, Karthik Vasudevan, Seungho Lee, Young-Jun Son, and Young-Jun Son. “Crowd Simulation for Emergency Response Using BDI Agent Based on Virtual Reality”. In: *Proceedings of the 38th Conference on Winter Simulation*. WSC ’06. Monterey, California: Winter Simulation Conference, 2006, pp. 545–553. ISBN: 1-4244-0501-7.

[9] Nuria Pelechano and Ali Malkawi. “Evacuation simulation models: Challenges in modeling high rise building evacuation with cellular automata approaches”. In: *Automation in construction* 17.4 (2008), pp. 377–385.

[10] Gideon Aschwanden, Jan Halatsch, and Gerhard Schmitt. “Crowd Simulation for Urban Planning”. In: *Architecture in Computro [26th eCAADe Conference Proceedings / ISBN 978-0-9541183-7-2] Antwerpen (Belgium) 17-20 September 2008, pp. 493-500* (Jan. 2008).

[11] Sung June Chang. “Film quality crowd locomotion animation using two-phase simulation”. In: *2007 International Conference on Control, Automation and Systems*. IEEE. 2007, pp. 1748–1751.

[12] Oliver Szymanezyk, Grzegorz Cielniak, et al. “Group emotion modelling and the use of middleware for virtual crowds in video-games”. In: (2010).

[13] M Schultz, S Lehmann, and H Fricke. “A discrete microscopic model for pedestrian dynamics to manage emergency situations in airport terminals”. In: *Pedestrian and evacuation dynamics 2005*. Springer, 2007, pp. 369–375.

[14] Andreas Keßel, Hubert Klüpfel, Joachim Wahle, and Micael Schreckenberg. “Microscopic simulation of pedestrian crowd motion”. In: *Pedestrian and evacuation dynamics* (2002), pp. 193–200.

[15] Samuel Lemercier, Asja Jelic, Richard Kulpa, Jiale Hua, Jérôme Fehrenbach, Pierre Degond, Cécile Appert-Rolland, Stéphane Donikian, and Julien Pettré. “Realistic following behaviors for crowd simulation”. In: *Comput. Graph. Forum* 31 (2012), pp. 489–498.

[16] Kardi Teknomo. “Microscopic Pedestrian Flow Characteristics: Development of an Image Processing Data Collection and Simulation Model”. In: *CoRR* abs/1610.00029 (2016). arXiv: `1610.00029`. URL: `http://arxiv.org/abs/1610.00029`.

[17] Nuria Pelechano, Kevin O’Brien, Barry Silverman, and Norman Badler. “Crowd Simulation Incorporating Agent Psychological Models, Roles and Communication”. In: *First International Workshop on Crowd Simulation* (Nov. 2005), pp. 21–30.

[18] Ernesto L Andrade and Robert B Fisher. “Simulation of crowd problems for computer vision”. In: *First International Workshop on Crowd Simulation*. Vol. 3. 2005, pp. 71–80.

[19] Funda Durupinar, Nuria Pelechano, Jan Allbeck, Ugur Gudukbay, and Norman I Badler. “How the ocean personality model affects the perception of crowds”. In: *IEEE Computer Graphics and Applications* 31.3 (2009), pp. 22–31.

[20] Stephen J. Guy, Sujeong Kim, Ming C. Lin, and Dinesh Manocha. "Simulating Heterogeneous Crowd Behaviors Using Personality Trait Theory". In: *Proceedings of the 2011 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*. SCA '11. Vancouver, British Columbia, Canada: ACM, 2011, pp. 43–52. ISBN: 978-1-4503-0923-3.

[21] Alexia Zoumpoulaki, Nikos Avradinis, and Spyros Vosinakis. "A Multi-agent Simulation Framework for Emergency Evacuations Incorporating Personality and Emotions". In: *Proceedings of the 6th Hellenic Conference on Artificial Intelligence: Theories, Models and Applications*. SETN'10. Athens, Greece: Springer-Verlag, 2010, pp. 423–428. ISBN: 978-3-642-12841-7. DOI: `10.1007/978-3-642-12842-4_54`.

[22] Xiaoshan Pan, Charles S Han, Ken Dauber, and Kincho H Law. "A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations". In: *Ai & Society* 22.2 (2007), pp. 113–132.

[23] Linbo Luo, Suiping Zhou, Wentong Cai, Malcolm Yoke Hean Low, Feng Tian, Yongwei Wang, Xian Xiao, and Dan Chen. "Agent-based human behavior modeling for crowd simulation". In: *Computer Animation and Virtual Worlds* 19.3-4 (2008), pp. 271–281.

[24] Karthik Vasudevan and Young-Jun Son. "Concurrent Consideration of Evacuation Safety and Productivity in Manufacturing Facility Planning Using Multi-paradigm Simulations". In: *Comput. Ind. Eng.* 61.4 (Nov. 2011), pp. 1135–1148. ISSN: 0360-8352. DOI: `10.1016/j.cie.2011.07.003`.

[25] Stephen J Guy, Jatin Chhugani, Sean Curtis, Pradeep Dubey, Ming C Lin, and Dinesh Manocha. "PLEdestrians: A Least-Effort Approach to Crowd Simulation." In: *Symposium on computer animation*. 2010, pp. 119–128.

