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A hybrid data gathering and agent based cognitive architecture for realistic crowd simulations

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ABSTRACT
This paper proposes a realistic agent-based framework for crowd simulations that can encompass the input phase, the simulation process phase, and the output evaluation phase. In order to achieve this gathering, the three types of real-world data (physical, mental and visual) need to be considered. However, existing research has not used all the three data types to develop an agent-based framework since current data gathering methods are unable to collect all the three types. This paper introduces anew hybrid data gathering approach using a combination of virtual reality and questionnaires to gather all three data types. The data collected are incorporated into the 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. Various types of settings (self-set parameters and random parameters) are simulated to demonstrate that the framework can produce real-world like simulation.

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Agent-based simulation; data gathering; virtual reality; questionnaire; cognitive architecture

1. Introduction

Agent-based simulation is the development of artificial objects (such as agents) that can reveal realistic behaviour of the real world (Davidsson, 2002; Kim et al., 2012; Railsback et al., 2006). Agent-based simulation has contributed to the development and understanding of real-world behaviours through simulating individual and social actions, and the interaction between autonomous agents (Lin & Manocha, 2010; Teahan, 2010). Researchers are given many advantages by implementing agent-based simulations. First, the ability to display numerous realistic behaviours by running a large group of heterogeneous agents that can each provide their own unique characteristics and decision making (Matthews et al., 2007). Second, the implementation of psychological aspects (personality and emotion) into agent-based simulation becomes feasible. This provides researchers with a means to influencing the agent's decision-making, parameters and movement. It also allows real-world data to be modelled into agent-based simulations and to produce real-life events. Last, agent-based simulation provides a means to help improve real-world situations (Shendarkar et al., 2006). For instance, we can simulate real-world traffic scenarios that will allow us to improve traffic conditions in built up areas.

Typical agent-based simulation is composed of three key phases: input, cognitive architecture model and output, where the input phase generates an input data for a cognitive architecture model to process whilst the output phase involves output generation, evaluation and validation. Although there have been many agent-based simulation approaches proposed in the field (Luo et al., 2008; Pan et al., 2007; Shendarkar et al., 2006), they share some common drawbacks. First, traditional approaches focus on the implementation, improvement and variations of the cognitive simulation model whilst relatively neglecting the input phase and the output phase (Keßel et al., n.d.; Schultz et al., 2007). Typically, the input data are randomly or manually generated to run a cognitive architecture model to demonstrate its applicability in a certain domain area. Second, some studies attempted to include richer input data such as psychological data (personality and emotion) in order to improve the overall performance, but the incorporation of the generated input data into the cognitive architecture model is implemented through low level parameters. These loosely coupled approaches are case-specific but not general enough to be used for various simulations. To the best of 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. Third, due to the random generation of input data, it is practically infeasible to quantitatively measure the performance of simulation output. Fourth, no overall framework encompassing the three key phases has been proposed to produce realistic simulations.

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In order to overcome the common drawbacks of traditional approaches, we propose a realistic agent-based simulation framework that collects realistic data in the input phase, build a flexible agent-based simulation architecture model based on fuzzy logic, probability, priority queue, memory structures to systematically manage mental (personality and emotion) and physical (speed and distance) data. We utilise a combination of Virtual Reality (VR) and Questionnaire (VR-Q) to collect realistic mental and physical data in order to improve the input phase. Note that we also collect visual data in order to observe objective individual behaviours from the third person point of view. These three types of data (mental, physical and visual) are used in the validation phase to quantitatively benchmark the performance of our proposed model against a model with random data generations.

The main contributions of this paper are as follows:

- introduce a new data generation approach that collects real world data using a combination of VR and questionnaire in order to capture realistic mental (personality and emotion), physical (speed and distance) and visual data (such as turns made and information centres visited);
- propose a flexible agent based simulation model that systematically incorporates the collected mental and physical data;
- evaluate, validate and benchmark the performance of our proposed model in order 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.

1. Preliminaries and related work

The fundamental design for developing an agent-based framework consists of three key phases: input, agent architecture model, and output. The input phase represents where the data is collected by using a data gathering method. The agent architecture model phase can be developed using the data collected in the input phase, and can also be processed using a cognitive architecture framework. The output phase provides data that is processed from the agent architecture model phase. This phase also involves the process of evaluating, validating and benchmarking of the agent architecture model. This section reviews past studies covering the overall development of agent-based simulation.

1.1. Data gathering

The main objective of data gathering is to collect data that can be used in the development and validation of simulation models. Collecting data for agent-based models are very important as it provides the ability to develop realistic models by using real-world data. There are many different data gathering methods that collect real world and have been used by researchers. This section focuses on reviewing some of the major approaches and a comparison can be found in Table 1, which displays all current data gathering approaches in regards to five important features and three data types. These five features are very important when considering collecting data for agent-based simulations (Guy et al., 2011; Kinateder et al., 2014). These important features include cost-effectiveness, time efficiency, reproducibility, ecological validity and experimental control. The three data types (physical, mental, visual) each represent important data that need to be collected in order to develop and validate agent-based simulations (Andrade & Fisher, 2005; Pelechano et al., 2005). Physical data are the perception of the body movement through the scenes rather than to the mind. Mental data (psychological aspects) focus on the mind such as emotion and personality. Visual data are the perception of an individual from an outsider's perspective.

The video-recording method provides researchers with a visual copy of real-world events or situations that have already occurred. This method provides ecological validity due to being visual copies of real life events, which can help compare and validate agent-based models. However, this method can only provide real-world data and behaviours in the form of physical and visual data. For instance, Sakellariou et al. (2014) collected data using video recordings of pilgrim performing the ritual of Sa'yee. The data provided the researcher with visual data of characteristic

Table 1. Comparison of data gathering approaches.

	Video	RW Scenario	User studies	Questionnaires	VR	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

behaviours of crowd and physical data in the form of real-world parameters. Mental data cannot be gathered due to no interaction with the people within the videos.

Real-world scenarios are locations and events that have happened in the real world that are used for research. Researchers model their simulation scenarios based on these events to prove that their project can simulate similar results. For instance, Shao and Terzopoulos (2006) demonstrated realistic human activity by having virtual agents walk around the reconstructed virtual original Pennsylvania train station. Real-world scenarios have a low cost-effectiveness and time efficiency as they can take a long time to run. Physical and visual data can be collected using this method; however, most researchers focus on using this method as a means to modelling their scenarios.

Questionnaires are a research tool that contains a series of questions collecting data from participants. This method allows the researcher to have full control over it as they develop the questions and can limit the possible responses. Jia and Yun (2014) implemented a multiple choice questionnaire to test staff decision-making under stress during a plant fire emergency. The data collected were then used to develop an agent's risk assessment, stress ability and decision-making ability. Questionnaires cannot collect visual and physical data as participants are not asked to do anything except answer questions. This method is better at collecting mental data as it allows researchers to directly ask participants about their personality and emotions.

VR is a virtual world in which real people are able to move and interact. This data gathering method allows researchers to collect a person's movement, actions, behaviours, decisions and responses (Dickinson et al., 2019). Olivier et al. (2014) used VR to examine the behavioural training in VR and the training declarative knowledge about adequate behaviour. They also used VR in the evaluation framework to compare the trajectories performed within a virtual environment to referenced trajectories obtained for either motion capture or generated using a virtual models. VR cost effectiveness can vary depending on the equipment used. For example, virtual simulations can be run using a mobile phone and VR headset or by purchasing an entire VR system such as Oculus Rift (https://www.oculus.com/). VR provides researchers with the ability to gather the visual data through the participants and their own point of view. Physical data can be collected by recording their position using the VR device as a GPS tracker. Although mental data cannot be collected using the VR method, it can be gathered by combining VR with other methods.

