Simulating Personality and Emotion in AI Agents through Individual-Based Modelling

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Contents

Abstract

The believability of artificial intelligence agents has become a crucial part of creating a positive player experience due to the development of more complex decision-making methods, raising the standard for believable AI agents within games and simulations. Agents within a population are often overlooked, demonstrating standard behaviours defined for the population as a whole and revealing very little uniqueness. Creating agents with individuality aspects, such as personality and emotion, has great potential to provide differential behaviours and improve upon typical populations to increase realism and dynamism. Scalable decision-making methods were researched, along with suitable techniques represent personality and emotion. An artefact was developed to investigate the effect that the OCEAN personality model and Plutchik's emotion model has on the believability of agents within a population. A Goal-Oriented Action Planning system was created, along with integrated personality and emotional parameters to decide on subsequent actions. The personality values are used as multipliers for the emotion values, causing varying emotional intensities and actions among the AI population. This artefact was tested against a questionnaire, providing valuable information regarding the connection between AI believability, the agent's actions and individuality characteristics. The study proved that simulating individual agent's personality and emotion can lead to believable emergent behaviour within a population, provoking alternative actions dependent on agent individuality.

Glossary

AI – Artificial Intelligence

BT - Behaviour Tree

DAG – Directed Acyclic Graph

EmoBet - Emotional Behaviour Tree

FSM - Finite State Machine

FuSM - Fuzzy State Machine

GOAP - Goal-Oriented Action Planning

HFSM - Hierarchical Finite State Machine

IBM - Individual-Based Modelling

LLM - Large Language Model

MAS - Multi-Agent Systems

MBTI - Myer-Briggs Type Indicator

NPC – Non-Player Character

OCC - Ortony, Clore, and Collins

OOP – Object-Oriented Programming

Introduction

Despite the advancement of Artificial Intelligence (AI) in many different technology sectors within the last decade, unique agents that can express emotion and personality are less commonly implemented within AI populations in games (Belle, et al., 2019).

AI in games can vastly range from a simple interactable Non-Player Character (NPC) to complex systems that aid world generation and story progression. However, as NPCs have the capability to traverse the environment, this makes them a stand-out and dynamic part of the otherwise static game world. Games will also have different requirements and complexities for these NPCs depending on varying factors, such as story and scope. However, the strive for AI believability has become more apparent in recent years, as intricate techniques and tools have been introduced to create more authentic characters. Believable AI could have a substantial impact on a game's success, as a realistic NPC is more likely to keep a player engaged for much longer than a simple and diluted version of the same character. This is because an increase in immersion and believability causes the player to retain focus, maintaining the illusion of realism within the game (Poivet, 2023). Once broken, the illusion is shattered, and engagement is lost. Due to this, AI believability is an incredibly important factor in increasing the general gaming experience. Therefore, improving the behaviour and believability of NPC AI in games could create a more immersive experience.

Cohesive AI populations can be important to create realism within a game environment. Whether the population consists of animal-based agents or human-based agents, this population must behave in a convincing manner to be believed by the player (AlJamma, et al., 2023). Complex Wildlife agents are only present within a small number of games that usually have an emphasis on the environment, such as Red Dead Redemption 2 (Rockstar, 2018). In this game, there are a vast number of different animals that closely replicate their real-life counterparts; interacting with each other to display predator/prey behaviours and pack behaviours, all which the players would expect to see exhibited by real wild animals. Human-based AI populations are more widely used, usually imitating towns and villages within different environments and genres. This is also seen in Red Dead Redemption 2, as many different AI populations are used to populate different settlements and gangs. These populations exhibit expected behaviour based on their role in the game, influencing the player's decisions and experience.

One way to increase the complexity and realism of AI populations is to add aspects of individuality to each agent (Baffa, et al., 2017). This adds extra depth to the population, as the members can exhibit different behaviours to make the overall look and feel of the population much more dynamic. The addition of emotion could allow each agent to be affected by certain situations, giving different reactions depending on how they feel. Moreover, giving each agent a personality could push this further, by altering the intensity of certain emotions that aligns with the agent's personality to provoke adapting reactions. These additions could work in tandem to vary behavioural outcomes and create the illusion of self-motivation and experience in each agent.

Few games include this level of individuality, but one such game to achieve this is The Sims 4 (Electronic Arts, 2014). The Sims 4 includes emotion and personality within its agents to create varying behaviours and interactions. The addition of this type of individuality increases the uniqueness and depth of each agent, making them much more realistic to the player (Belle, et al., 2022). If this type of individualism was added to every agent with an AI population, it could create dynamic and emergent behaviour that can be unpredictable, but still believable to the player.

Aims and Objectives

AI believability will be investigated, focusing on AI populations. Specifically, whether realistic, individually behaving agents with differing personalities and emotions could prove beneficial to a game world/simulation. An artefact will be developed, and the results will be tested to evaluate the believability of the agents to assess the potential for implementation of this type of AI in game worlds/simulations. To do this, the following aim and three objectives were derived:

- **(RQ1) Can the implementation of complex agents enhance a simulation's AI believability?** This is to evaluate whether the improvement to this type of AI can add to overall AI believability and improve player experience.
- **(RQ2) Can the addition of personality and emotion accurately differentiate behavioural outcomes to increase AI believability?** This is to evaluate the addition of emotion and personality, and whether these features work well together to create emotional behaviours and impact in certain scenarios.
- **(RQ3) What are the best methods for creating emergent behaviours with consideration of individuality aspects?** This is to test the implementation of the core features; to implement a scalable system that also uses the agent's emotional state and personality as parameters for decision-making.
- **(RQ4) What are the considerations needed to create a simulation involving individual-based modelling?** This is to investigate the implementation techniques and overall considerations for creating a simulation featuring many individually behaving agents, conveying this information in a clear way.

These questions are to be tested and evaluated against the primary research undertaken at the end of the artefact development to assess the success and viability of this research.

Literature Review

AI Believability

The implementation of believable AI is incredibly important for player experience, directly affecting player immersion and engagement during gameplay (Livingstone, 2006). Whilst playing a game, the player is controlling a character within a fictional world. This creates an illusion, in which the game world becomes more believable and rational over time through continuous gameplay. When an NPC is more believable to a player they are more likely to retain active focus, as the character mimics expectant behaviour and a sense of lifelikeness (Poivet, 2023). This creates a suspension of disbelief, in which the player is more likely to believe in the fictional world that they are interacting with (Rosenkind, 2015). As believability is linked directly to the perception of the player, understanding how players perceive believability and how this affects engagement is crucial in understanding how to improve and develop believable AI.

Believability vs Realism

There is a common misconception that believability and realism are the same. Yet, this is not the case; in games, believability- specifically, character believability- not only relies on the player's perception and expectations of AI (Emmerich, et al., 2018), but also the life experiences of the player (Simonov, et al., 2019), meaning that the evaluation of the believability of AI may differ between players. Character believability is constructed of a variety of different factors that all collate to form a believable NPC. One of these factors is realism, which defines the closeness of replication of real-life scenarios, characters, and other behaviours. The other factors that add to the believability of an NPC within a game include, but are not limited to (Guo, et al., 2023):

Behaviour

A character's behaviour must reflect their role in the game, acting accordingly and as the player expects in the given situation. The NPC behaviour and actions must be coherent and understandable by the player.

Awareness

Awareness is a broad term, referring to the character's capability to react appropriately to their surroundings, other NPCs, and potentially themselves. This creates the illusion that the NPC is conscious and alert of what is happening around them.

Emotion

Characters must be able to react to certain events around them and reflect how they feel, whether this is in connection to their personality, needs, or other NPCs. This expression of emotion shows uniqueness, conveying that this character has their own thoughts and feelings.

Personality

This overarching term ties closely with the other listed factors. The personality of an NPC should influence their behaviours greatly and is the fundamental addition to convey individuality. This addition is about creating unique and distinguishing agents, mitigating an overall generality between agents (Rosenkind, 2015). This can be conveyed in many ways, including: appearance, social cues, and behaviour. The NPC's actions should reflect their personality, conveying this clearly and coherently in different situations (Slorup Johansen, et al., 2022).

These factors, and many more, all contribute to the overall believability of an NPC in a game world as they give the illusion of life and individuality (AlJamma, et al., 2023). Despite this, the AI agent should aid the gameplay experience for the player. This fun factor is much more important than the agent's intelligence or believability, as the enjoyability of the game is ultimately the main goal for satisfying players (Umarov & Mozgovoy, 2012). This means that the AI's believability should only contribute to the fun factor of a game, otherwise the addition of these agents may be considered detrimental to the game. This fun factor and notion of AI believability is a delicate balance; a more powerful and omniscient agent can potentially be less believable and less fun, depending on the situation and role of the agent. In situations where the player is directly against the agent in some way, it would be considered unfair if the agent constantly outsmarted the player, winning every battle. This must be balanced, giving the player some chance to succeed to create a more believable AI and increase both immersion and fun for the player.

Measuring Believability

It is important to measure the believability of AI to determine the success of the implementation and impact on players, concluding whether any changes need to be made. There are various methods that can be used to measure the believability of AI based on the perception of players (Togelius, et al., 2012):

Subjective

This method of testing involves receiving feedback from players directly, through either free response form or questionnaire (Togelius, et al., 2012). Free response can allow the player to provide extensive feedback, detailing exact positives and negatives. However, the feedback from this method is often difficult to analyse and will often be summarised into short phrases. Moreover, this feedback cannot be enumerated into graphs or other analysis methods, which makes investigation of this data much more difficult and clouds the success of the test.

The reliability and effectiveness of questionnaire results is entirely dependent on the type of questions asked, which factors of believability are tested, and the relevance of the questions for the type of AI designed. Ideally, a standardised AI believability test should be used to collect data regarding different AI implementations to accurately compare results and determine the success of an AI's believability. A standardised test has been suggested (Guo, et al., 2023), which contains 36 questions covering many factors of believability, including: visual properties, behaviour, awareness, social relationships, intelligence, emotion, personality, agency, and overall believability. When using this standardised questionnaire, questions can be removed so that only the relevant aspects implemented are tested.

Due to the perception of AI believability being entirely subjective to the player, certain believability measuring methods can be biased (Livingstone, 2006). This makes some methods more unreliable than others, such as questionnaires.

Objective

An objective AI believability test may include facial/body tracking to record the player's responses whilst completing the test. This can measure the player's attention by measuring the player's head movement and eye gaze (Asteriadis, et al., 2008). This is done to observe where the player is most focused and immersed.

Gameplay-based

Gameplay-based believability testing involves the game itself, recording data from the player's experience and logging this throughout. This type of method could be used to determine the player's predicted feelings about the overall experience and any trends between players (Pedersen, et al., 2010).