[26] Stephen J Guy, Jur Van Den Berg, Wenxi Liu, Rynson Lau, Ming C Lin, and Dinesh Manocha. "A statistical similarity measure for aggregate crowd dynamics". In: *ACM Transactions on Graphics (TOG)* 31.6 (2012), pp. 1–11.

[27] Mubbasir Kapadia and Norman I Badler. "Navigation and steering for autonomous virtual humans". In: *Wiley Interdisciplinary Reviews: Cognitive Science* 4.3 (2013), pp. 263–272.

[28] Nuria Pelechano, Jan M Allbeck, and Norman I Badler. "Virtual crowds: Methods, simulation, and control". In: *Synthesis lectures on computer graphics and animation* 3.1 (2008), pp. 1–176.

[29] Nuria Pelechano, Jan Allbeck, and Norman Badler. "Controlling individual agents in high-density crowd simulation". In: *ACM SIGGRAPH/Eurographics Symposium on Computer Animation* (Jan. 2007), pp. 99–108.

[30] Q Sun et al. “A generic approach to modelling individual behaviours in crowd simulation”. PhD thesis. University of Salford, 2014.

[31] Craig W Reynolds. “Flocks, herds and schools: A distributed behavioral model”. In: *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*. 1987, pp. 25–34.

[32] Libi Fu, Weiguo Song, Wei Lv, and Siuming Lo. “Simulation of emotional contagion using modified sir model: A cellular automaton approach”. In: *Physica A: Statistical Mechanics and its Applications* 405 (2014), pp. 380–391.

[33] Núria Pelechano Gómez and Ali Malkawi. “Comparison of crowd simulation for building evacuation and an alternative approach”. In: *Proceedings of the 10th International Building Performance Simulation Association Conference and Exhibition*. 2007, pp. 1514–1521.

[34] Xiaoping Zheng, Tingkuan Zhong, and Mengting Liu. “Modeling crowd evacuation of a building based on seven methodological approaches”. In: *Building and Environment* 44.3 (2009), pp. 437–445.

[35] Jinghui Zhong, Nan Hu, Wentong Cai, Michael Lees, and Linbo Luo. “Density-based evolutionary framework for crowd model calibration”. In: *Journal of Computational Science* 6 (2015), pp. 11–22.

[36] Tianlu Mao, Qing Ye, Hao Jiang, Shihong Xia, and Zhaoqi Wang. “Evoking panic in crowd simulation”. In: *Transactions on edutainment VI*. Springer, 2011, pp. 79–88.

[37] Vassilios Kountouriotis, Stelios CA Thomopoulos, and Yiannis Papelis. “An agent-based crowd behaviour model for real time crowd behaviour simulation”. In: *Pattern Recognition Letters* 44 (2014), pp. 30–38.

[38] Jin Hyoung Park, Francisco Arturo Rojas, and Hyun Seung Yang. “A collision avoidance behavior model for crowd simulation based on psychological findings”. In: *Computer Animation and Virtual Worlds* 24.3-4 (2013), pp. 173–183.

[39] Juliana Aida Abu Bakar, Ruzinoor Che Mat, Azizi Ab Aziz, Norsyazatul Asyifa Noor Jasri, and Mohd Fitri Yusoff. “Designing agent-based modeling in dynamic crowd simulation for stressful environment”. In: *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)* 8.10 (2016), pp. 151–156.

[40] Richard J Dawson, Roger Peppe, and Miao Wang. “An agent-based model for risk-based flood incident management”. In: *Natural hazards* 59.1 (2011), pp. 167–189.

[41] Craig W Reynolds. “Steering behaviors for autonomous characters”. In: *Game developers conference*. Vol. 1999. Citeseer. 1999, pp. 763–782.

[42] O Burçhan Bayazıt, Jyh-Ming Lien, and Nancy M Amato. “Swarming behavior using probabilistic roadmap techniques”. In: *International Workshop on Swarm Robotics*. Springer. 2004, pp. 112–125.

[43] Celine Loscos, David Marchal, and Alexandre Meyer. “Intuitive crowd behavior in dense urban environments using local laws”. In: *Proceedings of Theory and Practice of Computer Graphics, 2003.* IEEE. 2003, pp. 122–129.

[44] Hui-Qing Chong, Ah-Hwee Tan, and Gee-Wah Ng. “Integrated cognitive architectures: a survey”. In: *Artificial Intelligence Review* 28.2 (Aug. 2007), pp. 103–130. ISSN: 1573-7462. DOI: 10.1007/s10462-009-9094-9.

[45] Anand S Rao and Michael P George. “BDI agents: From theory to practice”. In: *Proceedings of the First International Conference on Multi-Agent Systems (ICMAS-95).* 1995, pp. 312–319.

[46] John E. Laird. *The Soar Cognitive Architecture.* The MIT Press, 2012. ISBN: 9780262122962.

[47] Gerhard Weber. “ACT - Adaptive Control of Thought”. In: *Encyclopedia of the Sciences of Learning.* Ed. by Norbert M. Seel. Boston, MA: Springer US, 2012, pp. 60–62. ISBN: 978-1-4419-1428-6. DOI: 10.1007/978-1-4419-1428-6_533.