1.2. Cognitive architecture

Cognitive architectures (CA) are frameworks that have been designed to represent the process of the human mind. A cognitive architecture contains 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 (Chong et al., 2007). CA has been integrated into many different fields of research such as neurobiology, cognitive psychology, artificial intelligence and crowd simulations (Chong et al., 2007). 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 Belief-Desire-Intention (BDI) (Rao & George, 1995), State Operator And Result (SOAR) (Laird, 2012), Adaptive Control of Thought-Rational (ACT-R) ("Weber, 2012"), Connectionist Learning with Adaptive Rule Induction ON line (CLARION) (Sun, 2006), ICARUS (Langley & Choi, 2006) and Subsumption (Brooks, 1986).

BDI architecture is one of the most used framework in creating intelligent autonomous agents in agent-based simulations. 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 (Chong et al., 2007). 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 is are the actions that a BDI agent is obligated to perform in order to achieve its desires (Chong et al., 2007). The BDI framework provides agent-based simulations with the ability to perceive agents decision-making process in a more human-like manner (Trivedi & Rao, 2018). The BDI framework has been enhanced within agent-based simulations by incorporating psychological aspects like personality and emotions into the BDI framework (Trivedi & Rao, 2018; Zoumpoulaki et al., 2010). Zoumpoulaki et al. (2010) 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 (2011) 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. 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.

SOAR is one of the first ever cognitive architectures designed for artificial intelligence. SOAR was designed to handle many difference routines from simple to complicated through the concept of learning from experience (Chong et al., 2007). It provides an agent-based simulation 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. Lhommet et al. (2011) implements SOAR into the agents decision-making process in order to simulate a crisis, which provides emerging crowd behaviours from the individual agent behaviours based on emotional contagion. Lhommet et al. (2011) enhances their SOAR architecture by adding an appraisal module which is designed to deal with the events of appraisal, social relationships and emotional contagion of the agents.

ACT-R uses empirical data that has been gathered from experiments in cognitive psychology and brain imaging to design and model human cognition (Chong et al., 2007). 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 functional Magnetic Resonance Imaging (fMRI) (Chong et al., 2007). Although 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. Münchow et al. (2014) developed a WALK agent architecture based on the inspiration of the ACT-R architecture. The WALK agent architecture incorporates a declarative memory for long-term knowledge from the ACT-R architecture (Chong et al., 2007; Münchow et al., 2014).

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 psychological tendencies in artificial intelligence.

ICARUS was designed for physical and embodied agents. ICARUS achieves this by integrating perception and actions with cognition (Langley & Choi, 2006). ICARUS can also provide the ability to combine reactive execution with problem-solving, symbolic structures with numeric utilities, provides learning structures, and utilities in a cumulative method (Chong et al., 2007). This cognitive architecture has not yet been implemented into agent-based simulations, and this could be due to ICARUS being a large complex architecture.

Subsumption was designed to be 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 (Chong et al., 2007). 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.

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 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 due to 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.

1.3. Overall agent-based simulation framework

Although there have been some approaches for data gathering and cognitive architecture models, current existing frameworks have either ignored the input phase or have used limited real-word data or non-real-world data. For example, Zoumpoulaki et al. (2010) developed a multi-agent simulation framework using BDI enhanced with personality and emotion implemented into low-level parameters. However, this study failed to include a realistic data collection phase thus also failed to quantitatively evaluate and validate the proposed system.

Other studies have also implemented realistic agent-based frameworks in different ways. One of the widely implemented models of realistic agent-based simulation has been the focus of implementing psychological aspects into agent-based frameworks (Guy et al., 2011). However, most studies have focused on implementing psychological aspects into low level areas of agent-based models (Guy et al., 2011). Studies have incorporated psychological aspects into the high level area of agent-based frameworks; however, this is normally within a single area (Vasudevan & Son, 2011). 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. Also majority of these studies have either not gathered any psychological data from real world to represent real individual's behaviour or have just randomly generated the psychological data to implement into the framework.

There have also been realistic studies that have been conducted by combining neural networks and a data-driven approach towards agent-based simulations (Ma et al., 2016; Song et al., 2018). For instance, Ma et al. (2016) proposed simulating pedestrians movement behaviours based on artificial neural network training. Data were gathered through video recordings and microscopic pedestrian movement behaviour types were collected and placed into an artificial neural network. The data were used to train the neural network which would then be able to predict pedestrian movement within a simulated environment. Another example of this approach is (song et al., 2018) which proposes a multi-scenario adaptive neural network that can model pedestrian behaviour. A four-layer network was implemented that could learn from multiple scenario data by normalisation of the relative positions of the pedestrians. The data gathered for this to be achieved was gathered from recordings real-world experiments. However, these two studies focus only on gathering behavioural data and validating the real-world applications of their research from a navigational level. They ignore the decision-making factor that influences the reasoning behind and drives the navigation. These approaches also ignore the psychological factors that cause these participants to act the way that they do.

Some realistic studies have been conducted within agent-based simulations to improve the real-world by using other forms of decision making methods in place of cognitive architectures (Castilla-Rodríguez et al., 2020; Collins & Frydenlund, 2018; Hesham & Wainer, 2021). For instance, Collins and Frydenlund (2018) investigate strategic group formation by implementing cooperative game theory into group decision-making in agent-based models. Their focus was to improve the decision-making of individuals within groups using game theory, as current methods ignore group dynamics and focus solely on individuality. They implement their approach into a simulation in which agents compete against their neighbours for resources. The agent-based simulation showed their approach could produce a real-world mob scenario due to the agents forming large groups. Their method also revealed the benefit of implementing hybrid systems in which a combination of modelling and simulation approaches with methods/techniques from other fields of research can help develop real-world scenarios. However, this study does not provide any real-world data prior to the implementation of the simulation for comparison or validation which presents this research as only real world in theory. Another example of this approach is Hesham and Wainer (2021) implementation of an advanced agent-based model using Centroidal particle dynamics (CPD), which provide short-range collision-avoidance models for pedestrians in dense crowds. The focus of their research was to prove their method could reproduce multiple key emergent dense crowd phenomena on a microscopic level. To prove this, the agent-based model was implemented with a hierarchy system of three inter-operating levels: a cognitive model (decision-making), a global pathfinding model and the local dynamics model. The method was conducted using multiple real-world traffic-based scenarios such as vehicles driving through high density crowds under normal and emergency situations. Altthough this study has shown they have considered real-world scenarios by comparing their research to dense pedestrian activity at the Shibuya crossing in Tokyo, Japan, there is no detail of the cognitive model used. The cognitive model has not been provided to understand what type of decisions are being considered and how they can be considered realistic. Finally, Castilla-Rodríguez et al. (2020) presented the combined implementation of two different models and simulation levels to analyse the impact of incorporating a new technology within a real environment. The focus of their research was to study how a fleet of automated wheelchairs would affect the performance of a hospital for future improvements to productivity. The two different simulation levels used in this study were low- and high-level simulations. The low-level simulation dealt with performance details (such as speed, sensors and trajectory) of the automated wheelchairs while the high-level focused on the consequences in the form of resource usage and quality of services for a hospital. The simulation was implemented within a real-world hospital scenario which showed automated wheelchairs have the potential to be faster than manually being moved by a person. However, the automated wheelchairs decision-making is shown to be slower than a human being when dealing with unexpected obstacles. The study not only considers realistic scenarios, it is also considering implementation within the real world to improve hospitals. However, this is not to consider 100% agent-based modelling as there is no unique difference within the decision-making made by the AI robots showing no individuality.