Individual Behaviours

To implement believable agents in a simulation, natural behaviours must be explored to understand how and why these behaviours take place. Moreover, the differences in personality must be considered, as this can have an outstanding impact on the behaviour and outward emotion of a person/animal. The inclusion of personality and emotions is also incredibly important in establishing realistic and crucial behavioural differences in every agent, providing individuality.

The Aim of Individuality

AI believability falls heavily on the perception of the player and the agent's closeness to real-life equivalents (Emmerich, et al., 2018). Part of this realism can be explored in the form of individuality. Unique thoughts, feelings, and reactions to certain events only enhance and advocates for the person's opinions and beliefs. Differences in likes and dislikes is crucial within human and animal behaviour, creating distinctive personalities that enhance many aspects of life.

This can be implemented into an AI agent to replicate these traits and simulate an agent that seemingly has a unique personality. This increases realism, as this type of agent can act according to their beliefs, traits, and emotions, resonating with the player. This creates diverse behaviour and complex agents within the simulation/game environment.

Personality Models and Classifications

Before implementing this type of behaviour in an AI agent, different personality theories must be understood to accurately replicate differing behaviours and how these influence other characteristics.

OCEAN/Five-Factor Model

One model is the OCEAN model, also known as the Five Factor-Model. This model describes five personality types that affect different relevant traits to have more, or less, of an impact in certain scenarios (Baffa, et al., 2017). The personality types and traits are as follows (Li, et al., 2007):

Openness

Openness describes a creative and independent-minded individual, depicting someone who is likely to think imaginatively and open to new ideas/experiences. This may also define someone who is open to self-examination and change.

Conscientiousness

This personality type describes someone who is organised, reliable, and self-disciplined. They are usually very dependable, completing work on time and always punctual.

Extraversion

A person with the Extraversion personality type is usually very outgoing, sociable, and talkative; loving to interact with other people, as communication is a strong skill.

Agreeableness

Agreeableness describes a good-natured and sympathetic person, often thriving in co-operative environments. This type of person is often trusting and kind to others.

Neuroticism

This personality type tends to experience more negative emotions, such as anxiety, jealousy, and guilt. They may present as very nervous and insecure.

Figure 1 displays the traits that are associated with each factor of OCEAN. The high score traits increase that factor's prevalence, whereas the low score traits decrease this. Moreover, each OCEAN factor affects certain emotions, altering the intensities so certain emotions are shown more and others less, due to the agent's personality. This creates agents with different emotional states, and when applied to an agent's decision-making, this creates dynamic and emergent behaviour.

	High Score Traits	Low Score Traits
Openness	Creative, Curious, Complex	Conventional, Narrow, interests, Uncreative
Conscientiousness	Reliable, Well-organized, Self-disciplined, Careful	Disorganized, Undependable, Negligent
Extraversion	Sociable, Friendly, Fun-loving, Talkative	Introverted, Reserved, Inhibited, Quiet
Agreeableness	Good natured, Sympathetic, Forgiving, Courteous	Critical, Rude, Harsh, Callous
Neuroticism	Nervous, High-strung, Insecure, Worrying	Calm, Relaxed, Secure, Hardy

Figure 1 Traits associated with each OCEAN factor (Li, et al., 2007).

Myer-Briggs Type Indicator

The Myer-Briggs Type Indicator (MBTI) personality classification model describes eight traits (comprised of four opposite pairs) that can be chosen and combined with other chosen traits to create a four-letter personality classification. This creates a total of 16 possible combinations acting as different personality types. The eight traits are as follows (Randall, et al., 2017):

Introversion/Extraversion

This classification describes how a person behaves socially. A person with the extraversion classifier is more outgoing and social, focusing their time and energy outwards on other people and the world. The opposite describes a person with introversion; depicting a person who is quieter and focuses their time inwards, enjoying alone time more than large social settings.

Sensing/Intuition

This classification describes how a person processes information. Sensing describes more observant people that can view the real situation at hand. However, people with the intuition classifier often spot patterns and can view situations from a different perspective, providing further insight and possibilities.

Thinking/Feeling

This classification describes a person's decision-making process. People with the thinking classifier focus on the logical solution to a scenario, often acting rationally and sensibly after examining the scenario. People with the feeling classifier are the opposite; often considering the thoughts and opinions of others before committing to an action, siding with their beliefs rather than logic.

Judging/Perceiving

This classification describes how a person lives day-to-day. A person with the judging classifier tends to plan their day and enjoys having control over their daily activities. However, a person with the perceiving classifier likes to live spontaneously, letting their day happen organically without any rigid structure.

The MBTI is one of the most widely used tools for personality classification. This method has been used in many studies to determine performance differences (Ke, 2024) and emotional intelligence variations (Furnham, 2024) between people with different personality types. It has also been frequently used outside the field of psychology, proving a useful tool in AI development. The MBTI model has also been used both in conjunction with the OCEAN model (Baffa, et al., 2017) as these models can be converted to one another, and alone as a personality classifier for NPCs in games (You, 2009).

Emotion theories

Emotions are affected greatly by the personality of an agent. Different traits and personality types cause certain emotions to appear more and others to appear less, as the agent's reaction to certain events is entirely dependent on its personality. There are many theories and models created to understand and classify different emotions.

Ortony, Clore, and Collins Model

Another emotion theory is the Ortony, Clore, and Collins (OCC) Model. This model suggests 22 emotions, ranging from joy to hate (Belle, et al., 2022), with 11 positive emotions and 11 negative emotions (Li, et al., 2007); see for the 22 emotions and their descriptions.

Joy:	(pleased about) a desirable event
Distress:	(displeased about) an undesirable event
Happy-for:	(pleased about) an event presumed to be desirable for someone else
Pity:	(displeased about) an event presumed to be undesirable for someone else
Gloating:	(pleased about) an event presumed to be undesirable for someone else
Resentment:	(displeased about) an event presumed to be desirable for someone else
Hope:	(pleased about) the prospect of a desirable event
Fear:	(displeased about) the prospect of an undesirable event
Satisfaction:	(pleased about) the confirmation of the prospect of a desirable event
Fears-confirmed:	(displeased about) the confirmation of the prospect of an undesirable event
Relief:	(pleased about) the disconfirmation of the prospect of an undesirable event
Disappointment:	(displeased about) the disconfirmation of the prospect of a desirable event
Pride:	(approving of) one's own praiseworthy action
Shame:	(disapproving of) one's own blameworthy action
Admiration:	(approving of) someone else's praiseworthy action
Reproach:	(disapproving of) someone else's blameworthy action
Gratification:	(approving of) one's own praiseworthy action and (being pleased about) the related desirable event
Remorse:	(disapproving of) one's own blameworthy action and (being displeased about) the related undesirable event
Gratitude:	(approving of) someone else's praiseworthy action and (being pleased about) the related desirable event
Anger:	(disapproving of) someone else's blameworthy action and (being displeased about) the related undesirable event
Love:	(liking) an appealing object
Hate:	(disliking) an unappealing object

Figure 2 All 22 emotions and their descriptions from the OCC model (Steunebrink & Dastani Mehdi, 2009)

The emotions are a product of internal and external stimuli (Li, et al., 2007), including communication with other NPCs, interactable objects, and events. Emotions can also be influenced by an agent's personality, as certain traits and characteristics can make certain emotions much more likely (Ma, 2011).

This model includes the intensity of an emotion, stating that an emotion occurs and becomes prominent within the agent when the potential of that emotion exceeds a certain threshold, which is calculated using intensity (Gluz & Jaques, 2017). This occurs as the result of an appraisal evaluation process, in which the agent compares the outcome of a situation in relation to their own goals and desires. This creates negative emotions if the situation hinders their goals, and positive emotions if the situation aids their goals.

This model is excellently adapted for usage with other personality models and is widely used with the OCEAN model (Orozco, et al., 2010), allowing the classification of personality with an emphasis on how this affects emotions.

Plutchik’s Model

One emotion theory derived by Plutchik (2001) describes the connections between eight primary emotions and their intensities. The eight primary emotions described by Plutchik are: joy, sadness, anger, fear, trust, disgust, surprise, and anticipation. Figure 3 presents the relationship between these emotions and how primary emotions can combine with neighbours to create secondary emotions.

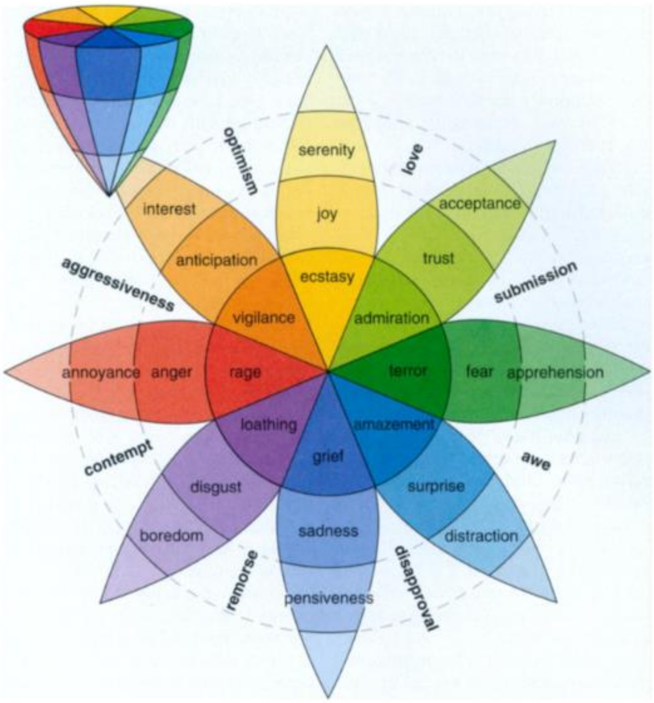

Figure 3 Plutchik’s emotion model describing the connection of different emotions, their products, and their intensities (Plutchik, 2001).

Plutchik describes ten postulates to explain the purpose and classification of these emotions (Kamińska & Pelikant, 2012), describing their interconnectivity and role in creating more complex secondary emotions.

One of Plutchik’s postulates suggests that emotions serve as a primal indicator for certain survival threats, aiding certain instinctive behaviours such as the fight or flight response (Baffa, et al., 2017). The fight or flight response is usually triggered in situations that provoke fear, causing the receiver to act instinctively in one of two ways: extreme fear- triggering behaviours such as running away or freezing in place (Handler & Honts, 2008), or defensively- in which the receiver acts with violence in order to protect themself from the given threat. These opposite reactions can be summarised to two opposite emotions: anger and fear. This highlights another one of Plutchik’s’ model’s principles, which states that primary emotions can be pairs or solar opposites (Kamińska & Pelikant, 2012). The pairing of primary emotions can be described in four different ways, known as dyads (Baffa, et al., 2017).