[48] Ron Sun. “The CLARION Cognitive Architecture: Extending Cognitive Modeling to Social Simulation.” In: *Cognition and multi-agent interaction: From cognitive modeling to social simulation.* Sun, Ron: Department of Cognitive Science, Rensselaer Polytechnic Institute, Troy, NY, 12180, rsun@rpi.edu: Cambridge University Press, 2006, pp. 79–99. ISBN: 0-521-83964-5 (Hardcover).

[49] Pat Langley and Dongkyu Choi. “A Unified Cognitive Architecture for Physical Agents”. In: *Proceedings of the 21st National Conference on Artificial Intelligence - Volume 2.* AAAI’06. Boston, Massachusetts: AAAI Press, 2006, pp. 1469–1474. ISBN: 978-1-57735-281-5.

[50] Rodney A. Brooks. “Artificial Intelligence at MIT”. In: ed. by Patrick Henry Winston and Sarah Alexandra Shellard. Cambridge, MA, USA: MIT Press, 1990. Chap. A Robust Layered Control System for a Mobile Robot, pp. 2–27. ISBN: 0-262-23150-6.

[51] Ashutosh Trivedi and Shrisha Rao. “Agent-Based Modeling of Emergency Evacuations Considering Human Panic Behavior”. In: *IEEE Transactions on Computational Social Systems* 5 (Mar. 2018), pp. 277–. DOI: 10.1109/TCSS.2017.2783332.

[52] S Pluchino, CMG Tribulato, A Caverzan, A Mc Quillan, GP Cimellaro, and S Mahin. “Agent-based model for pedestrians’ evacuation after a blast integrated with a human behavior model”. In: *Structures Congress 2015*. 2015, pp. 1506–1517.

[53] Jason Tsai, Natalie Fridman, Emma Bowring, Matthew Brown, Shira Epstein, Gal Kaminka, Stacy Marsella, Andrew Ogden, Inbal Rika, Ankur Sheel, et al. “Escapes: evacuation simulation with children, authorities, parents, emotions, and social comparison”. In: *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 2*. International Foundation for Autonomous Agents and Multiagent Systems. 2011, pp. 457–464.

[54] Natalie Fridman, Gal A. Kaminka, and Avishay Zilka. “The Impact of Culture on Crowd Dynamics: An Empirical Approach”. In: *Proceedings of the 2013 International Conference on Autonomous Agents and Multi-agent Systems*. AAMAS ’13. St. Paul, MN, USA: International Foundation for Autonomous Agents and Multiagent Systems, 2013, pp. 143–150. ISBN: 978-1-4503-1993-5.

[55] Jason Tsai, Emma Bowring, Stacy Marsella, and Milind Tambe. “Empirical evaluation of computational emotional contagion models”. In: *International Workshop on Intelligent Virtual Agents*. Springer. 2011, pp. 384–397.

[56] Tibor Bosse, Mark Hoogendoorn, Michel CA Klein, Jan Treur, C Natalie Van Der Wal, and Arlette Van Wissen. “Modelling collective decision making in groups and crowds: Integrating social contagion and interacting emotions, beliefs and intentions”. In: *Autonomous Agents and Multi-Agent Systems* 27.1 (2013), pp. 52–84.

[57] Du Lei, W Wenjun, and Z Xiankun. “An agent-based decision-making model in emergency evacuation management”. In: *J. Converg. Inf. Technol.* (2012).

[58] Margaux Lhommet, Domitile Lourdeaux, and Jean-Paul Barthès. “Never Alone in the Crowd: A Microscopic Crowd Model Based on Emotional Contagion”. In: *Proceedings of the 2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology - Volume 02*. WI-IAT ’11. Washington, DC, USA: IEEE Computer Society, 2011, pp. 89–92. ISBN: 978-0-7695-4513-4. DOI: 10.1109/WI-IAT.2011.149.

[59] Stefan Münchow, Ia Enukidze, Stefan Sarstedt, and Thomas Thiel-Clemen. "Walk: A modular testbed for crowd evacuation simulation". In: *Pedestrian and Evacuation Dynamics 2012*. Springer, 2014, pp. 1417–1424.

[60] Haifa Abdelhak, Aladdin Ayesh, and Damien Olivier. "Cognitive emotional based architecture for crowd simulation". In: *Journal of Intelligent Computing* 3.2 (2012), pp. 55–66.

[61] Margaret Lyell and Mark Becker. ""Simulation of cognitive pedestrian agents: crowds in crisis situations "". In: *Systemics, Cybernetics and Informatics* 4.3 (2005), pp. 79–84.

[62] Anthony Guye-Vuilleme and Daniel Thalmann. "A high-level architecture for believable social agents". In: *Virtual Reality* 5.2 (2000), pp. 95–106.

[63] Wei Shao and Demetri Terzopoulos. "Populating reconstructed archaeological sites with autonomous virtual humans". In: *International Workshop on Intelligent Virtual Agents*. Springer. 2006, pp. 420–433.

[64] Walid Ali and Bernard Moulin. "How artificial intelligent agents do shopping in a virtual mall: A 'believable'and 'usable'multiagent-based simulation of customers' shopping behavior in a mall". In: *Conference of the Canadian Society for Computational Studies of Intelligence*. Springer. 2006, pp. 73–85.

[65] Natalie Fridman, Avishy Zilka, and Gal A Kaminka. "The impact of cultural differences on crowd dynamics in pedestrian and evacuation domains". In: *Bar Ilan University, Computer Science Department, MAVERICK Group, available at http://www. cs. biu. ac. il/ galk/Publications/, Tech. Rep. MAVERICK* 1 (2011), pp. 1–60.