2. Realistic cognitive architecture framework

Our proposed agent framework is a modified and refined version of BDI (Luo et al., 2009), and it is depicted in Figure 1. Details of each component are explained in subsequent subsections. The framework

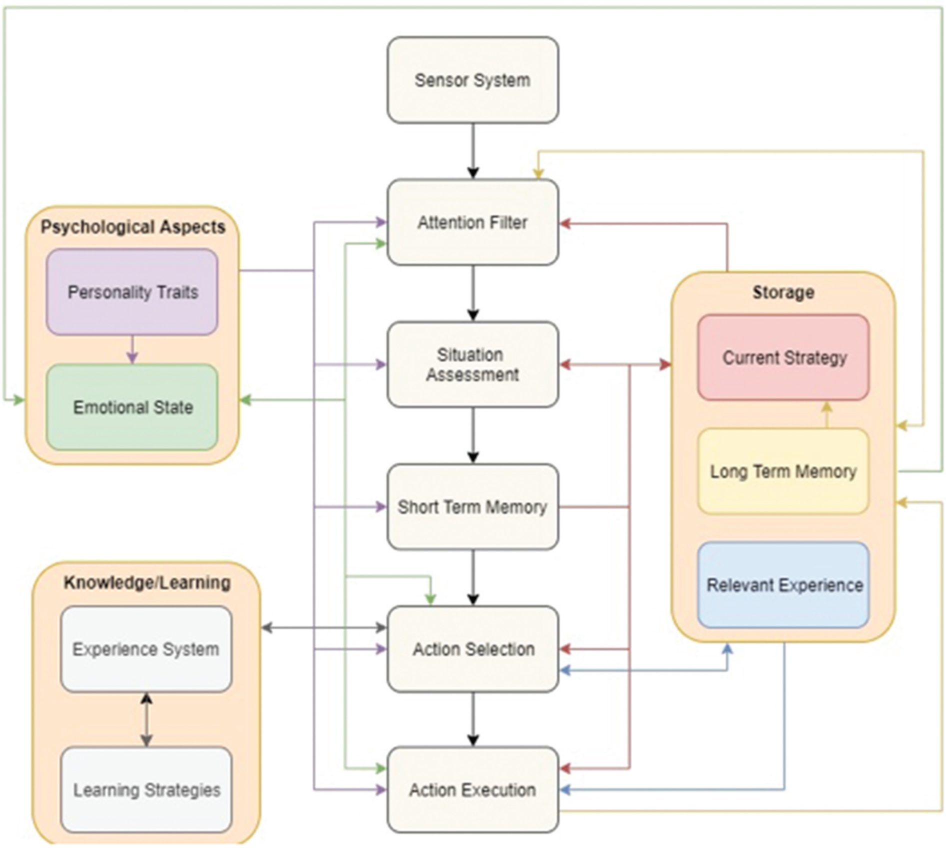


Figure 1. Proposed cognitive architecture framework for agent-based simulations.

has 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 are explained in subsequent subsections.

2.1. Sensor system

The framework starts with determining whether information from the world will affect or influence the agent. In order 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), please see Figure 2 for details. The Sensor System is represented using 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. 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. Each sensor has its own range and angle providing the agent with a sense of realism to their 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.

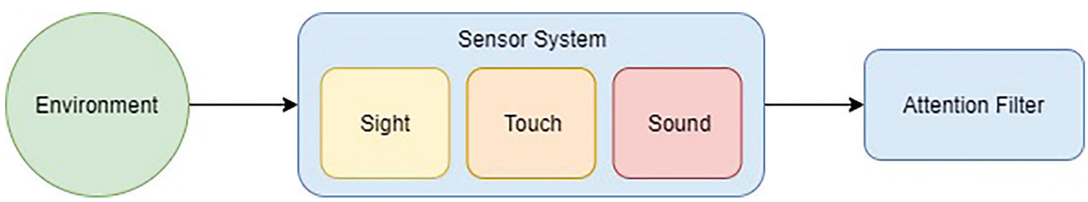


Figure 2. An overall structure of sensor system module.

2.2. Attention filter

Attention Filter is tasked with gathering all the data sent 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 ignore or not process everything they see or hear (Broadbent, 1958; TREISMAN, 1964). 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 3 describes details of Attention Filter.

The probability is calculated in three modules. The first module 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 (Barrick & Mount, 1991). The conscientiousness can represent a person's ability to pay attention to details. The second module 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 module increases or decreases the probability value using the agent's current emotional state. 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 and 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.

2.3. Situation assessment

Situation Assessment focuses on determining what behaviour should be performed based on the each piece of data sent from the Attention Filter module (see Figure 4).

In order to accomplish this, we implement a Multilayered Fuzzy Logic System (MFS) to provide the decision-making process. An 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.

We run four fuzzy systems: Goal-Orientated, Movement-Based, Audio-
Based and Object-Based. First, Goal Orientated Fuzzy System (GOFS) focusing on behaviours related to the agent's goal. The GOFS functions within the experiment by providing the agent with the ability to focus on and search for their goals. These behaviours are: Seek, Explore and Ignore (will be further explained below in behaviour description). GOFS uses fuzzy rules to determine if the data sent is related to the agent's goal and what behaviour is the best suited (see Equation 1). The data's relation to the agent's goal is described using three fuzzy sets: High, Medium and Low (Bede, 2012). For a given set X of goal oriented behaviours and *data* denoted by d, the agent's behaviour is decided as:

$$GOFSBehaviour = max(x_i, d), \quad x_i \in X, \tag{1}$$

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

Second, Movement-Based Fuzzy System (MBFS) focuses on behaviours related to how an agent

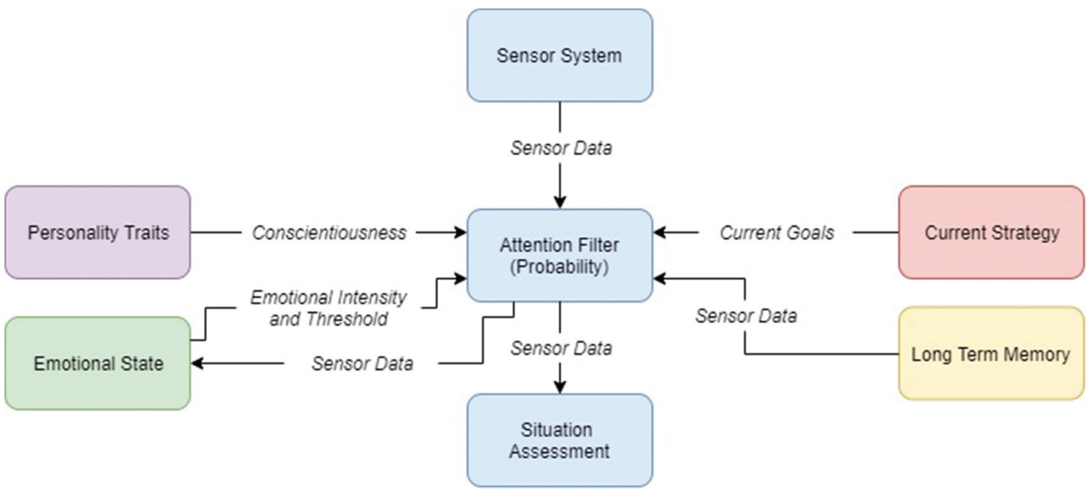


Figure 3. An overall flow of Attention Filter module.