Primary dyads are adjacent on the wheel and are experienced most often, such as joy and trust. Secondary dyads have 2 axis distance between them and are not experienced as often as primary dyads, such as joy and fear. Tertiary dyads have three axis distance between them and are experienced even less than primary and secondary dyads, such as joy and surprise. Lastly, opposite dyads are in opposite positions on the wheel and cannot be combined, such as joy and sadness.

Bicalho et al. (2020) describes an implementation using both OCEAN and Plutchik's model, with the factors of OCEAN affecting certain emotion values. Figure 4 demonstrates this relationship; with each OCEAN factor altering the likelihood for an emotion to appear and be more intense.

PERSONALITY TRAITS INFLUENCING POSITIVE EMOTIONS

Fear	Trust	Joy	Surprise	
-1	1	1	-1	O
0	0	0	0	C
0	1	1	1	E
0	1	1	1	A
1	-1	-1	1	N

PERSONALITY TRAITS INFLUENCING NEGATIVE EMOTIONS

Anger	Disgust	Sadness	Anticipation	
0	-1	-1	-1	O
-1	0	1	1	C
0	0	1	-1	E
0	-1	0	-1	A
1	1	1	1	N

Figure 4 The effect of OCEAN on the emotions in Plutchik's model (Bicalho, et al., 2020)

Emotions In Non-Human Species

Deciphering emotions in non-human species is a problematic task due to communicative, cognitive, and evolutionary differences, making it difficult to measure indicators of emotion (Mendl, et al., 2022). Moreover, there is a lack of familiarity and clarity when testing animal emotions, as the felt emotion cannot be confirmed.

The Plutchik model is valid for non-human species, as he states that emotions are applicable to all evolutionary levels but are expressed in a variety of ways for different species (Kamińska & Pelikant, 2012). Due to this, similarities can be observed when certain emotions are expressed in many different species.

However, there are other theories focusing on the classification of animal emotions. One theory suggested by Panksepp (2011) defines seven primary mammalian emotions: SEEKING, FEAR, RAGE, PANIC, LUST, CARE, and PLAY. Much like the primary emotions defined by Plutchik, these emotions play a vital role in the survival of the animal, eliciting appropriate responses to certain stimuli to evade threats. These emotional states are described as follows:

SEEKING

This emotion promotes motivation and learning in the form of exploring and survival; ensuring the animal seeks out basic resources such as food and water. This causes the emotion to produce certain behaviours such as hunting and foraging.

FEAR

This emotion helps animals, especially prey, to escape dangerous and life-threatening situations. This contributes to the freeze and flee responses when faced with a fight or flight scenario.

RAGE

This emotion enforces violence in frustrating and restraining situations. This emotion contributes to the fight response in a flight or fight scenario, aiming to cause FEAR in their opponent.

PANIC

This emotion, also known as the Separation Distress PANIC System, is a primal response by young mammals, signalling distress and invoking an immediate response from the maternal figure. As young animals as solely dependent on others, this response is crucial for survival.

LUST

This emotion promotes reproduction, the predecessor of the CARE emotion for maternal figures.

CARE

This emotion ensures that maternal and paternal figures care for their offspring, ensuring their survival. This also encourages bonding with the offspring.

PLAY

This emotion helps young animals gain social knowledge and the experience of social interactions needed to interact correctly with others. This builds a social foundation for the animal as they learn how to communicate appropriately.

Figure 5 describes four of the seven mammalian emotions described by Panksepp (2011). Some of the observed behaviours connected to these emotional states are shown; for example, RAGE denotes aggressive behaviours, such as attacking, biting, and fighting. This model for classifying emotions in animals may help replicate accurate behaviours in simulations and understand how emotions affect behaviour at an instinctual and evolutionary level.

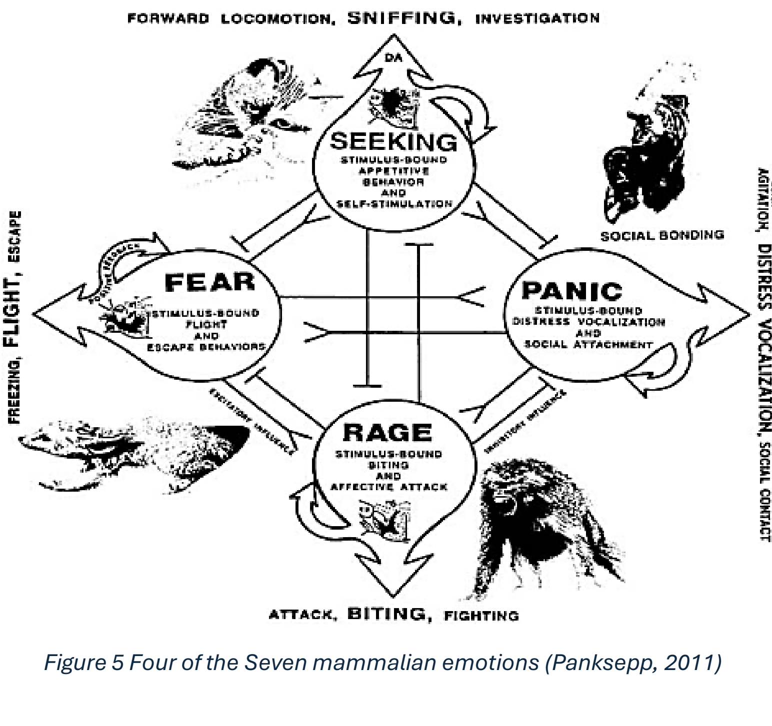

Figure 5 Four of the Seven mammalian emotions (Panksepp, 2011)

Decision-Making Methods

AI agents can be implemented using various methods, depending on the desired outcome. A more complex agent will require more extensive systems in place to convey the correct realistic behaviours needed for the game or simulation.

State Machines

Finite State Machines

Finite State Machines (FSMs) are often used to implement AI behaviours for simpler agents with fewer states. An FSM is a structure that manages the agent's states using conditional values, jumping to relevant states when a certain condition changes. This can be achieved in many ways, such as setting an enumeration and executing a corresponding behaviour. This creates rigid conditions where the behaviour can change, which can be perfect for an agent with a smaller number of states. However, this proves uncontrollable for bigger systems, as the biggest disadvantages of this method are the lack of scalability and dynamism between states. If there are too many states within the structure, it becomes quickly unmanageable and disorganised (Kangqiao, 2021). Moreover, the structure can only have one active state at a time, which hinders dynamic and complex agent behaviour.

Hierarchical Finite State Machine

Hierarchical Finite State Machines (HFSMs) employ substates which work together to complete a singular state. Each child substate should aid the parent state in completing the parent state (Roberts, 2023). This means that despite only having one state active, the structure can execute more than one action. This creates more complex behaviours and allows each individual state to be comprised of multiple actions.

Fuzzy State Machine

Fuzzy State Machines (FuSMs) utilises fuzzy logic in the decision-making process. Fuzzy logic describes a changing state that is not one definitive value; it can float between two set values to represent a degree or activation. For example, a fuzzy logic value for an agent's speed could range between 0 and 1; with 0 being the slowest and 1 being the fastest. The agent's speed can scale with this value, allowing the agent to change speed dynamically depending on environmental factors and conditions. This concept is employed in the FuSM but can be implemented in different ways (Millington, 2019); a FuSM is considered as such if fuzzy logic is utilised somewhere within the structure. This method requires less states that FSMs, yet creates much less predictable behaviour from agents, producing much more dynamic behaviour (Waltham & Moodley, 2016).

Behaviour Trees

Behaviour Trees (BTs) are tree structures with different nodes that control the flow of data depending on certain conditions to execute different tasks. The traversal of the tree structure is to find a task depending on the given condition at that point, and after the task is executed, the child node returns the success state (success, failure, or running)

(Kangqiao, 2021). This requires a more complex implementation as it needs different types of nodes: leaf, instructional (or decorator) and composite (Roberts, 2023).

Leaf nodes hold the instruction for the agent to complete, telling them what to do to achieve the behaviour. Instructional nodes control the flow of data in various ways and only have one child, including repeatedly calling its child node or inverting the return value. Composite nodes can have multiple child nodes but can change the order that the child nodes are executed. Two of the main types of composite node are sequence and selector composite nodes. The sequence composite node executes all child nodes in order from left to right but returns a failure state on the first child to return a failure state. The selector composite node executes all children in a specified order and returns a success state when the first child node returns a success state.

Emotional Behaviour Trees

BTs can be expanded to include certain characteristics and features to make the behaviour of an agent much more complex and unique. One of these ways is to implement an Emotional Behaviour Tree (EmoBet), which expands behaviour trees to include emotions and personality in the decision-making process; this creates emergent and distinctive behaviour, showcasing an agent's individuality.

EmoBets can be implemented in a variety of ways, including using a FuSM that places emotional parameters into a standard BT (Waltham & Moodley, 2016). This works by having a FuSM for every agent that is constantly updating the agent's emotional state. This data is then accessible to all BT nodes, taking the current emotional state as a parameter before eliciting a relevant action dependent on the given emotion. In this case, a FuSM is used as the agent can be in more than one emotional state at a time, meaning that various combinations or intensities of emotions can influence the agent's behaviour greatly.

Another implementation includes adding an emotional selector node (Johansson & Dell'Acqua, 2012), which orders the child nodes based on the planning effort, the risk, and the time to perform the action. Planning effort is calculated to mimic the consideration of an action, risk evaluates how dangerous an action could be, and time ensures that the action can be completed within a set time interval. These values are then combined and used to order the child nodes, with the lowest weighted node acting as the best option. After this, a random probability value can be added to each node to provide further unpredictability, giving the chance for a less optimal node to be chosen. This differentiates the behavioural outcome to create complex and seemingly self-motivated behaviour.

To take this further, an emotion adder and E-selector can be implemented, which add an emotion to the agent and select an action based on the agent's mood respectively (Belle, et al., 2019). This implementation requires the addition of mood; defined as a more persistent state of feeling, set according to recent emotions and the lasting effects of them. Much like the last implementation, this method requires three prerequisites to use the framework: influence, persistence, and interface. Influence refers to the fact that the emotions felt by the agent must influence their actions and effect the agent's overall mood. Persistence describes the prolonged emotional state of the agent and explains that emotions should affect the agent's average mood and dictate their decisions long after the dominant emotion has passed. Finally, interface is for the developers, suggesting that the framework should be an easy-to-use tool.