[66] Wei-Ming Chao and Tsai-Yen Li. "Simulation of social behaviors in virtual crowd". In: *Computer Animation and Social Agents*. 2010.

[67] Wei-Ming Chao and Tsai-Yen Li. "Simulating riot for virtual crowds with a social communication model". In: *International Conference on Computational Collective Intelligence*. Springer. 2011, pp. 419–427.

[68] David Wolinski. "Microscopic Crowd Simulation: Evaluation and Development of Algorithms". PhD thesis. Université De Rennes 1, 2016.

[69] Daniel Thalmann and Soraia Raupp Musse. *Crowd Simulation*. Berlin, Heidelberg: Springer-Verlag, 2007. ISBN: 184628824X.

[70] Rahul Narain, Abhinav Golas, Sean Curtis, and Ming C. Lin. "Aggregate Dynamics for Dense Crowd Simulation". In: *ACM Trans. Graph.* 28.5 (Dec. 2009), 122:1–122:8. ISSN: 0730-0301.

[71] Mohamed Adi Bin Mohamed Azahar, Mohd Shahrizal Sunar, Daut Daman, and Abdullah Bade. "Survey on real-time crowds simulation". In: *International Conference on Technologies for E-Learning and Digital Entertainment*. Springer. 2008, pp. 573–580.

[72] Kiran Ijaz, Shaleeza Sohail, and Sonia Hashish. "A Survey of Latest Approaches for Crowd Simulation and Modeling Using Hybrid Techniques". In: *Proceedings of the 2015 17th UKSIM-AMSS International Conference on Modelling and Simulation*. UKSIM '15. Washington, DC, USA: IEEE Computer Society, 2015, pp. 111–116. ISBN: 978-1-4799-8713-9.

[73] Fawwaz Mohd Nasir and Mohd Shahrizal Sunar. "A survey on simulating real-time crowd simulation". In: *2015 4th International Conference on Interactive Digital Media (ICIDM)*. IEEE. 2015, pp. 1–5.

[74] Anne-Hélène Olivier, Julien Bruneau, Gabriel Cirio, and Julien Pettré. "A Virtual Reality Platform to Study Crowd Behaviors". In: *Transportation Research Procedia* 2 (2014). The Conference on Pedestrian and Evacuation Dynamics 2014 (PED 2014), 22-24 October 2014, Delft, The Netherlands, pp. 114–122.

[75] Eric Bonabeau. "Agent-based modeling: Methods and techniques for simulating human systems". In: *Proceedings of the National Academy of Sciences* 99.suppl 3 (2002), pp. 7280–7287. ISSN: 0027-8424.

[76] Max Kinateder, Enrico Ronchi, Daniel Nilsson, Margrethe Kobes, Mathias Müller, Paul Pauli, and Andreas Mühlberger. "Virtual reality for fire evacuation research". In: *2014 Federated Conference on Computer Science and Information Systems*. IEEE. 2014, pp. 313–321.

[77] Mizar Luca Federici, Andrea Gorrini, Lorenza Manenti, and Giuseppe Vizzari. "Data collection for modeling and simulation: case study at the university of milan-bicocca". In: *International Conference on Cellular Automata*. Springer. 2012, pp. 699–708.

[78] Ilias Sakellariou, Omar Kurdi, Marian Gheorghe, Daniela Romano, Petros Kefalas, Florentin Ipate, and Ionut Niculescu. "Crowd formal modelling and simulation: The Sa'yee ritual". In: *2014 14th UK Workshop on Computational Intelligence (UKCI)*. IEEE. 2014, pp. 1–8.

[79] Mingbi Zhao. "A clustering based approach for realistic and efficient data-driven crowd simulation". In: *arXiv preprint arXiv:1506.04480* (2015).

[80] Liu Jia and Chen Yun. "Simulation on staffs evacuation behavior in plant fire emergencies". In: *Systems Research and Behavioral Science* 31.4 (2014), pp. 527–536.

[81] Patrick Dickinson, Kathrin Gerling, Kieran Hicks, John Murray, John Shearer, and Jacob Greenwood. “Virtual reality crowd simulation: effects of agent density on user experience and behaviour”. In: *Virtual Reality* 23.1 (Mar. 2019), pp. 19–32. ISSN: 1434-9957.

[82] Max Kinateder, Paul Pauli, Mathias Müller, Jürgen Krieger, Frank Heimbecher, Inga Rönnau, Ulrich Bergerhausen, Götz Vollmann, Peter Vogt, and Andreas Mühlberger. “Human behaviour in severe tunnel accidents: Effects of information and behavioural training”. In: *Transportation research part F: traffic psychology and behaviour* 17 (2013), pp. 20–32.

[83] Funda Durupinar, U. Gudukbay, Aytek Aman, and Norman Badler. “Psychological Parameters for Crowd Simulation: From Audiences to Mobs”. In: *IEEE Transactions on Visualization and Computer Graphics* 22 (Nov. 2015), pp. 1–1. DOI: 10.1109/TVCG.2015.2501801.