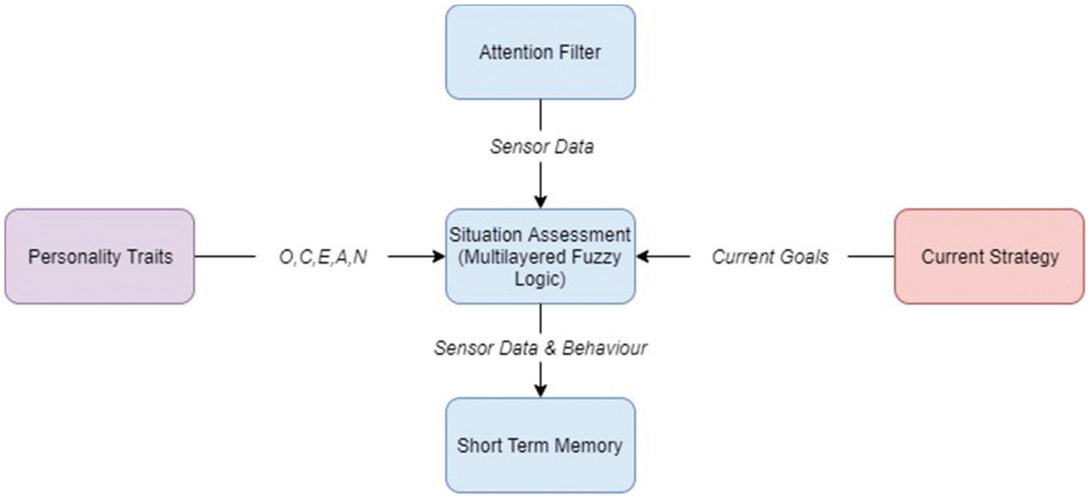


Figure 4. An overall flow of Situation Assessment module.

reacts to its current speed. The MBFS functions within the experiment by providing the agent with the ability to react to the current situation of the crowd and movements in front of them such as congestion agents based on their personality. These movement-based behaviours are: Impatience, Wait and Ignore (will be further explained below in behaviour description). MBFS uses fuzzy rules to determine the behaviour the agent feels based on the movement speed and the agent's personality traits conscientiousness, extroversion and agreeableness. 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:

$$\begin{aligned} MBFSBehaviour &= max[\mu_{y_i}(d), \mu_{c_i}(C), \mu_{e_i}(E), \mu_{a_i}(A)], \\ & y_i \in Y, \quad c_i \in C, \quad e_i \in E, \quad a_i \in A, \end{aligned} \tag{2}$$

where $max[.,.]$ returns the maximum relatedness between two, μ_{y_i} is a function of $y_i \in Y$ that checks the equality of y_i, C is for conscientiousness, E is for extroversion whilst A is for agreeableness.

Third, Audio-Based Fuzzy System (ABFS) focuses on behaviours related to data that have come from the Attention Filter that has audio. The ABFS functions within the experiment by providing the agent with the ability to react to sound from within its surrounding area based on their personality. 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, extroversion and neuroticism. 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:

$$\begin{aligned} ABFSBehaviour &= max[\mu_{y_i}(d), \mu_{c_i}(C), \mu_{n_i}(N), \\ & y_i \in Y, \quad c_i \in C, \quad n_i \in N, \end{aligned} \tag{3}$$

where $max[.,.]$ returns the maximum relatedness between two, μ_{y_i} is a function $y_i \in Y$ that checks the equality of y_i, C is for conscientiousness; and N is for Neuroticism.

Last, Object-Based Fuzzy System (OBFS) is the last fuzzy system and focuses on the data on what type of object it is and what behaviour is suited to it. The OBFS functions within the experiment by providing the agent with the ability to focus on and react to other visual objects that are not goal-related. 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 extroversion 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:

$$\begin{aligned} OBFSBehaviour &= max[\mu_{y_i}(d), \mu_{e_i}(E), \mu_{g_i}(G), \\ & y_i \in Y, \quad e_i \in E, \quad g_i \in G, \end{aligned} \tag{4}$$

where $max[.,.]$ returns the maximum relatedness between two, μ_{y_i} is a function $y_i \in Y$ that checks the equality of y_i, E is for extraversion, whilst G is for the object Goal Relatedness.

Once all data are 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 are 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.

There are 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 due to 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 to share information;
- Ignore: forget the data sent from the Attention Filter.

Once all data are cycled through the Situation Assessment module, the behaviours selected and data related to each of the behaviours is sent 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 are 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.

2.4. 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). This module represents short-term memory as the data is only stored here for a limited time. Short-term memory is the ability to hold a limited amount of information within the mind for a short period of time. Short-Term Memory is designed to store the visual data (Attention Filter data) and be influenced by the mental data (personality). Once the MFS has selected an appropriate behaviour, it is sent along with the data from the Attention Filter to the Short-Term Memory. All the data sent are added to a priority list representing Short-Term Memory. We focus on two key aspects of STM: they are limited capacity and limited time. According to Atkinson and Shiffrin (1971), people have the capacity to store up to seven items at a time on average. We represent this 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). If the priority list reaches to the full capacity, the first behaviour and sensor data in the list are removed making the room for more recent data.

$$PriorityCapacity = 7 * ((O + C)/14), \qquad (5)$$

where O stands for openness whilst C stands for conscientiousness.

According to Atkinson and Shiffrin (1971), STM is very fragile and can only last for a certain amount of time. They claim that the maximum time that information can be retained is between 15 and 30 seconds.

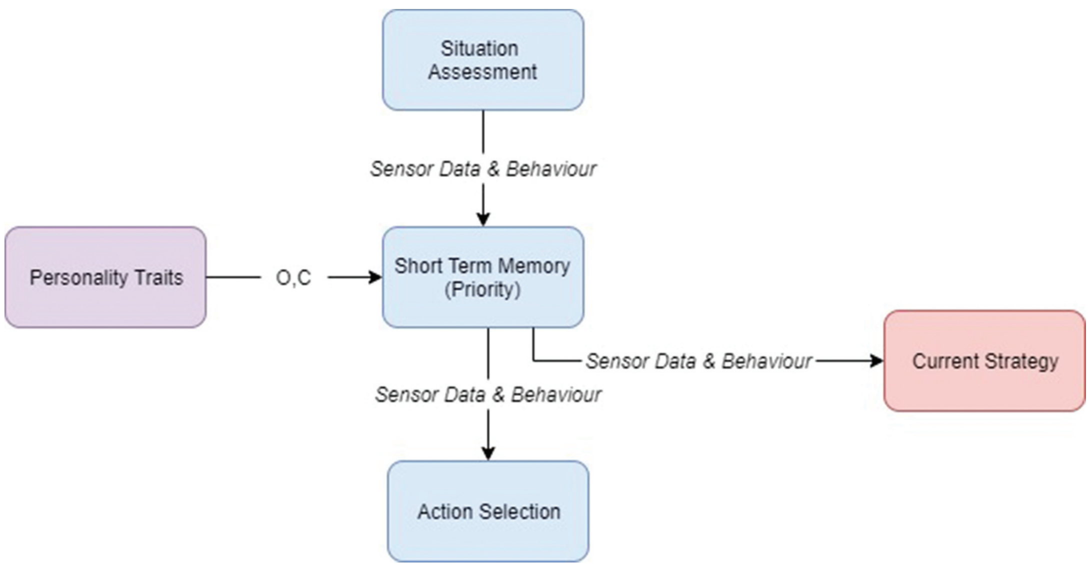


Figure 5. An overall flow of short-term memory module.