Goal-Oriented Action Planning

Goal-Oriented Action Planning (GOAP) was created to simplify the creation of FSMs; so that instead of creating a new state for every behavioural action, these can be grouped into a singular state (Shehabi & Al, 2022). This method is based on the Belief-Desire-Intention (BDI) Model, in which the agent carries out a series of tasks to reach a certain end objective (David Marın, 2022). GOAP follows this model closely, reordering actions to reach a goal. GOAP has four major components: Goal, Action, Plan, and Formulate.

Goal

The goal is the final desired state that the agent wants/needs to reach, or a problem to solve. This is selected by examining the world/agent conditions, which are the variables set regarding the world or the agent. This could be decided in a variety of ways, for example the lowest need could be the priority for an agent to solve.

Action

The actions are the potential behaviours that the agent can perform. Each action has two components: the precondition and the effect (Britton, 2021). The precondition defines the condition(s) that must be true for that action to become active. The effect defines the condition(s) that become true after the active action has been completed.

Plan

The plan defines the arrangement of actions that must be completed to reach the goal state. These actions must be completed in First in Last Out (FILO) order, meaning that the actions are executed in the opposite order compared to the plan creation process (Britton, 2021).

Formulate

The formulate stage describes the process of preparing the plan by examining the end goal, preconditions, and effects of the possible actions. The plan can be created using the A* algorithm or a Directed Acyclic Graph (DAG), creating a series of realistic steps that the AI follows (Britton, 2021).

The plan is re-evaluated at certain intervals and after every action, to ensure that the current and next actions are still valid. If the next action is discovered to be invalid, the plan will be re-formulated to create an alternative route to the same goal. In GOAP, the plan can be changed numerous times throughout its execution. From an AI believability perspective, this creates the illusion of self-thought and self-motivation, as the agent appears to evaluate the situation and problem solve to reach a rational solution.

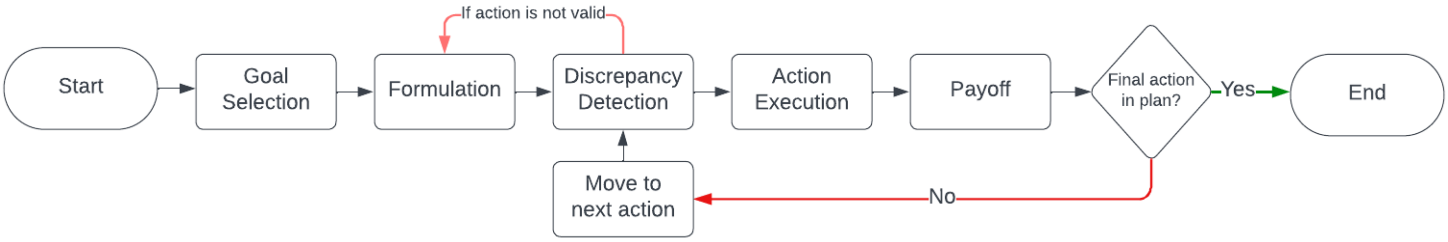

Figure 6 The five main steps of GOAP (Britton, 2021)

GOAP follows five main steps to create cohesive agent AI out of the major components listed above (Britton, 2021). Figure 6 shows the whole process, from attaining a goal to completion. Individually, these steps complete the following:

Goal Selection

This first step selects a goal for the agent by analysing the world conditions, selecting a certain condition to resolve depending on the limitations and possibilities set by the programmer,

Formulation

Once a goal is chosen, A* could be used to create a list of actions to form a plan. A* is used as this algorithm always chooses the lowest cost- or shortest path- possible. This creates a stable and realistic route to the goal (Britton, 2021). If there is more than one action with the same effects, priorities can be assigned so that one action can be chosen more often than the others (Shehabi & Al, 2022). However, it is still best to add an element of randomness to maintain the illusion of choice and diminish predictability.

Alternatively, a DAG could be used to traverse the actions in a GOAP system (Mateev, 2024). With this method, all actions must have their dependent actions defined as children, creating a tree structure with the goal action at the top of the tree. At runtime, a goal action is chosen, and the DAG tree is recursively traversed to find and execute the first valid action by checking all child actions. This continues until either the goal action is complete or there are no valid actions to execute, at which point a different goal action is pursued. Much like the A* method, actions can be weighted with a priority value to give a preference to one child action over the others, this can affect which action is chosen in certain circumstances.

Discrepancy Detection

This step checks if an action is still valid. To do this, the next action's preconditions are checked against the previous action's effects and any changes to the world/agent conditions. This determines whether the next action is still valid and can still take place. If the action is invalid, the plan will be re-formulated and a different route will be calculated.

Action Execution

After the validity checking, the action itself is executed.

Payoff

This step updates the world/agent conditions with the effects of the action that has just taken place. This step is important to ensure the next step is valid.

Repeat

Discrepancy Detection, Action Execution, and Payoff are then repeated for every action within the plan. After all actions are executed, the end goal should be achieved, and this process can start again from the very beginning.

GOAP creates diverse behaviour from the given options, enhancing the believability of the AI agent. Moreover, the scalability of the system ensures that behaviours can be added in the future without hassle.

Large Language Models

Due to a substantial increase in AI technology over the recent years, new software is available to utilise for various purposes, including creation of AI agents for games and simulations. Large Language Models (LLMs) have become more widely used over the last decade, allowing generative responses to queries and other inputs that are becoming increasingly accurate and realistic as more content is studied by the neural network used in the LLM's creation. LLMs have recently been used to create realistic agents, using an LLM to input certain parameters and social responses to generate appropriate actions in each situation to mimic human behaviour. This creates dynamic and diverse behaviour, therefore increasing believability dramatically.

Comparison of Methods

Each method presents a different way to implement decision-making behaviour in AI agents. However, each method has different suitability depending on the complexity needed for the agents.

State Machines are better for simpler agents that can execute a smaller number of individual behaviours. These are extremely simple to implement and work very well for games where NPCs are not the focus (McQuillan, 2015). Moreover, State Machines are a better choice for smaller systems due to its simplicity and low computational cost (Waltham & Moodley, 2016). Despite this, HFSMs and FuSMs can be used to overcome some of the simplicity that limits FSMs.

BTs are more complex than State Machines, enabling more behaviours to be implemented and switched between when certain conditions are met. This method is ideal for more intricate agents that have a slightly bigger role within a game. BTs are a scalable, reusable, and efficient solution to creating dynamically behaving agents whilst being memory efficient easy to debug (McQuillan, 2015). This method has been widely utilised in recent years, surpassing FSMs due to the ability to create more complex behaviours and patterns (Simonov, et al., 2019).

EmoBets build upon standard BTs to take extra parameters into account when deciding on an action. This system is more complex to create, as extra functionality is needed to evaluate agent emotions and choose the correct corresponding action based on the situation. This can make for more believable decision-making agents, as it increases an agent's lifelikeness (Waltham & Moodley, 2016) and creates dynamism with less predictable, yet believable behaviour.

Figure 7 presents an overview of the different decision-making methods listed above, highlighting their advantages and disadvantages. Every method listed is a valid system that can successfully complete AI behaviours. The decision for which to use relies heavily on the needed complexity of the agents and the amount of player interaction the agent will have.

Technique	Advantages	Disadvantages
The Finite State Machine	- Simple. - Low computational cost.	- Difficult to manage in large systems. - Deterministic.
The Fuzzy State Machine	- Works with incomplete information. - Requires knowledge of simple boolean logic. - Experts in the field may define fuzzy rules to be used. - Less states required to provide less predictable behaviour. - FSM can easily be converted to a fuzzy state machine.	- Fuzzy rules may take longer to develop and be of less quality when experts are not available.
The Behaviour Tree	- Scales well with system. - Modular. - Memory efficient. - Easy to debug. - Extensible. - Tool support available in various game engines.	- Deterministic.
Emotion	- A way to add unpredictable behaviour to agents.	- Not sufficiently tested within game environments.

Figure 7 Comparison of decision-making methods (Waltham & Moodley, 2016)

GOAP is a much more complex system than those listed above. However, it excels at creating dynamic and unpredictable behaviour from given actions (Suyikno & Setiawan, 2019), allowing behaviours to change dynamically and executing a different plan for every goal (Long, 2007). GOAP is a largely scalable method that can create dynamically changing plans quickly to suit the state of the environment/world without creating specific transitions between actions (Romero, et al., 2020). This makes GOAP a good choice for dynamically behaving agents that have a prominent role in the game, as this method can create agents that give the illusion of rationality and reasoning.

LLMs provide the most realistic agent behaviour due to the previous training content experienced by the machine learning algorithm, allowing the LLM to return more accurate results based on previously experienced interactions and situations. Moreover, an LLM can adapt based on the actions and situations undertaken within previous runs/playthroughs of simulations and games. This improves the LLM over time, creating better and more accurate results the more it is used for a specific purpose. Despite LLMs proving to have great potential, there are certain challenges and ethical issues that must be considered (Nagarkar, 2024). Certain precautions must be controlled to ensure the LLM responds suitably in all situations, giving accurate and appropriate responses to queries. Also, LLMs can produce hallucinations, which are inaccurate or even impossible results that the LLM believe is true, misleading the player. Moreover, hardware must be considered, as using an LLM with a large program is currently not possible due to hardware limitations (Gallotta, et al., 2024).

There are many other decision-making methods that have not been covered in this paper, such as Hierarchical Task Networks and Domain Independent Planning. All mentioned methods are valid and suitable, but the type of method chosen to simulate an agent's behaviour is a crucial decision, and all factors (time limit, project size, and complexity of the agent) must be considered before deciding on a method.

Considerations of Simulations

Simulations can be utilised to replicate many different events, evolutionary, and environmental changes. Systems like these can help others in different fields of research understand certain situations with clarity and can even assist to make predictions about what these situations could lead to in the future.

Multi-Agent Systems vs Individual-Based Modelling

There are two types of simulation implementations that involve multiple agents: Multi-Agent Systems (MAS) and Individual-Based Modelling (IBM). Both simulation types focus on an agent body that can interact and real a common goal. However, MAS focuses on the decision-making process, coordinating each agent to create a solution for a given problem (Bousquet & Le Page, 2004). IBM focuses more on individual variation in each agent within an agent body, highlighting small differences in each agent that can affect the overall outcome of the simulation (DeAngelis & Mooij, 2005). This includes the implementation of personality, traits, and other characteristics that increase individuality.

Existing Simulations

There have been many simulations created over the years to view or recreate certain behaviours exhibited by animals. For example, the "Boids" simulation (Reynolds, 1987) simulates flocking and migration behaviours in birds, demonstrating how certain bird flocks fly as a group and maintain an acceptable distance, but remain cohesive. This simulation especially served as a basis for realistically replicating natural animal behaviours. The Boids algorithm has also been used and built upon in recent years in many different sectors, including to improve Driver Assistance Systems in cars (Knievel, et al., 2023) and to create search and rescue drones for quicker and more efficient rescue missions (Hengstebeck, et al., 2024). This highlights the importance of simulations, and the unlikely connection that helped use the Boids algorithm to improve features in different sectors.