[84] Marina Ntika, Ilias Sakellariou, Petros Kefalas, and Ioanna Stamatopoulou. “Experiments with emotion contagion in emergency evacuation simulation”. In: *Proceedings of the 4th International Conference on Web Intelligence, Mining and Semantics (WIMS14)*. 2014, pp. 1–11.

[85] Lynda Saı”fi, Abdelhak Boubetra, and Farid Nouioua. “Approaches to modeling the emotional aspects of a crowd”. In: *2013 8th EUROSIM Congress on Modelling and Simulation*. IEEE. 2013, pp. 151–154.

[86] Stephen J Guy. “Psycho-physical Crowds”. In: *Proceedings of Motion on Games*. 2013, pp. 7–12.

[87] Jacob Sinclair and Carrie Siu Man Lui. “Psychological and socio-psychological factors in behavioral simulation of human crowds”. In: *Proceedings of the Fourteenth International Conference on Electronic Business and the First Global Conference on Internet and Information Systems* (2014), pp. 191–202.

[88] Cagatay Turkay, Emre Koc, and Selim Balcisoy. “Integrating information theory in agent-based crowd simulation behavior models”. In: *The Computer Journal* 54.11 (2011), pp. 1810–1820.

[89] Paul M Torrens. “Moving agent pedestrians through space and time”. In: *Annals of the Association of American Geographers* 102.1 (2012), pp. 35–66.

[90] Paul M Torrens. “High-fidelity behaviours for model people on model streetscapes”. In: *Annals of GIS* 20.3 (2014), pp. 139–157.

[91] Ioanna Stamatopoulou, Ilias Sakellariou, and Petros Kefalas. “Formal agent-based modelling and simulation of crowd behaviour in emergency evacuation plans”. In: *2012 IEEE 24th International Conference on Tools with Artificial Intelligence*. Vol. 1. IEEE. 2012, pp. 1133–1138.

[92] Bas R Steunebrink, Mehdi Dastani, and John-Jules Ch Meyer. “The OCC model revisited”. In: *Proc. of the 4th Workshop on Emotion and Computing*. Association for the Advancement of Artificial Intelligence. 2009.

[93] Jérémie Bordas and Fabien Tschirhart. “Contaminating crowds' emotional states.” In: *SummerSim*. 2014, p. 42.

[94] Mirza Waqar Baig, Emilia I Barakova, Lucio Marcenaro, Carlo S Regazzoni, and Matthias Rauterberg. “Bio-inspired probabilistic model for crowd emotion detection”. In: *2014 International Joint Conference on Neural Networks (IJCNN)*. IEEE. 2014, pp. 3966–3973.

[95] Mirza Waqar Baig, Emilia I Barakova, Lucio Marcenaro, Matthias Rauterberg, and Carlo S Regazzoni. “Crowd emotion detection using dynamic probabilistic models”. In: *International Conference on Simulation of Adaptive Behavior*. Springer. 2014, pp. 328–337.

[96] Mouna Belhaj, Fahem Kebair, and Lamjed Ben Said. “A computational model of emotions for the simulation of human emotional dynamics in emergency situations”. In: *International Journal of Computer Theory and Engineering* 6.3 (2014), p. 227.

[97] Walid Ali and Bernard Moulin. “2D-3D multiagent geosimulation with knowledge-based agents of customers' shopping behavior in a shopping mall”. In: *International Conference on Spatial Information Theory*. Springer. 2005, pp. 445–458.

[98] Xiaoshan Pan, Charles S Han, Ken Dauber, and Kincho H Law. “Human and social behavior in computational modeling and analysis of egress”. In: *Automation in construction* 15.4 (2006), pp. 448–461.

[99] QH Nguyen, Frederic D McKenzie, and Mikel D Petty. “Crowd behavior cognitive model architecture design”. In: *Proceedings of the 2005 conference on behavior representation in modeling and simulation (BRIMS)*. 2005, pp. 55–64.

[100] Kuo-Chung Wen. “A Dynamic Simulation of Crowd Flow in Taipei Railway and MRT Station by Multi-Agent Simulation System”. In: *Urban Planning and Design Research* 1.4 (2013), pp. 59–68.

[101] Xueling Jiang and Shuijie Qin. “Simulating a crowd with dynamic emotional transmission based on Hidden Markov Model”. In: *COMPUTER MODELLING AND NEW TECHNOLOGIES* (2014).

[102] Nan Xiang, Zhigeng Pan, and Mingmin Zhang. “Using emotion transmission to simulate spectator behaviors”. In: *Proceedings of the 11th ACM SIGGRAPH International Conference on Virtual-Reality Continuum and its Applications in Industry*. 2012, pp. 51–54.

[103] Daniel Thalmann, Soraia Raupp Musse, and Marcelo Kallmann. “Virtual humans’ behaviour: Individuals, groups, and crowds”. In: *Digital Media: The Future*. Springer, 2000, pp. 239–256.

[104] Tim Balint and Jan M Allbeck. “Is that how everyone really feels? emotional contagion with masking for virtual crowds”. In: *International Conference on Intelligent Virtual Agents*. Springer. 2014, pp. 26–35.

[105] Bernard Moulin and Walid Ali. “A Multi-Agent Geo-Simulation Approach to Assess the Impact of Environment Changes on Crowd Behavior”. In: *Ulaval Canada* (2006).

[106] Wei-Ming Chao and Tsai-Yen Li. “Simulating Crowd Behaviors with a Communication Model”. In: *Proc. of Computer Animation and Social Agents*. Citeseer. 2008.