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 are forgotten. However, Atkinson and Shiffrin (1971) also state 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 Short-Term Memory within the allocated time frame. In order 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. A value of 0.5 is also given if the behaviour data sent by the sensor data is the same. The second way a priority value can increase is by being related to an agent's goal. If any data within the priority list is similar to the agent's goal, the data's priority value is doubled. This is completed to ensure that 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 Short-Term Memory organises the priority list based on the priority values and sends 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.

2.5. 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 6).

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 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

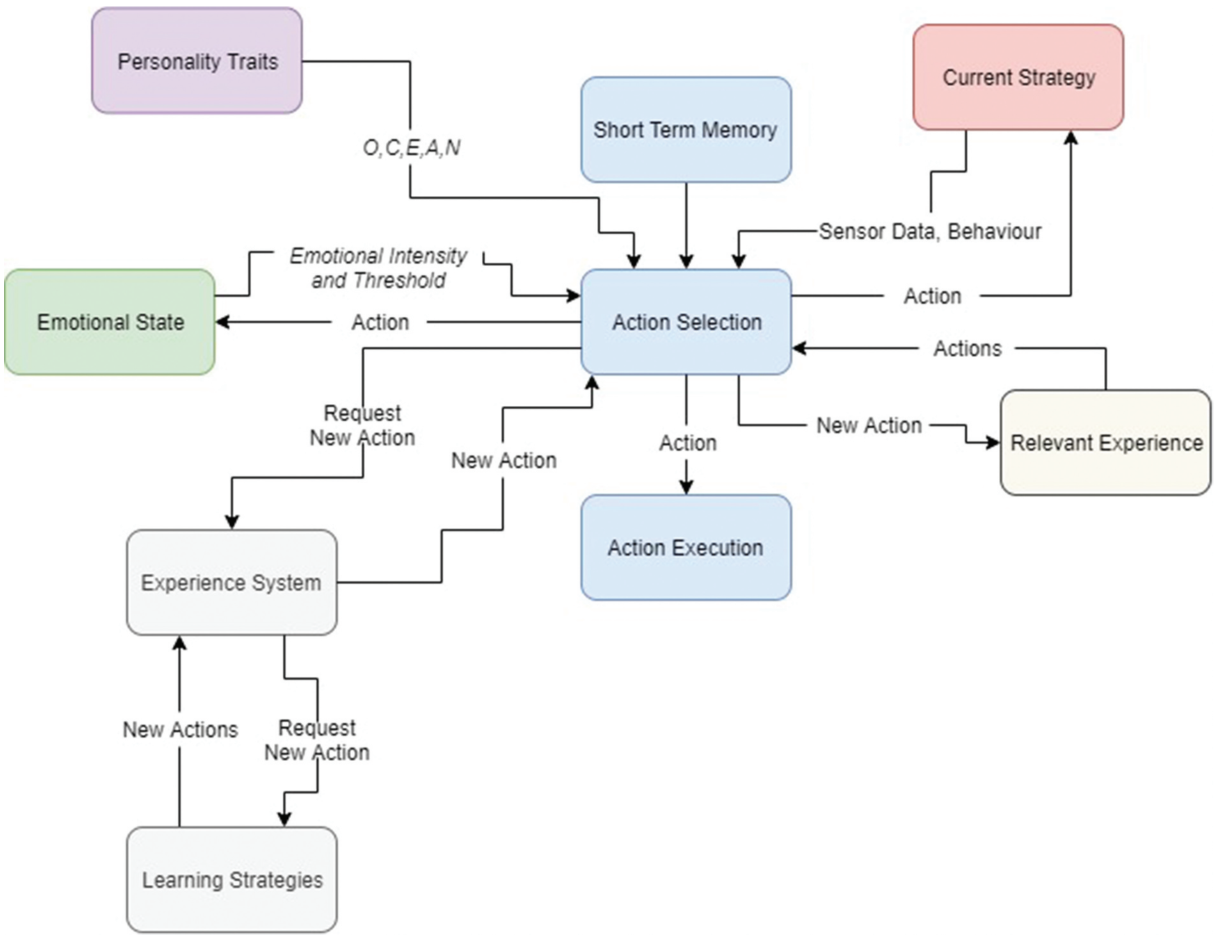


Figure 6. An overall flow of Action Selection module.

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. The Action Selection will then receive a new action and check to see if it already exists in relevant experience. If the agent does not 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 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 their 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.

2.6. 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 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 their 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 too 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 (e.g., 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. 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.

2.7. Storage

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

2.7.1. 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 that are 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. Finally, 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) and visual data (behaviours).

2.7.2. 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. Finally, this module stores the agent's goals and has the ability to send, remove and update them when needed.

2.7.3. Long-term memory

Long-Term Memory (LTM) is where information and knowledge is 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) 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 Bahrick et al. (1975), LTM can only be accessed 60% of the time.

2.8. Knowledge/learning

This stage consists of Experience Systems and Learning Strategies modules.

2.8.1. 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 have 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 that there is no new action available.

2.8.2. 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 that are 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.

2.9. Psychological aspects

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

2.9.1. Personal trait

Personality Trait generates the agent's personality traits using the OCEAN model: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism. This module is designed to influence the low level and high level of the framework using the mental 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 traits 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.

2.9.2. Emotional state

Emotional State generates the agent's emotions using the OCC model (Ortony, Clore and Collins) (Steunebrink et al., 2009). 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. Finally, 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 (Admiration, Anger, Disappoint, Distress, Fear, Fears Confirmed, Gloating, Gratification, Gratitude, Happy For, Hate, Hope, Joy, Love, Pity, Pride, Relief, Remorse, Reproach, Resentment, Satisfaction, Shame) (Steunebrink et al., 2009). 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 goal-based emotions by whether the information is desirable or not. Consequences of events break down into three branches: 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 (Steunebrink et al., 2009), 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. 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 2).

Table 2. Emotion fuzzy rule set.

Emotion	Fuzzy Rule
Joy	IF (Desirability is Desirable) AND (Expectaion 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

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 (El-Nasr et al., 2000). We multiply the desirability 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 of 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 do 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. We use fuzzy logics to check if the information's previous goal relation value matches the new one and if it does then it is confirmed otherwise it is disconfirmed. The agent then re-evaluates its Expectations. After that we apprise one of four emotions (Satisfaction, Fears-Confirmed, Relief and Disappointment) based on the outcome.

The fortune of other branch relates to how the agent feels about another agent successfully or failing to achieve its goal. We compute this using the three fuzzy logic systems: desirability, expectation and appraisal for others. We 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. We appraise the results to one of four emotions: Happy-for, Resentment, Gloating or Pity (see Table 2). The chosen emotion intensity is then increased using the calculation in Table 3. 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.

First, we need to determine if the action was performed by the agent itself or the other agent. For either outcome, we determine the action's praiseworthiness by whether the agent approves or disapproves the results of an action performed. We compute this 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 3. 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 3. 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 are a total of four compound emotions: Gratification, Remorse, Gratitude and Anger. These emotions are calculated based on other emotions (see Table 3).

Table 3. Calculations for the increase of emotion intensity.