Simulations have been used to create realistic behaviour for fictional species. For example, The Oz Project introduces the Hap architecture, which is specifically designed to create expressive and believable AI agents (Loyall, 1997). This also takes into consideration personality and emotion, showcasing reactions in response to events affecting their goals (Bates, et al., 1992).

Due to the recent improvement to LLMs, these have been more widely used to create realistic human-like behaviour. The implementation presented by Omirgaliyev, et al. (2024) allows the agents to evolve and adapt over time to create a simulated village and a stable society. This project adds various features that add to the agent's believability, such as: memory, complex interactions, environment interaction, skills, traits, and survival needs. The addition of these greatly replicate complex human-like behaviour, creating a sense of realism within the agents.

Similarly, the LLM-based project shown by Park, et al. (2023) creates believable day-to-day activities in an established village of 25 agents. These agents uphold a daily routine, based on their respective jobs. Moreover, like the implementation by Omirgaliyev, et al. (2024), these agents possess memory which gives them the ability to recall past events and reflect on these. This creates emergent and dynamic behaviour within the simulation, allowing agents to interact, create friendships, and even plan social events with success.

Research Methodologies

The Design Science Research Methodology, specifically Systems Development Research Methodology (Venable, et al., 2017) will be utilised. In this methodology, research is undertaken, an artefact is created, and the artefact is tested, to determine the success of the research, aim, and objectives.

Artefact Creation

The artefact will be created in C++, using the SDL2[1] library to render the scene, Dear ImGui[2] and ImPlot[3] to display information about specific agents, and the GLM[4] (OpenGL Mathematics) library to handle vector-related functionality. The presentation of this will involve a 2-Dimensional grid-based scene in which agents will roam, interacting with aspects of the environment and each other to elicit emotional responses (Jiang, et al., 2007). The artefact will include the implementation of the research that has been completed, aligning with the aim and objectives. Personality and emotion will be integrated into individual agents to investigate the impact of this on believability in AI populations. Personality will follow the OCEAN/Five Factor model and emotion will follow Plutchik's model, with both aspects working together to create unique responses to emotional influences. Moreover, the discretised environment will allow A* to be implemented to allow agents to traverse the environment easily.

[1] SDL2 – Simple DirectMedia Layer 2 [https://www.libsdl.org/index.php]
[2] Dear ImGui – C++ graphical user interface library [https://github.com/ocornut/imgui]
[3] ImPlot – Immediate Mode Plotting, Dear ImGui library [https://github.com/epezent/implot]
[4] GLM – OpenGL Mathematics library [https://github.com/g-truc/glm]

These specific models were chosen due to the research conducted. The OCEAN model's connected traits presented by Li, et al. (2007) and the connection of this to Plutchik's emotion model presented by Bicalho, et al. (2020) fuse these models perfectly. Figure 8 presents a table that describes the factors of the OCEAN model, which traits correspond (positively or negatively) to which factor (Li, et al., 2007), and which emotions are affected by the different OCEAN factors (Bicalho, et al., 2020). Three traits have been chosen per positive and negative factor to give an equal chance to all factors, as the original table displayed by Li, et al. (2007) included varying numbers of traits in each section. This collaboration between the two models allows them to be used together accurately within the simulation.

OCEAN Factors	High Score Traits	Low Score Traits	Effect On Emotion As Factor Increases
Openness	Creative Curious Complex	Uncreative Conventional Narrow-minded	-Surprise +Trust +Joy -Fear -Anticipation -Sadness -Disgust
Conscientiousness	Reliable Careful Self-disciplined	Disorganised Undependable Negligent	+Sadness -Anger +Anticipation
Extraversion	Sociable Friendly Talkative	Introverted Quiet Reserved	+Trust +Joy +Sadness -Anticipation
Agreeableness	Sympathetic Forgiving Courteous	Critical Rude Harsh	+Joy +Surprise +Trust -Anticipation -Disgust
Neuroticism	Nervous Insecure Worrying	Calm Relaxed Secure	+Anger +Surprise -Trust +Disgust +Fear -Joy +Anticipation +Sadness

Figure 8 OCEAN factors, subsequent traits (Li, et al., 2007), and affected emotions (Bicalho, et al., 2020).

The agent's personality will be determined by random upon the program's start, calculating the OCEAN values and emotion modifiers. Each agent will be given six traits out of the thirty available, with each trait eliciting a positive or negative response in one of the OCEAN factors. These traits will determine the intensity of each OCEAN factor, represented as a fuzzy value. Each OCEAN factor will then affect the intensities of the agent's emotions, making some more prominent, and others less prominent, depending on the influence of each OCEAN factor.

For each given trait, the subsequent emotional modifiers will be calculated and stored. This will repeat for all traits, adding the new trait's modifications to the previously calculated total modifier value. Once all traits have been assessed, each agent will have a final emotional modifier that stores all modifiers, positive or negative, for every emotion. Then, these can be applied when the agent's emotions are updated.

GOAP will be used for the agent's decision-making system. Figure 9 displays the workflow for this, and how the different components will interact to take emotion as a parameter for decision-making (Roohi & Skarbez, 2022). The actions within the GOAP system will be traversed and executed using a DAG, which will find and execute the first valid action. This diagram also displays when the agent's emotions are updated in the GOAP process; as every action has effects, these are applied to the agent and world upon completion of the action. But the emotional state is also updated according to the current world and agent conditions at the end of the task, as this could be affected by other agents. This has the potential to affect the agent's plan as it may make the next action invalid. When this occurs, the plan is reformulated, and a new currently valid plan is made.

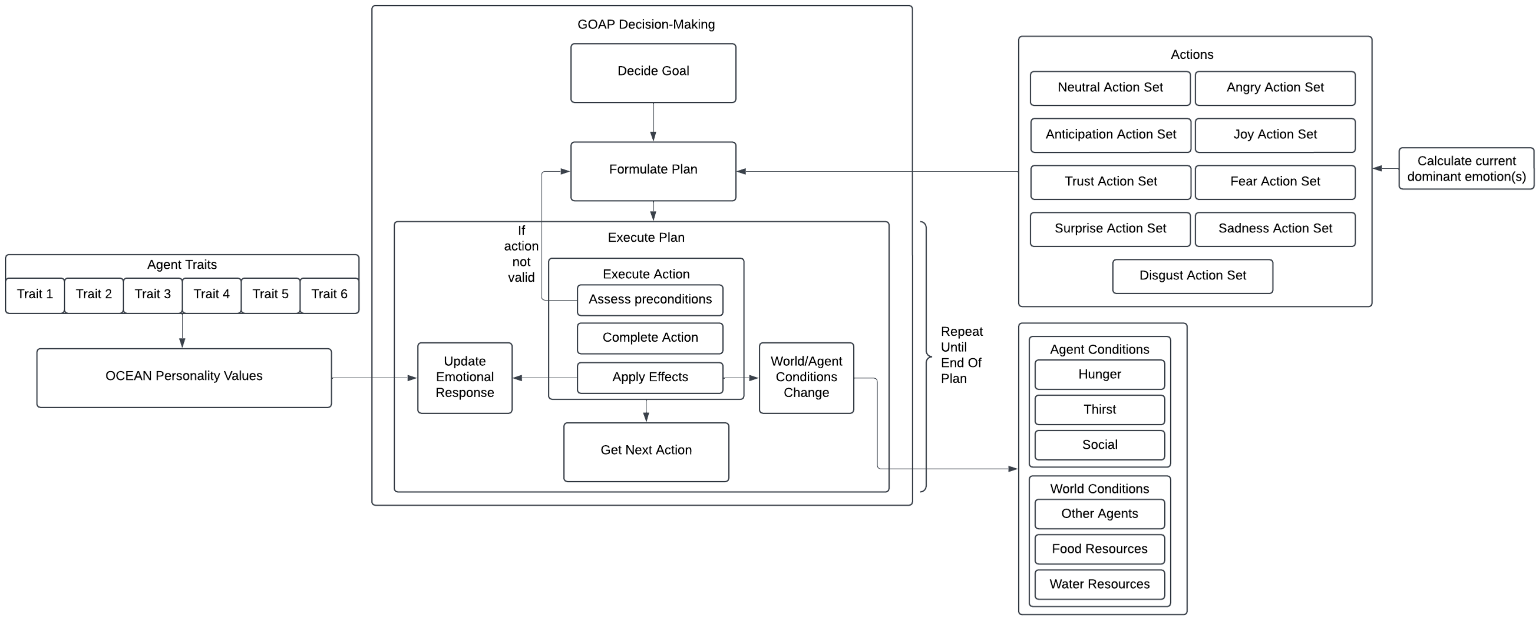

Figure 9 Artefact Workflow Diagram

The simulation will be created using an Object-Oriented Programming (OOP) approach, with every agent existing as an object of an agent class. This class will feature all necessary components for a functioning agent, including rendering necessities, GOAP decision-making capabilities, needs, and a defined personality that affects other components. The personality will differ between existing instances of each agent, changing the outputs of GOAP and creating dynamic behaviour.

Artefact Testing

Once the artefact has been created, primary research will be collected through the form a self-completion questionnaire. The questionnaire will ask a variety of participants different questions regarding the believability of the AI population within the artefact, most of which were derived from the standardised questionnaire suggested by Guo, et al. (2023). Each question will have four possible answers, in which the participant must choose only one: “Extremely”, “Fairly”, “Poorly”, and “Inadequately”. The questions to be used are as follows:

- **Question 1.** Disclaimer approval – participant must agree to continue
- **Question 2.** How appropriate was the agent's behaviour in the given context?
- **Question 3.** How natural was the agent's behaviour?
- **Question 4.** How did the agents react to the environment around it?
- **Question 5.** How did the agents react with each other?
- **Question 6.** How did the traits convey the agent's personality?
- **Question 7.** How did the agent deal with its own needs?
- **Question 8.** How did the agents make their own decisions?
- **Question 9.** Overall, how believable were the AI agents?

The questions cover varying features of the project, aiming to determine whether one or more features were more/less valuable than others. This allows more extensive comparisons to be made and to establish which additions potentially add to the believability of AI populations to answer the research questions clearly.

A questionnaire has been chosen to test the believability of the AI population within the artefact due to the subjective nature of AI believability; people from varying backgrounds and life experiences can have different perceptions of what believable behaviour entails. This is why it is important to collect data from a variety of different people concerning their opinion of the believability within the artefact, so that this can be analysed.