[107] Gao-qi He, Yu Yang, Zhi-hua Chen, Chun-hua Gu, and Zhi-geng Pan. “A review of behavior mechanisms and crowd evacuation animation in emergency exercises”. In: *Journal of Zhejiang University SCIENCE C* 14.7 (2013), pp. 477–485.

[108] Oğuzcan Oğuz, Ateş Akaydın, Türker Yılmaz, and Uğur Güdükbay. “Emergency crowd simulation for outdoor environments”. In: *Computers & Graphics* 34.2 (2010), pp. 136–144.

[109] Jerome Comptdaer, E Chiva, and D Bourguignon. “A new microscopic approach to crowd modeling applied to urban crisis management training”. In: *Conference on Behavior Representation in Modelling and Simulation*. 2005.

[110] Sean Curtis, Basim Zafar, Adnan Gutub, and Dinesh Manocha. “Right of way”. In: *The Visual Computer* 29.12 (2013), pp. 1277–1292.

[111] Nuria Pelechano, Catherine Stocker, Jan Allbeck, and Norman Badler. “Being a part of the crowd: towards validating VR crowds using presence”. In: *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems-Volume 1*. International Foundation for Autonomous Agents and Multiagent Systems. 2008, pp. 136–142.

[112] Mira Crouch and Heather McKenzie. “The logic of small samples in interview-based qualitative research”. In: *Social Science Information* 45.4 (2006), pp. 483–499.

[113] Greg Guest, Arwen Bunce, and Laura Johnson. "How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability". In: *Field Methods* 18.1 (2006), pp. 59–82.

[114] Shari L. Dworkin. "Sample Size Policy for Qualitative Studies Using In-Depth Interviews". In: *Archives of Sexual Behavior* 41.6 (Dec. 2012), pp. 1319–1320. ISSN: 1573-2800.

[115] Sharon L. Lohr. *Sampling: Design and Analysis*. 2nd. Chapman and Hall/CRC, 2019. ISBN: 9780429296284.

[116] Jacob Sinclair, Hemmaphan Suwanwiwat, and Ickjai Lee. "A Virtual Reality and Questionnaire Approach to Gathering Real World Data for Agent Based Crowd Simulation Models". In: *Simulation Modelling Practice and Theory* (2019). submitted Dec. 2019.

[117] T. Silva da Silva, A. Martin, F. Maurer, and M. Silveira. "User-Centered Design and Agile Methods: A Systematic Review". In: *2011 Agile Conference*. Aug. 2011, pp. 77–86.

[118] Arjan Egges, Sumedha Kshirsagar, and Nadia Magnenat-Thalmann. "A Model for Personality and Emotion Simulation". In: *Knowledge-Based Intelligent Information and Engineering Systems*. Ed. by Vasile Palade, Robert J. Howlett, and Lakhmi Jain. Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 453–461. ISBN: 978-3-540-45224-9.

[119] MURRAY R. BARRICK and MICHAEL K. MOUNT. "THE BIG FIVE PERSONALITY DIMENSIONS AND JOB PERFORMANCE: A META-ANALYSIS". In: *Personnel Psychology* 44.1 (1991), pp. 1–26.

[120] Samuel D. Gosling, Peter J. Rentfrow, and William B. Swann. "A very brief measure of the Big-Five personality domains". In: *Journal of Research in Personality* 37 (2003), pp. 504–528.

[121] Michael D. Robinson and Ben S. Kirkeby. "Happiness as a Belief System: Individual Differences and Priming in Emotion Judgments". In: *Personality and Social Psychology Bulletin* 31.8 (2005). PMID: 16000273, pp. 1134–1144.

[122] A. Ortony, G. L. Clore, and A. Collins. *The Cognitive Structure of Emotions*. Cambridge, UK: Cambridge University Press, 1988.

[123] Alessandro Murgia, Parastou Tourani, Bram Adams, and Marco Ortu. "Do Developers Feel Emotions? An Exploratory Analysis of Emotions in Software Artifacts". In: *Proceedings of the 11th Working Conference on Mining Software Repositories*. MSR 2014. Hyderabad, India: ACM, 2014, pp. 262–271. ISBN: 978-1-4503-2863-0.

[124] Linbo Luo, Suiping Zhou, Wentong Cai, Malcolm Yoke Hean Low, and Michael Lees. "Toward a Generic Framework for Modeling Human Behaviors in Crowd Simulation". In: *Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology - Volume 02*. WI-IAT '09. Washington, DC, USA: IEEE Computer Society, 2009, pp. 275–278. ISBN: 978-0-7695-3801-3. DOI: 10.1109/WI-IAT.2009.163.

[125] D. E. Broadbent. *Perception and communication*. Pergamon Press, 1958. ISBN: 9781483225821. DOI: 10.1037/10037-000.

[126] Funda Durupinar, Mubbasir Kapadia, Susan Deutsch, Michael Neff, and Norman I Badler. "Perform: Perceptual approach for adding ocean personality to human motion using laban movement analysis". In: *ACM Transactions on Graphics (TOG)* 36.1 (2016), pp. 1–16.

[127] Barnabas Bede. *Mathematics of Fuzzy Sets and Fuzzy Logic*. Springer Publishing Company, Incorporated, 2012. ISBN: 9783642352201.