Emotion	Intensity Calculation
Joy	((1 − Desirability)* expectations)/2
Destress	(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

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 (Durupinar et al., 2015), and run it every 20 seconds (see Equation. 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 (Durupinar et al., 2015) 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.

$$e_t = e_t - _1 - \beta e_t - _1. \tag{6}$$

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.

Emotional empathy represents the cognitive and emotional reaction of an agent received from another. Based on past studies (Durupinar et al., 2015), 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 (Durupinar et al., 2015) (see Equation. 7) that will be spread to other agents.

$$\varepsilon_j = 0.34\Psi_j^O + 0.17\Psi_j^C + 0.13\Psi_j^E + 0.3\Psi_j^A + 0.02\Psi_j^N.[0, 1] \tag{7}$$

Based on Durupinar et al. (2015), the correlation values empathy ε will take a value between 0 and 1 then compute it for the agent j.

2.10. Algorithm

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

3. Experimental setup

This section discusses the relation between the experiment setup (through the participants, virtual agents and scenario) and how we gather data in order to study agent behaviour.

3.1. Participants

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 and 50 could be adequate (Crouch & McKenzie, 2006; Dworkin, 2012; Guest et al., 2006). 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 (Lohr, 2019) is around 16%. There was no experience (e.g., 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 and 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 and 56 years old with the average age being 28.

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, SD_i), Behaviour List (BL, BL_i), Action (A), Current Action (CA), Current Behaviour (CB), Current Sensor Data (CSD), and Action Success (AS);

1: **procedure** SENSOR SYSTEM
2: Collect SD from Agent sensors;
3: if the number of $SD > 0$ then
4: Send *SD* to Attention Filter procedure;
5: **procedure** ATTENTION FILTER
6: Receive *SD*;
7: Check LTM for *Goal Related Memories* (*GM*);
8: **if** *GM* exists **then**
9: Add *GM* to *SD*;
10: **for** each SD_i **do**
11: Calculate the *Probability* (*P*) of Agent notices SD_i; .
▹ Using Personality, Emotion and Goals (Current Strategy)
12: Generate *Random Value* (*Rand*);
13: **if** *Rand* < P **then**
14: Keep SD_i;
15: **else**
16: Remove SD_i;
17: Send *SD* to Emotional Start module;
▹ Emotional Start module sets SD to the agent's emotional intensity;
18: Send *SD* to Situation Assessment procedure;
19: **procedure** SITUATION ASSESSMENT
20: Receive *SD*;
21: **for** each SD_i **do**
22: Compute *B* from SD_i;
▹ Using Multilayered Fuzzy Logic, Agent Personality, and Goals (Current Strategy)
23: Run Goal Fuzzy Logic Layer;
▹Finds the best behaviour related to the agent's goals
24: if *B* is found then
25: Add *B* to *BL*;
26: Break;
27: Run Movement Fuzzy Logic Layer;
▹ Finds best behaviour related to agent's movements
28: **if** *B* is found *then*
29: Add *B* to *BL*;
30: Break;
31: Run Audio Fuzzy Logic Layer;
▹ Finds the best behaviour related what the agent hears
32: **if** *B* is found **then**
33: Add *B* to *BL*;
34: Break;
35: Run Object Fuzzy Logic Layer;
▹ Finds the best behaviour related what the agent is seeing
36: **if** *B* is found **then**
37: Add *B* to *BL*;
38: Break;
39: Send *BL and SD* to Short-Term Memory procedure;
40: **procedure** SHORT-TERM MEMORY
41: Receive *BL and SD*;
42: **for** each SD_i **do**
43: **if** SD_i *and* BL_i exist in *Short-Term Memory List* (*SML*) then
44: Increase priority of SML_i;
45: **else**
46: Add SD_i *and* BL_i *to* *SML*;
47: Find highest priority in *SML*;
48: Send highest priority SML_i (SD_i,BL_i) to Current Strategy module;
▹ Current Strategy module sets *Di* and BL_i from SM_i to *CSD* and *CB*;
49: **procedure** ACTION SELECTION
50: Get *CSD and CB* from Current Strategy module;
51: Get all known *Actions (A)* from Relevant Experience;

52: **for** each *Ai* **do**
53: **if** *Ai* is related to *CSD and CB* then
54: Add *Ai* to *Related Actions (RA)*;
55: Check if Agent learns new action;
56: **if** RA = = 0 **then**
57: Learn new *A* from Experience System;
58: **else**
59: Calculate probability of learning new action using Agent's Personality (O);
60: Generate *Rand*;
61: **if** *Rand* < *P* **then**
62: Learn new *A* from Experience System;
63: **else**
64: Select an *A* from *RA*;
65: Send *A* to Current Strategy module; .
▹Current Strategy sets *A* as current action
66: Send *A* to Emotional Start module;
▹Emotional Start module influences the agent's emotional intensity with *A*
67: **procedure** ACTION EXECUTION
68: Get *Current Action* (*CA*) from Current Strategy;
69: Perform *CA*;
70: Compute *CA Success Probability* (*ASP*) using *Action Experience* (*AE*) *and Personality*;
71: Generate *Rand*;
72: **if** *Rand* < *ASP* **then**
73: Perform Action Success (AS);
74: else
75: Fail to perform Action Success (AS);
76: Once CA is performed
77: Send AS to Emotional Start module;
78: Send AS to Relevant Experience;
79: Send CA,CSD,CB to Long-Term Memory;
80: Remove CA,CSD,CB from Current Strategy;

3.2. Virtual agent

Eight parameter setting variations of virtual agents were implemented for testing. The parameters implemented in both settings were speed, which represents physical data, personality, and emotion modelling mental data (see Table 4). Visual data cannot be inputted into the parameters as this data type represents external data while the other two represent internal data.

The first setting executed all self-set parameters that were collected from the VR-Q data gathering. 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.

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

Table 4. Parameter range.

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

3.3. Scenario

The scenario was designed to be simple but believable that motivates participants to encounter the design tasks we are evaluating (Da Silva et al., 2011). 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, two entrances/exits, two maps stations and an information centre (see Figure 7). Due to ethical standards footage showing the participants within the real-world and virtual environments was excluded.

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 min to wander freely around the environment, once the minute has passed they were asked to find three booths (archaeology, physics and education) one at a time. When the participant has completed finding all three booths they were asked to go to one of the two exits within the expo and leave. Once the participant reached the exit, the test was completed.

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

Figure 7. Experimental environments: (a) real-world environment; (b) virtual world environment; (c) top-down virtual view of the real-world environment; (d) top-down view of the virtual world environment.

participants would remember where the three 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 three 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 understanding 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 since no noticeable difference was found. To view the VR questionnaire and the real-world questionnaire, see (Sinclair, 2020).

3.4. 4.4 . Data types collected

All data collected from the VR-Q and real-world experiments are used in the comparison with 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.

3.4.1. Physical data

Physical data were collected in the form of distance, time and speed by using the motion suit ability to record and transmit the participant's movements. The 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. The virtual agents physical data were collected employing the same method that was used in collecting the distance, time and speed from the real-world and VR-Q participants.

3.4.2. 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.

In order to gather and measure personality data from the questionnaire, the ten-item personality measure (TIPI) method (Gosling et al., 2003) 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 within a questionnaire. Each of the 10 traits are then measured to one of the five personality traits within the OCEAN model.

Participants were also 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. These 40 emotions represented 20 positive emotions and 20 negative emotions. Based on previous research (Robinson & Kirkeby, 2005) 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 (Ortony et al., 1988) which is then used to compare between the two data-gathering methods.