Self-completion questionnaires have the benefit of subjecting all participants to the exact same content, without the disadvantage of interviewer effects or variability due to an absence of an active interviewer (Bryman, 2016).

Furthermore, a questionnaire has been prioritised over other primary research methods due to the ability to quickly and easily display the data graphically, making comparisons and trends much more obvious. This also helps compare answers for the same exact section, mitigating ambiguity over answers which can happen in other primary research methods such as with free response, as questionnaire data is quantitative.

To ensure fair testing for more accurate results, the same variables will be used for each testcase, including the world generation and the starting agents. These variables will remain the same through testing so that each participant is exposed to identical scenarios.

Data Analysis

As all questions asked will produce ordinal variables, each ranked category will be totalled. This will produce four totals for every question, as there are four possible answers. These amounts can be compared to potentially find a correlation. This will generalise the results, stating how many people agree or disagree that the AI population is believable. This deductive approach will test the research questions described in this paper (Bryman, 2016).

Then, Descriptive Analysis will be conducted on the data using a Univariate Analysis method specifically (Taherdoost, 2020). This type of analysis was chosen as this research is looking to answer the research questions defined in this paper and determine the statistical success of the research (Taherdoost, 2022). To conduct Univariate Analysis, the results will be displayed graphically in bar graphs to easily interpret and understand the outcomes. This then allows the measurement of central tendency, such as calculating the mean, median, and mode results to receive a consensus to determine the success of the project and answer the research questions. By calculating these values, outliers and other interesting results can be analysed further to determine the cause of these.

Results and Findings

11 responses have been collected as part of the testing process. Every participant answered eight questions relating to the believability of the agents within the simulation, providing insight into the success of the artefact and potential improvements to be made. Every question has five potential replies, including: “Inadequately”, “Poorly”, “Fairly”, “Very”, and “Extremely”. The number and types of responses were enumerated into graphs to easily visualise the information.

Questionnaire Results

Question One

The first question covers the appropriateness of the agent’s decisions in varying situations. Figure 10 shows that 73% of the participants chose to answer “Very”. This implies that the agents were responding suitably in a variety of different situations, changing their behaviours dependent on how they are feeling.

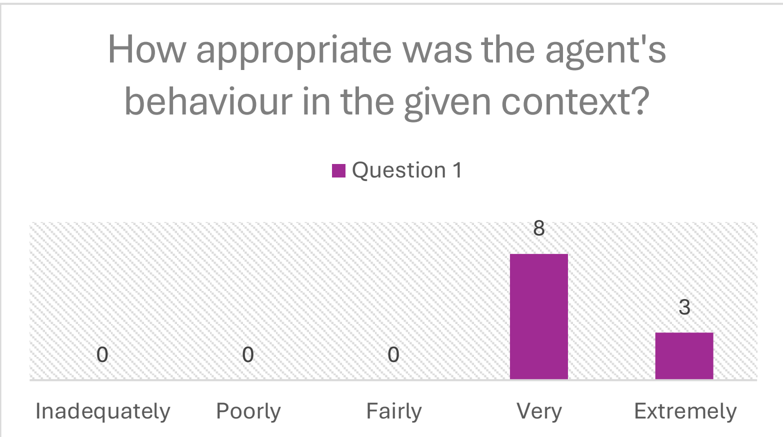

Figure 10 Bar chart showing the results for question one

Question Two

This question assesses the naturality of the behaviours shown. Figure 11 reveals that of the participants, 27% answered “Fairly”, 45% answered “Very”, and the final 27% answered “Extremely”. Whilst no participants answered “Inadequately” or “Poorly” for this question, there is a 62.5% drop in the “Extremely” category compared to question one. This suggests that whilst responding appropriately in situations, it can be concluded that the agents did not react as the participants expected, and therefore potentially reducing the believability of the agent’s behaviour.

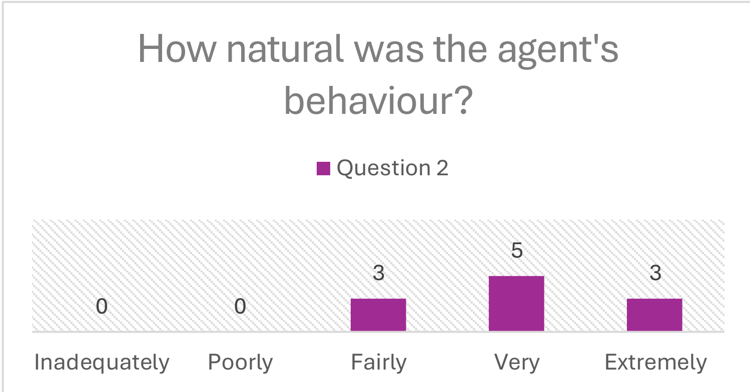

Figure 11 Bar chart showing the results for question two

Question Three

This question evaluates the interactions between the agents and the environment. Figure 12 shows that this question presents an increase in both the “Fairly” and “Extremely” responses, whilst showing a drop in the “Very” response. This response is directly opposite to the previous question, dividing the participants as 36% replied “Fairly”, whereas 45% replied “Extremely”. This concludes that some participants have varying opinions on how the agent should react with the environment.

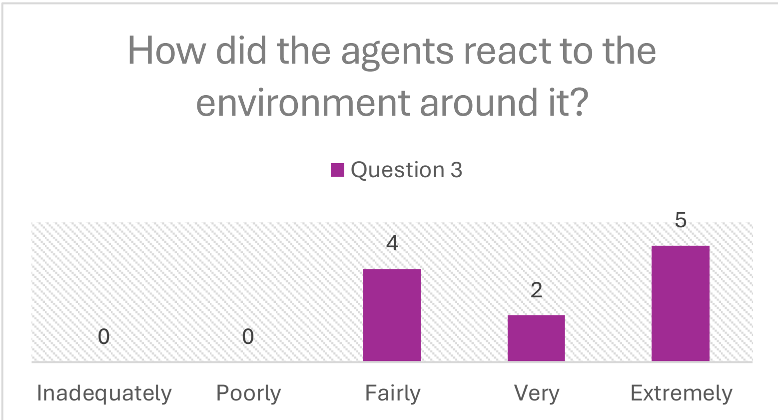

Figure 12 Bar chart showing the results for question three

Question Four

This question assesses the interaction between the agents themselves. Figure 13 shows that the responses are almost identical to the previous question, with one less response in the “Fairly” and one extra in “Extremely”, which concludes that the participants believe that the agents interacted better with each other than the environment.

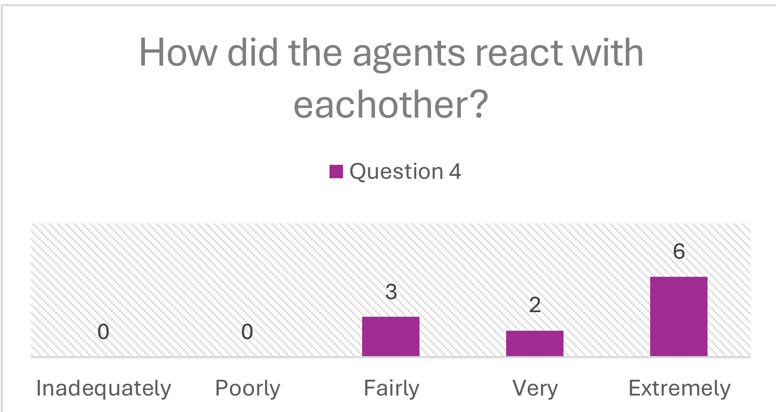

Figure 13 Bar chart showing the results for question four

Question Five

This question covers the trait system, asking the participants how well they conveyed the agent's personality during the simulation. Figure 14 shows that 45% of participants responded "Very", with an equal divide of 27% each between "Fairly" and "Extremely" response types. This once again concludes that the participants had varying expectations on how the traits were conveyed.

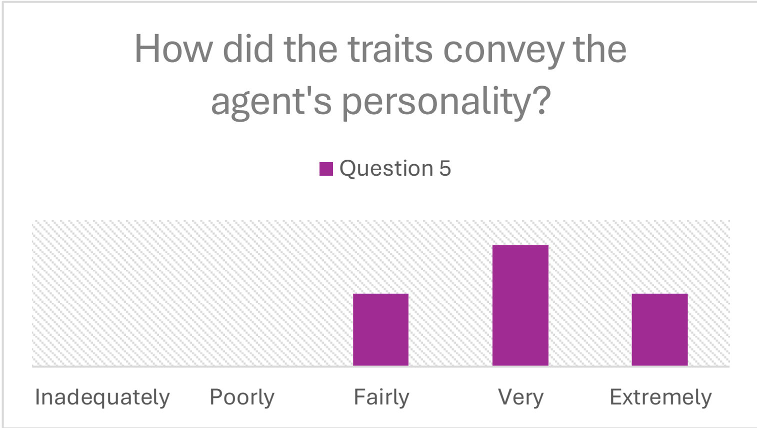

Figure 14 Bar chart showing the results for question five

Question Six

This question assesses the resolution of the agent's needs. Figure 15 shows that a total of 90% of participants answered "Very" or "Extremely". This implies that the participants understood the need system and saw the agents resolving their needs. This may be because the agent's goal is always focused on their needs, which means every action is working to resolve either hunger, thirst, or social.

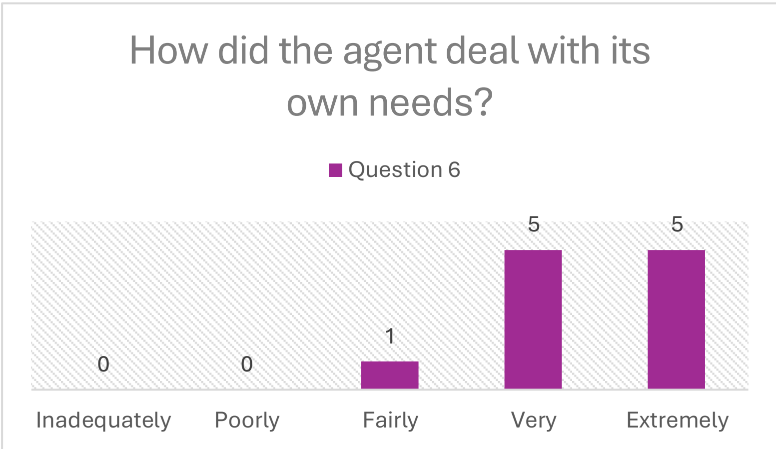

Figure 15 Bar chart showing the results for question six

Question Seven

This question covers the how well each agent made their own decisions. Figure 16 shows that 55% of the participants responded "Very" and 36% responded "Extremely". This suggests that each individual agent made correct decisions based on their needs and emotions.