[128] Jeremy R Gray and Todd S Braver. "Personality predicts working-memory—related activation in the caudal anterior cingulate cortex". In: *Cognitive, Affective, & Behavioral Neuroscience* 2.1 (2002), pp. 64–75.

[129] Rhonda Shaw, Robert Buckingham, and Greg Baker. "The relationships between visuo-spatial working memory, short-term memory and personality." In: *International Conference on Memory-5*. 2011.

[130] Richard C. Atkinson and Richard M. Shiffrin. "The control of short-term memory". In: *Scientific American* 225.2 (1971), pp. 82–90. ISSN: 0036-8733. DOI: 10.1038/scientificamerican0871-82.

[131] H. P. Bahrick, P. O. Bahrick, and R. P. Wittlinger. "Fifty Years of Memory for Names and Faces: A Cross-Sectional Approach". In: *Journal of Experimental Psychology: General* 104.1 (1975), pp. 54–75. DOI: 10.1037/0096-3445.104.1.54.

[132] Magy Seif El-Nasr, John Yen, and Thomas R Ioerger. "FLAME—Fuzzy Logic Adaptive Model of Emotions". In: *Autonomous Agents and Multi-Agent Systems* 3.3 (2000), pp. 219–257. ISSN: 1573-7454. DOI: 10.1023/A:1010030809960.

[133] "Chi-square Goodness of Fit Test". In: *The Concise Encyclopedia of Statistics*. New York, NY: Springer New York, 2008, pp. 72–76. ISBN: 978-0-387-32833-1.

[134] V. Interrante, B. Ries, and L. Anderson. "Distance Perception in Immersive Virtual Environments, Revisited". In: *IEEE Virtual Reality Conference (VR 2006)*. Mar. 2006, pp. 3–10. DOI: 10.1109/VR.2006.52.

[135] Andrea Canessa., Paolo Casu., Fabio Solari., and Manuela Chessa. “Comparing Real Walking in Immersive Virtual Reality and in Physical World using Gait Analysis”. In: *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - Volume 2: HUCAPP,* INSTICC. SciTePress, 2019, pp. 121–128. ISBN: 978-989-758-354-4. DOI: 10.5220/0007380901210128.

[136] Joseph J. LaViola Jr. “A Discussion of Cybersickness in Virtual Environments”. In: *SIGCHI Bull.* 32.1 (Jan. 2000), pp. 47–56. ISSN: 0736-6906.

[137] Danny McCarroll. *Simple Statistical Tests for Geography.* Chapman and Hall/CRC Press, 2017.

[138] Ryan E Rhodes, Kerry S Courneya, Chris M Blanchard, and Ronald C Plotnikoff. “Prediction of leisure-time walking: an integration of social cognitive, perceived environmental, and personality factors”. In: *International Journal of Behavioral Nutrition and Physical Activity* 4.1 (2007), p. 51.

[139] Liam Satchell, Paul Morris, Chris Mills, Liam O’Reilly, Paul Marshman, and Lucy Akehurst. “Evidence of big five and aggressive personalities in gait biomechanics”. In: *Journal of nonverbal behavior* 41.1 (2017), pp. 35–44.

[140] Magdalena I Tolea, Antonio Terracciano, Eleanor M Simonsick, E Jeffrey Metter, Paul T Costa Jr, and Luigi Ferrucci. “Associations between personality traits, physical activity level, and muscle strength”. In: *Journal of research in personality* 46.3 (2012), pp. 264–270.

[141] Christina Massoth, Hannah Röder, Hendrik Ohlenburg, Michael Hessler, Alexander Zarbock, Daniel M Pöpping, and Manuel Wenk. “High-fidelity is not superior to low-fidelity simulation but leads to overconfidence in medical students”. In: *BMC medical education* 19.1 (2019), p. 29.

[142] Anupam Makhija, Deborah Richards, Jesse de Haan, Frank Dignum, and Michael J Jacobson. “The influence of gender, personality, cognitive and affective student engagement on academic engagement in educational virtual worlds”. In: *International Conference on Artificial Intelligence in Education.* Springer. 2018, pp. 297–310.

[143] Jesse de Haan and Debbie Richards. “Navigation paths and performance in educational virtual worlds”. In: *Navigation* (2017).

Appendix A

Appendix

A.1 Consent Form

INFORMED CONSENT FORM

PRINCIPAL INVESTIGATOR: Jacob Sinclair
PROJECT TITLE: Relationships of Personality, Emotion, and Human Navigation Behaviour
COLLEGE: College of Business, Law, and Governance

I understand the aim of this research study is **to use movement data collected by motion sensors and virtual reality technologies for creating realistic human navigation behaviour in computer simulation**. I consent to participate in this project, the details of which have been explained to me, and I have been provided with a written information sheet to keep.

I understand that my participation will involve ***participating a user testing of virtual reality experience, be videotaping of my movement during the testing and completing a questionnaire after the test*** and I agree that the researcher may use the results as described in the information sheet.