3.4.3. Visual data

Five types of visual data were collected using participant observation to examine the external behaviour of the participant. This means that all data collected in this section are 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. Second, both experiments presented the participants with two options when starting, and that was either to walk straight or turn left. These data were 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. These data were collected to see if the participants would recognise that there was help set up 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. They were the exit the participants started the scenario, located in the South-west corner or the exit located in the North-east corner. These data were 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 rarely happened between all the participants.

The agent's visual data were collected similarly 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.

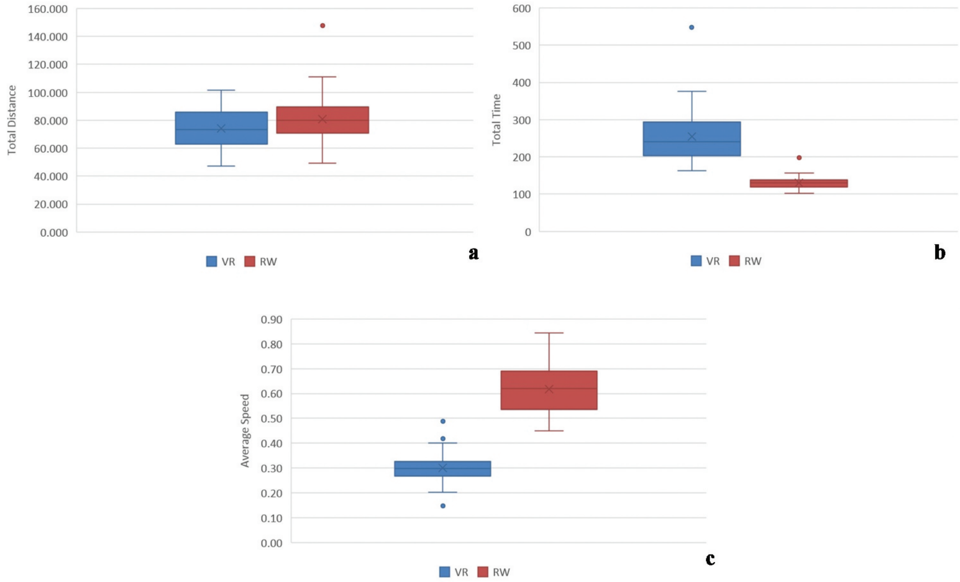


Figure 8. Physical data comparison: (a) total distance (*y*-axis: metre); (b) total time (*y*-axis: second) (c) average speed (*y*-axis: m/s).

4. Experimental results

4.1. Physical data analysis

The results of the physical data are displayed in Figure 8. The total average distance travelled from the two data gathering methods reveals that the VR participants (74.11 m) moved at a similar distance to the real-world participants (80.72 m). 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. 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.

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 (Interrante et al., 2006) 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 (Canessa. et al., 2019) that demonstrates that time does display a significant distance when within a VR environment. Also, cybersicknesss and motion sickness could represent possible reasons for the inefficiency of task completion (LaViola, 2000).

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. 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. An adjusted agent data value is computed as below:

$$AATV = UATV \times \frac{RWTV}{VRTV}, \tag{8}$$

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 (Canessa. et al., 2019; Interrante et al., 2006; LaViola, 2000). After the adjustment, $AATV$ becomes 137.131 which is relatively similar to $RWTV$ (130.766). Equation (8) 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.

4.2. Mental data analysis

The results of the data collected based on the overall average of all participants' personality are compared in Table 5. 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 results showed the VR-Q can provide similar results to the real world. The average personality offset found between the real-world participants, and the VR-Q participants was only 0.21.

The results of the data collected based on the overall average of all participants emotions are compared in Table 6. 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 are extremely similar to the real-world data. 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 5. Average personality comparison (values between 1 and 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

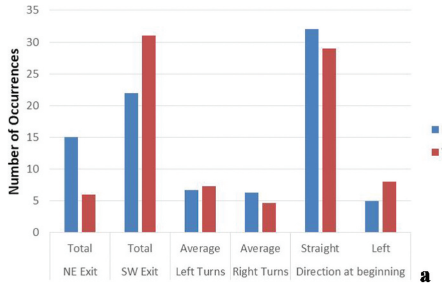
Table 6. Average emotion comparison.

	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

4.3. Visual data analysis

The results of the visual data collected from all participants are compared in Figure 9. During the real-world experiment, only eight 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. This is also due to the user experience with the digital interface. This is consistent with the study (Kuliga et al., 2015) reporting the difference how users experience a real building and a high-fidelity model of the same building.

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) more than right (average of 4.70). In the real-world experiment, participants were given the option at the start to either turn left or walk straight when entering the environment. Note that, this is contextual, and depends on the experimental design. The data collected reveal that 86.5% of the participants would start by walking straight then turning left. In the VR-Q experiment, the participants were given the same option and it was found that 78.4% of participants



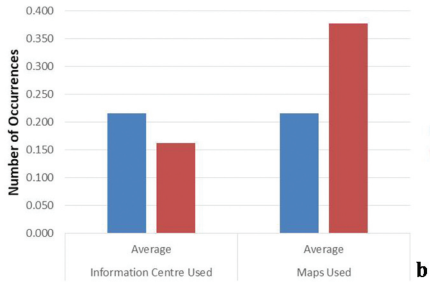


Figure 9. Visual data comparison (*y*-axis: the number of occurrences): (a) visual data; (b) information centres and maps used.

would prefer to walk straight on. Based on these results, VR-Q does not change how people respond or react, which shows that real-world data can come from VR-Q.

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-Qexperiment 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. This again supports the VR-Q approach could provide real-world data for agent-based simulations.

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 was not 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.

4.4. 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. 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.

5. Further experimental results with various agent settings

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. A chi-square goodness-of-fit test is also used as a significance test to compare the different data sets.

5.1. Physical data analysis

A two-sample equal variance t-test (McCarroll, 2017) on the physical data which includes distance, time and speed from both tests and compared them to the VR-

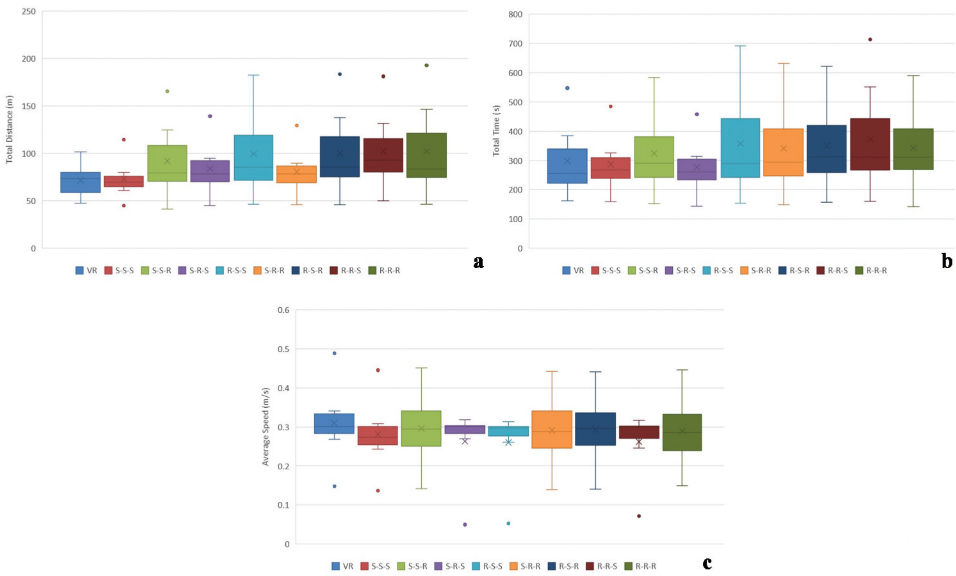


Figure 10. *t*-test on physical data (Personality-Emotion-Speed; S: Self-set, R: Random): (a) Average total distance; (b) Average time; (c) Average speed.