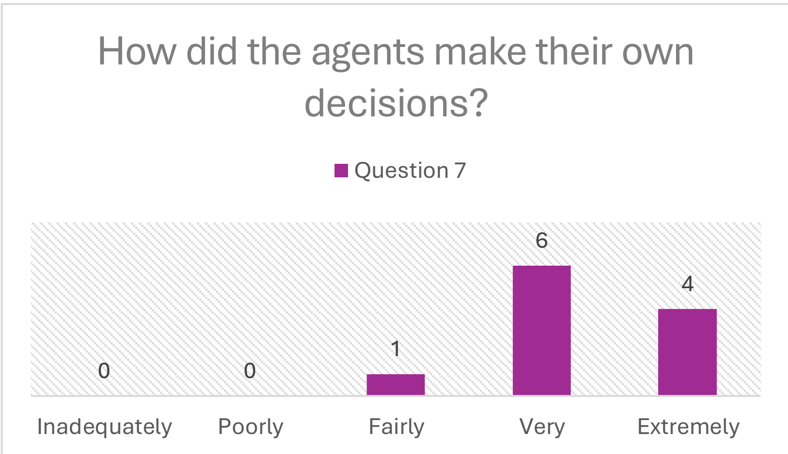

Figure 16 Bar chart showing the results for question seven

Question Eight

The last question asks the participant how believable they think the agents were. This question aims to sum up the participant's thoughts, taking all aspects of the simulation into account. Figure 17 shows that this question receives identical results to question seven, which may be coincidence or may be due to the participants believing that the overall believability relies on the agent's decision-making aspect alone.

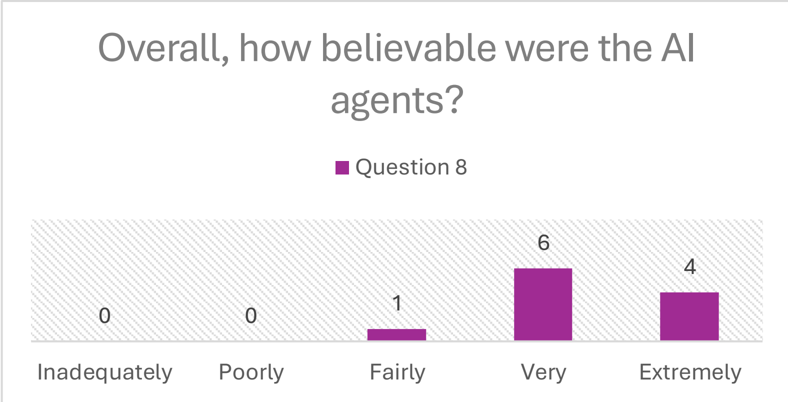

Figure 17 Bar chart showing the results for question eight

Total Responses

Figure 18 presents the collated responses to all questions and shows the distribution of the replies, revealing that none of the participants answered "Poorly" or "Inadequately" for any of the questions. Moreover, it shows spikes in the data, such as question 1 having eight replies in the "Very" response type, showing that this question received an almost unanimous vote for this question.

Figure 19 shows the total collated count for the response types. The mode reply type is "Very" which receives 39 replies, with the "Extremely" response receiving 33 replies and "Fairly" receiving 16 replies. This establishes that the distribution largely falls between the "Very" and "Extremely" responses for all questions.

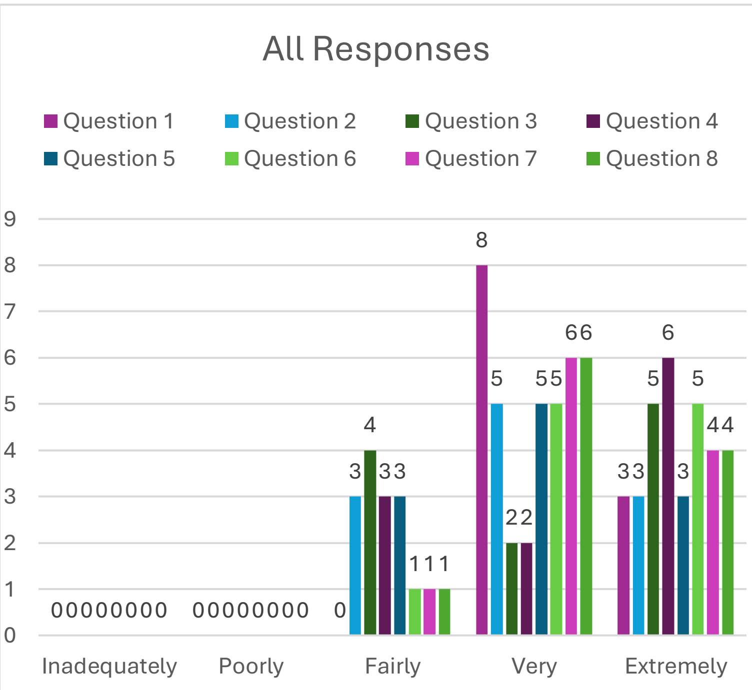

Figure 18 Bar chart showing collated results for all questions

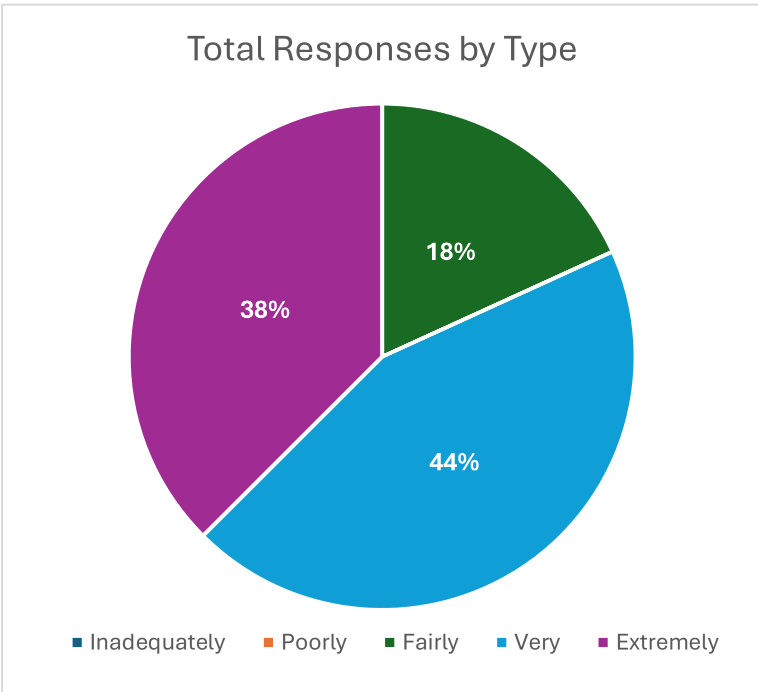

Figure 19 Pie chart showing total count of each response type

Discussion and Analysis

The artefact aimed to combine complex decision-making systems with emotional parameters to alter behaviour depending on how the agent is currently feeling, creating dynamic behaviours and interesting outcomes. The success of the artefact and investigation relies heavily on the findings, signifying the suitability of the methodology used and whether the objectives and final aim were met.

Investigation Findings

Analysing the data from the investigation causes patterns to emerge and gives insight into the simulation from the participants' perspectives. This provides understanding about what went well with the investigation and what could be changed to produce better and potentially more reliable results.

Identical Results

It is shown that the replies for questions seven and eight are identical. This could be due to the decision-making aspect being the focal point of the simulation, which may have caused the participants to answer the final question based on the agent's decision-making only. This is especially true since the two questions are one after another, so the answer to question seven could have influenced this. The final question was intended to cover all aspects of believability, and to collate central opinions on the believability of the agents to assess the completion of the final research aim.

Participant Reception

The answers to certain questions infer that parts of the simulation were received better than others. This can be seen in questions three and four, which assess the agent's interactions with the environment and other agents respectively. Question four received slightly higher results, which could indicate that participants found the agent-to-agent actions more compelling than the agent-to-environment actions. This may be due to the increase in action options with agent-to-agent interactions compared to that of the agent-to-environment interactions. As the social action has different variants that depend on emotion, the agents appear more reactive and dynamic when socialising with other agents. However, there are only two environment actions- eat and drink, this may start to feel stale and predictable. To potentially fix this issue, more environment actions could be implemented to provoke varying behaviours, expanding the current pool of agent-to-environment interactions.

Furthermore, this difference in reception can be observed in questions one, six, and seven, which cover the agents' decision-making abilities and needs throughout the simulation. Question seven scores slightly lower than one and six; this may be due to conflicts between the needs. Currently, all needs decrease at the same rate, meaning that the agent must prioritise a need when they fall below a certain point. This could cause the agent to make slightly different decisions than the participants expected. Moreover, when an agent is spoken to, they stop moving for the duration of the social action. This could cause needs to hit very low values without the agent responding. An improvement of this would be to enable agents to break out of a social interaction to fulfil a dangerously low need.

The Potential Impact of User Interface

During the investigation and creation processes, it was clear that the artefact required an abundance of information to be conveyed to the user. This information was shown using graphs, displaying the information visually so that the user could easily digest the information. However, the graphs were presented at the side of the simulation screen on a scrollable menu. This was implemented to ensure the information could be displayed without taking up too much of the screen space. Conversely, the testing results infer that the information located at the very bottom of the scrollable screen was not perceived as well as the information at the top of the screen.

Due to this, questions one and six may have scored higher due to the placement of the actions and needs on the user interface. The agents act according to their lowest need, and this is shown in a graph at the top of the user interface along with a list of actions that the agent has recently completed, making the agent's intentions clear. The list of actions on every agent is one of the first things displayed to the participant, followed closely by the needs graph. Due to the accessibility of this information, the agent's current goal is constantly displayed. Moreover, the agent's dominant emotion is clearly shown, as the agent changes colour to their dominant emotion which is displayed on a chart next to the needs graph and actions list, easily correlating this information.

The opposite can be seen in question five, which received an overall drop in reception compared to other questions. This question focuses on how well the traits conveyed the agent's personality, but the graph for the agent's personality and the list of the agent's traits are displayed at the very bottom of the scrollable screen. If the participant did not scroll to the very bottom, these values could easily have been missed. This is another area for improvement, as these values could be relocated to a more easily accessible area of the user interface.

It is also worth noting that the drop in question five may also be due to the lack of understanding of the connection between the traits and OCEAN values, as it is not displayed within the simulation itself. The connections and values were explained to every participant but could have been quickly forgotten or overshadowed by the other information present within the simulation. An improvement to this could include adding an explanation screen, which displays concise information regarding the traits, personality values and their connection to the emotion intensities.

Methodology Evaluation

The Design Science Methodology was used to conduct the investigation, supplying an artefact and a questionnaire to assess the impact of emotional influences to the decision-making abilities of agents.