I acknowledge that:

- taking part in this study is voluntary and I am aware that I can stop taking part in it at any time without explanation or prejudice and to withdraw any unprocessed data I have provided;

- that any information I give will be kept strictly confidential and that no names will be used to identify me with this study without my approval;

(Please tick to indicate consent)

I consent to participate in a virtual reality experience		**Yes**		**No**
I consent for virtual reality experience to be video taped		**Yes**		**No**
I consent to complete a questionnaire		**Yes**		**No**
I consent to complete an interview		**Yes**		**No**

Name: *(printed)*	
Signature:	**Date:**

A.2 Virtual Reality Questionnaire - Page 1

Questionnaire

Demographics

1) **What is your year of birth? 19___**
2) **Gender : Male / Female**
3) **What is your experience of using virtual reality headset**
    a. **I have never used it before this study**
    b. **I have used in before**
    c. **I own a virtual reality headset**

4) **Please write a number next to each statement to indicate the extent to which you agree with the following statements.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

1. ____ I had a sense of being in the scenes displayed in the virtual reality experience.
2. ____ I felt I was visiting the place in the virtual reality experience
3. ____ I felt that the virtual characters and /or objects could almost touch me.
4. ____ I felt involved in the virtual reality experience.
5. ____ I enjoyed the virtual reality experience.
6. ____ My experience was intense.
7. ____ The content of the virtual reality experiment seemed believable to me
8. ____ I had a strong sense that the characters and objects were solid.
9. ____ The virtual reality environment seemed natural.
10. ____ I felt dizzy in the virtual reality experience.
11. ____ I felt disorientated in the virtual reality experience.
12. ____ I can close my eyes and easily picture a scene.
13. ____ I remember everything visually.
14. ____ I can easily remember a great deal of visual details.
15. ____ I have excellent ability in technical graphics such as building blueprint.
16. ____ I was very good in 3D geometry.
17. ____ I am good at playing spatial games.

1

5) **Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.**

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

I see myself as:

1. ____ Extroverted, enthusiastic.
2. ____ Critical, quarrelsome.
3. ____ Dependable, self-disciplined
4. ____ Anxious, easily upset
5. ____ Open to new experiences, complex
6. ____ Reserved, quiet
7. ____ Sympathetic, warm.
8. ____ Disorganized, careless
9. ____ Calm, emotionally stable.
10. ____ Conventional, uncreative

6) **Please indicate the amount of emotion you have experienced in the virtual reality environment:**

None	Small Amount	Moderate Amount	Large Amount	Extreme Amount
1	2	3	4	5

1. ____ Affection
2. ____ Cheerful
3. ____ Confident
4. ____ Delighted
5. ____ Elated
6. ____ Energetic
7. ____ Enthusiastic
8. ____ Excited
9. ____ Gratified
10. ____ Happy
11. ____ Inspired
12. ____ Interested
13. ____ Joyful
14. ____ Lively
15. ____ Passionate
16. ____ Peaceful
17. ____ Pleasant
18. ____ Proud
19. ____ Thrilled
20. ____ Worthy
21. ____ Afraid
22. ____ Angry
23. ____ Annoyed
24. ____ Anxious
25. ____ Ashamed
26. ____ Blue
27. ____ Depressed
28. ____ Disappointed
29. ____ Distressed
30. ____ Down
31. ____ Fearful
32. ____ Frightened
33. ____ Guilty
34. ____ Irritable
35. ____ Lonely
36. ____ Miserable
37. ____ Moody
38. ____ Nervous
39. ____ Upset
40. ____ Worried

7) Please describe your experience and feeling when facing the virtual characters/obstacles.

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____

8) Please describe your decision of the paths taken to avoid the virtual characters/obstacles. What are the factors influencing your decision?

____
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9) Please describe how your movement to avoid the virtual characters/obstacles in the virtual reality experience will be different from your movement in real world?

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____

A.3 Real World Questionnaire - Page 1

Questionnaire

Demographics

1) **What is your year of birth? 19___**
2) **Gender : Male / Female**

3) **Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.**

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

I see myself as:

1. ____ Extroverted, enthusiastic.
2. ____ Critical, quarrelsome.
3. ____ Dependable, self-disciplined
4. ____ Anxious, easily upset
5. ____ Open to new experiences, complex
6. ____ Reserved, quiet
7. ____ Sympathetic, warm.
8. ____ Disorganized, careless
9. ____ Calm, emotionally stable.
10. ____ Conventional, uncreative

4) **Please indicate the amount of emotion you have experienced in the real world environment:**

None	Small Amount	Moderate Amount	Large Amount	Extreme Amount
1	2	3	4	5

1. ____ Affection
2. ____ Cheerful
3. ____ Confident
4. ____ Delighted
5. ____ Elated
6. ____ Energetic
7. ____ Enthusiastic
8. ____ Excited
9. ____ Gratified
10. ____ Happy
11. ____ Inspired
12. ____ Interested
13. ____ Joyful
14. ____ Lively
15. ____ Passionate
16. ____ Peaceful
17. ____ Pleasant
18. ____ Proud
19. ____ Thrilled
20. ____ Worthy
21. ____ Afraid
22. ____ Angry
23. ____ Annoyed
24. ____ Anxious
25. ____ Ashamed
26. ____ Blue

1

27. ____ Depressed
28. ____ Disappointed
29. ____ Distressed
30. ____ Down
31. ____ Fearful
32. ____ Frightened
33. ____ Guilty
34. ____ Irritable
35. ____ Lonely
36. ____ Miserable
37. ____ Moody
38. ____ Nervous
39. ____ Upset
40. ____ Worried