Q physical data results (see Figure 10). 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 (Self-set Personality – Self-set Emotion – Self-set Speed) 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 is 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 10 and Table 7.

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 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 interval, between the set parameter agents (*m*=267.4; *sd*=65.29) and the VR-Q participants (M = 255; SD = 74.08). However, S-R-S produced a less 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 provide similar results to the VR-Q

Table 7. Two sample *t*-test of equal variance total average distance comparison with 95% confidence interval.

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

Table 8. Two sample *t*-test of equal variance total average time comparison with 95% confidence interval.

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

participants over the other six 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 10 and Table 8. What was also be 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.

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 interval 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 8 and Table 9), showing the S-S-S parameter agents are able to maintain a similar designed pace. 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 9. Two sample t-test of equal variance average speed comparison with 95% confidence interval.

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 finally 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 requirs an adjustment factor in order to minimise the physical movement

Table 10. 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

gap between the real world and the VR world caused by cybersickness, motion sickness or perception difference (Canessa. et al., 2019; Interrante et al., 2006; LaViola, 2000). Past studies (Canessa. et al., 2019; Interrante et al., 2006; LaViola, 2000) 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 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 interval.

5.2. 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 11. 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.

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 10. Although 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.

Finally, it was revealed that all the parameter variations agents experienced more positive emotions than negative, which coincides with the VR-Q participants results collected. 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.

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, revealed all parameter variations of the test showed significantly

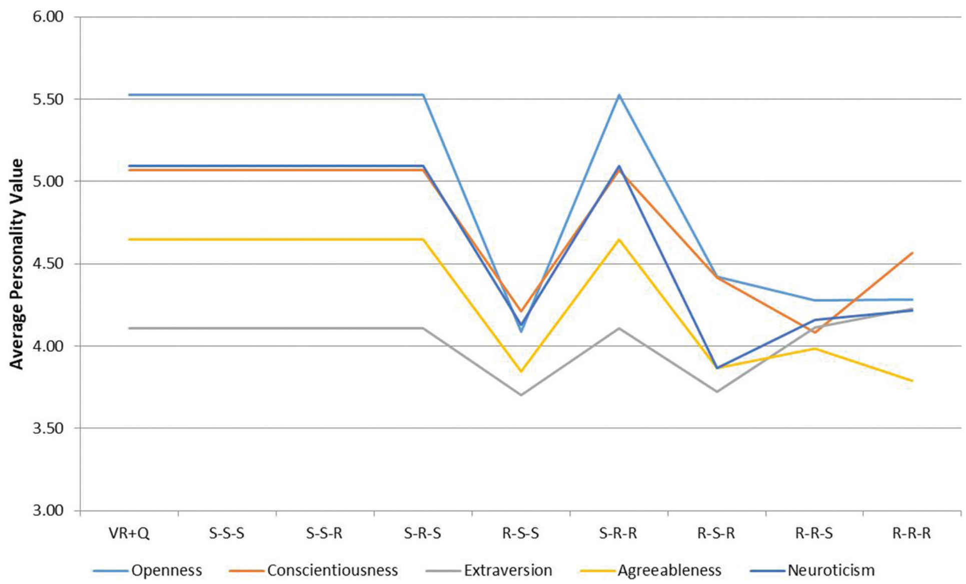


Figure 11. A comparison of OCEAN personality (y-axis represents the average personality value across all agents).

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 interval and can be used from crowd simulations to represent real-world data.

The personality statistical significance test 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 have shown this framework is capable of producing real-world data for agent-based crowd simulations.

5.3. Visual data analysis

The results from the visual data collected from the agents are compared in Figure 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 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. Although 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 12). What was also revealed was the S-S-S

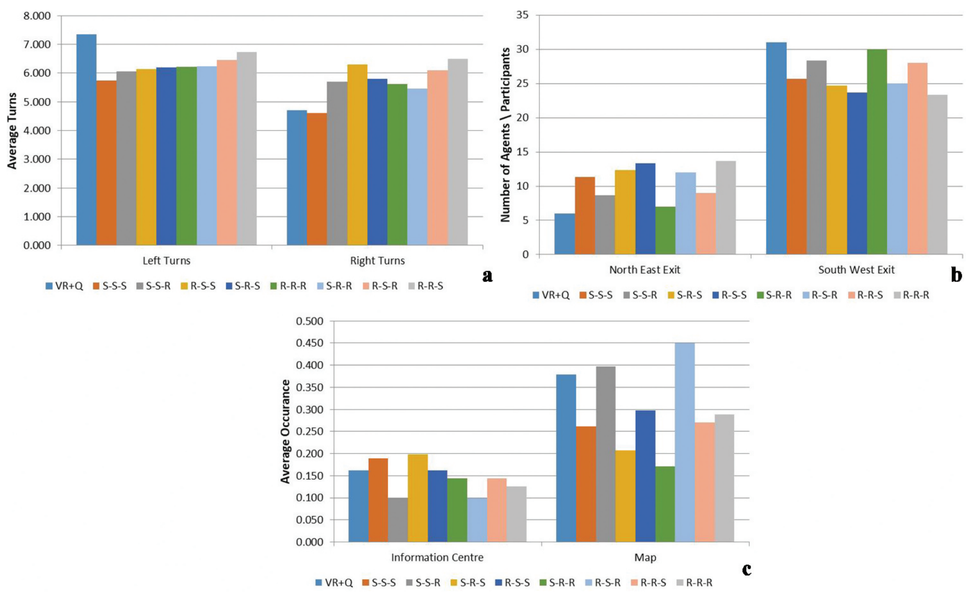


Figure 12. A comparison of visual data collected (x-axis represents the number of instances). (a) Left vs Right Turns; (b) Exits Used; (c) Average use of Maps and Information Centre.

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 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 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. 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.

5.4. 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. 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.

6. Conclusion

In this paper, we discussed that current data gathering methods do not collect all three data types (visual, mental, physical) for agent-based simulations. We also discussed that because of this all three data types have not been implemented into developing and validation of agent-based frameworks to produce real-world data. We have addressed the first issue by using (Sinclair et al., 2020), which combines the VR and questionnaire to form the hybrid data gathering method called VR-Q. The second issue has been addressed by using the data collected from the VR-Q method to develop an agent-based framework using all three data types. We also used the VR-Q data to validate the output data from the framework to compare whether the framework can produce real-world data.

We propose a flexible agent-based simulation model that systematically incorporates three types of data in order to produce realistic crowd simulations. Extensive experimental results demonstrate that our proposed data gathering approach, VR-Q, is able to generate realistic data capturing physical, mental and visual information. In addition, broad experimental results show superior performance of our proposed fuzzy-logic and probability-based cognitive architecture with a case study. Statistical tests have been conducted to validate our framework.

To further prove that this framework has the potential to provide a more realistic data and be compared to the real world further testing can be conducted. Combinations between the set and random parameters (e.g. Set Personality, Random Emotion, Set Speed) can be conducted to further provide validation of the current results and the frameworks diversity. In the future research, a case study can be conducted to validate the framework flexibility and adaptability to different scenarios and environments.

Disclosure statement

No potential conflict of interest was reported by the author (s).

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