The artefact consists of a simulation that presents a variable number of agents and food sources, allowing each agent to engage in dynamic behaviours to alter emotion states. There are variations for the wander goal and social goal, in which the action type depends on the agent's current dominant emotion. Combining the emotional intensities and varying emotional actions, agents will complete actions and receive an emotional response. Then, inflict a response on to another agent through a social action. This cycle continues, and different emotions arise and settle through the course of the simulation.

Action responses from other agents also vary depending on the agent's emotions. For example, if an angry agent tries to fight another agent, the outcome varies depending on the other agent's dominant emotion. If the other agent is also angry, they will fight. Otherwise, the agent will flee from the attacking agent. This aims to simulate the fight or flight response to create variable and believable behaviours.

According to the outcome of the testing process, it can be concluded that the artefact displayed all the crucial features needed to convey emergent behaviours in agents. This shows that the Design Science methodology worked well to answer the research aim and objectives to assess the suitability of emotionally behaving agents.

Limitations

There were limitations with the creation and testing process, providing gaps in knowledge and investigation outcomes.

As the questionnaire was derived from a proposed standardised questionnaire (Guo, et al., 2023), only multiple-choice questions were featured. Due to the answers being displayed graphically, the participants' answers could easily be seen, and common trends could be observed. But the lack of qualitative questions presented a lack of understanding around the reasoning behind the replies, leaving the causes of these opinions to pure speculation. The addition of qualitative questions would allow the participants to express their opinions explicitly about what worked well and what could be improved, providing clear insight into why the participants gave certain response types.

Moreover, as stated above, the results could have been impacted by the user interface. The results show that the aspects displayed at the top of the scrollable agent information window were understood and focused on more than the those at the bottom of the scrollable window. If the user interface were to be improved, the results of the trait and personality questions may have been higher.

In addition, the correlation between the traits, personality, and emotions is not explicitly shown or explained to the users, so a lack of understanding could also have affected the results. Once again, if this were to be explained in a clear way, the trait and personality question may have yielded higher responses.

The developed emotional GOAP system aims to create emotion-based behaviours for both human and non-human species. Moreover, the implemented behaviours are suitable for all species, as they only consist of eating, drinking, and socialising actions. However, the asset used to represent each agent resembles an abstract human shape, which may have led participants to judge the system based on human emotional behaviours only. As the agent species is not specified in the simulation and this issue is not addressed during the testing process, it cannot be confirmed how this was judged by the participants. This means that the suitability of the emotional GOAP system for non-human species cannot be assessed accurately.

Completion of Aims and Objectives

The artefact was created, and the investigation was completed to answer the aim and objectives. This was to test the suitability of agents that change behaviours dynamically based on personality and emotion.

Can the addition of personality and emotion accurately differentiate behavioural outcomes to increase AI believability?

This objective aimed to answer whether the addition of individualistic characteristics, such as personality and emotion, could influence an agent's behaviour and dynamically change it in a believable manner.

From the results received in the investigation, it can be concluded that the emotional influences successfully created dynamic behaviours, allowing the agents to adapt depending on their current emotion (Jiang, et al., 2007). This can be seen especially in questions one, six, seven, and eight, which cover the decision-making abilities of the agents and their overall believability. These were the highest scoring questions, which suggests that the decision-making aspect of the agents were the most well-received by participants.

What are the best methods for creating emergent behaviours with consideration of individuality aspects?

This objective aimed to explore different decision-making methods, finding the best method for developing agents capable of dynamic behaviours. This also aimed to find a scalable system in which new actions can be easily added to.

The artefact showcases a GOAP system with added emotional considerations, which can choose actions dynamically based on agent needs and their current dominant emotional state (Roohi & Skarbez, 2022). From the conducted testing, it is shown that this method was very well received by all participants. This can be seen in questions one, two, and seven, in which participants highly rated the decision-making aspect of the agents.

To evaluate the difference between the addition of emotions to GOAP and other decision-making methods, they would also have to be included in the artefact and tested to see which method provides the best results. However, the scalable GOAP system successfully displays dynamic and emergent behaviours, completing the requirements for the simulation (Long, 2007).

What are the considerations needed to create a simulation involving individual-based modelling?

This objective aimed to implement a successful simulation that could demonstrate a population of agents executing different actions, all whilst displaying this information in an understandable manner.

As mentioned beforehand, the user interface may have hindered the trait and personality dynamic of the simulation, potentially providing a lack of understanding among the participants. Due to this, it is concluded that the simulation's data needs to be conveyed in a much more simple, concise, and fair way to ensure all users of the simulation understand the outputted information. This would resolve confusion about the trait and personality system within the simulation.

Can the implementation of complex agents enhance a simulation's AI believability?

This overall aim aimed to answer whether the addition of personality and emotion could improve AI believability in the agents within a simulated population, adding individuality and dynamism. Collating the objectives above, it can be concluded that the simulation successfully demonstrates behaviour variants based on emotional influences.

It is important to note that AI believability is subjective, with each participant's viewpoint and life experiences impacting their views on what makes AI believable (Suyikno & Setiawan, 2019). Due to this, an accurate believability test would have to include a larger number of participants of various subsets- such as age and culture, and gaming experience- to truly capture any potential differences in expectations. The subsets can be analysed to potentially reveal patterns to further understand how they affect perception of AI believability. However, the results indicate that the addition of emotionally driven behaviours positively impacted the AI believability for this set of participants.

Conclusion

AI believability has increased in popularity and importance as complex decision-making systems become more widely used. Improving the behaviour of AI agents can have a positive influence, creating a more immersive and intriguing experience for players. The conducted investigation shows that the addition of individuality aspects to agent populations can create dynamically behaving agents that act uniquely within their group. These individuality aspects, such as personality and emotion, are crucial when forming more complex AI agents, providing the opportunity for individual agents to act according to their core characteristics. These characteristics have the potential to greatly increase AI believability, adding life-like qualities and uniqueness to otherwise standard populations.

To assess the suitability of including personality and emotion in individual AI agents in a population, decision-making methods, personality models, and emotion models have been explored. An artefact was created and tested, which presents a GOAP system, dynamically executing actions that are based emotions to fulfil the decreasing needs of agents. The artefact integrates a simulated personality using the OCEAN model and emotions from Plutchik's model into the decision-making system to assess future decisions. The simulation displays the changing emotions of agents, impacted by their needs, actions, and responses to other agents in the population to further fuel their next decisions.

The combination of the chosen decision-making method, personality model, and emotion model proved suitable in eliciting the correct emotional actions. The GOAP implementation allows modular actions to easily be created and added to the selection process, meaning that emotional requirements and responses could be encapsulated within the action itself. Moreover, the blend of the OCEAN personality model and

Plutchik's emotion model allows emotions to be manipulated by varying intensities, displaying emotions that correspond with the given personality type. The emotion model itself provides a variety of different emotions that can provoke behavioural responses, clearly showcasing variety within the population.

The results of the testing process highlight the suitability of the proposed method. All participants expressed a heightened sense of AI believability from the simulation, ensuring that the inclusion of these aspects benefit the decision-making process. This suggests that the addition of personality and emotion has the potential to further enhance AI populations within games. This could create more lifelike behavioural motivations to give AI agents the illusion of reasoning and rationality, increasing player immersion. Therefore, the addition of such aspects could provide a new standard for complex human and non-human AI populations in games.

As also shown by the results, it is crucial that the individual aspects of the agents are displayed clearly in the game or simulation; ensuring the agent's motive and reasoning is clear. If this is unclear, it could result in confusion and negatively impact the player's immersion. This delicate balance is critical for the heightened AI believability and gameplay experience. Moreover, due to the subjectivity of AI believability, it can never be perfected. This is important to note as AI believability must strive for improvement, but not at the expense of player experience.

Overall, the investigation proves successful, confirming that personality and emotion improve existing AI agent decision-making methods to create dynamically behaving agents, enhancing AI populations. Further investigation should be conducted into the combination of believability aspects, such as social relationships, intelligence, and memory. The assessment of these features could reveal further improvement of AI believability, heightening the dynamism and focusing more on the agent's simulated self to make decisions. This could lead to an increase in player immersion as the agents may present more lifelike behaviour, positively impacting AI believability in games and providing a foundation for creating more believable agents.

Recommendations

Despite the successful investigation, there are features that could be added or improved to provide more reliable results. One of these improvements involves the testing process, as the questionnaire would greatly benefit from added qualitative questions, allowing participants to express specific reasoning behind the answers they chose. This addition could provide clarity into the results, rather than relying on speculation and interpretation only. This would also reveal any unforeseen patterns or issues that arose during testing that cannot be inferred from the multiple-choice quantitative questions. This could be done by including a written field after every multiple-choice question, asking the participant to explain why the previous result was chosen. This could aid the analysis process, ensuring all inferences made are correct.

Likewise, during testing, it must be made clear the correlation between the OCEAN values and Plutchik's emotion model to ensure accurate results. These aspects must be explained concisely to remove confusion from the testing process, guaranteeing that the participants understand how the emotion and personality system function. This would prove beneficial to the test results, helping provide clear insight into the perceived behaviours of the agents from the perspective of the participants. This could be done outside the simulation via a verbal or written explanation, or inside the simulation by providing a pop-up screen of information that can be accessed anytime. The latter may prove more advantageous, as the participant can reread the explanation repeatedly.

In addition, it would prove beneficial to the investigation for the user interface to display all information equally, removing scrolling windows entirely. This could involve a larger screen height and width, with a wider area taking up graph space. This way, all graphs and agent information can be easily viewable to the user without having to scroll between information; with all information visible constantly, no features will be overshadowed. It is also important to note that the user should be able to pause the simulation at any moment to closely investigate the information shown.

The questionnaire could also feature questions regarding the species of the agent, inferring whether the behaviour and system could be suitable for non-human species. Furthermore, the artefact may be augmented to allow the user to change certain the visual aspects between specified options, such as the agent sprite from a human-like figure to another animal. This may help the participants differentiate the two, allowing separate judgement for human and non-human species to accurately test the suitability this method for both types.

Moreover, to ensure a robust emotional decision-making method was chosen, different methods should be tested and analysed. This would involve implementing a variety of decision-making methods with adding emotional parameters, allowing variable actions to be chosen depending on the agent's dominant emotion. These methods could be tested, revealing the best method for creating a dynamic and scalable decision-making system entirely dependent on emotions.

The recommendations listed could potentially retrieve more accurate results on this subject. However, the investigation presented confirms that the inclusion of personality and emotions in individual AI agents within a larger population positively impacts AI believability. The addition of individuality aspects is shown to alter behaviour, allowing the agents to act according to their own feelings and beliefs, creating a more dynamic population.

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