TÉCNICO LISBOA

Expectancy and Emotions in Synthetic Characters

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Dedicated to my parents, Baltazar Rodrigues and Gena Rodrigues, for raising me as you did,
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Abstract

Believable interactions between synthetic characters are an important factor defining the success of a game relying on the player being able to create emotional bonds with the game characters. As important as the character being themselves believable is that the interaction with or between such characters is believable. Although research in synthetic characters has developed several models to improve character believability, interactions are generally not the focus of such works. This may be one of the reasons why state of the art models from Academia are still not being used in commercial products. In this thesis, we bridged affective computing and traditional animation principles and create a model for character interaction based on anticipation and emotion that allows for precise affective communication of intention-based behaviors. We also present a study with 52 subjects supporting that our proposal is able to increase scene believability when compared to traditional approaches.

Keywords: Believability, video games, emotions, anticipation, agent interaction

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Chapter 1

Introduction

1.1 Motivation

In today's cinematographic world, many movies conquer the audiences and create an imaginary world where the audience lose themselves in. This is called immersion, "state of being deeply engaged or involved."[1]

But how can movies create such immersion? Let's take for example movies like "The Lord of the Rings"[2] and their fervorous battles, when a character moves or attacks mid-combat it is always clear for the viewer its intention, either by the movement of their eyes or their body: when Legolas shoots his arrows to a distant target, the target is usually shown first, then the camera passes to Legolas preparing and shooting the arrow, and then the target again, being shot. This flow creates anticipation in the audience and a sense of presence, where the audience can feel as being there, which refers to what is called the suspension of disbelief, the notion that the implausibility of something can be suspended for the sake of enjoyment.

Many video games try and succeed in creating the suspension of disbelief by introducing pre-scripted scenes and narrowing the player's playable area and actions, giving it a more cinematic feel. Take for example the game "Call of Duty: Ghosts"[3], with a fantastic campaign where we're put in a soldier's shoes mid-war, with frenetic and over-the-top scenes on par with many of today's action movies. Here the player can easily feel immersed and feel that he's cooperating with his synthetic companions, mainly because of the restraints of the game.

But in open-world games this kind of immersion is hard to achieve, mainly because of the interactions between synthetic character and the player. Often the way one can interact with the characters is by a set of predefined actions, example shown in figure 1.1, these interactions appear unnatural and often break the suspension of disbelief and annoy players.

The same applies to when a battle is under way. Many times there is no verbal or non-verbal communication between characters, creating a mechanical and over simplified battle sequence with no sense of

[1] Dictionary.com: `http://dictionary.reference.com/browse/immersion`
[2] Created by J. R. R. Tolkien and distributed by Jackson from New Line Cinema
[3] Call of Duty: Ghosts. 2013, Infinity Ward, Activision.

Figure 1.1: Interaction system with predefined interaction actions. (Image from Fable II, Lionhead Studios)

immersion. It is good to point out that many of the human's communication is made in a non-verbal way, by the movement of the hands or eyes, indicating the other person's intent. Emotions are also essential to correctly perceiving and delivering an intention, and many of the times such is not shown in video games, except for pre-scripted scenes. In Lord of the Rings during a battle characters frequently show their intentions through gestures, guiding his colleagues to safety and leading the audiences expectation.

These interactions lead to what we can call scene's believability. Opposed to the character's believability, which focuses on the believability of a specific character in a scene, the scene's believability, as the name suggests, is focused on the overall believability of a scene, including the environment, the characters and their interactions, meaning that just for having a very believable character does not mean the audience will be immersed in the scene. Let's take for example a scene where a very believable character interacts with an unbelievable one, while the former has a coherent discourse, the latter babbles about, breaking the suspension of disbelief.

Additionally the scene's believability can also involve the characters' interactions with the environment and even the behavior of the characters in that environment, meaning that the characters should act differently in different environments: one acts differently in a bar with friends and at work with his colleagues.

1.2 Problem

In most games today, there is little concern with non-scripted real-time scene believability. Character interaction in such scenes is often superficial or neglected. The non-existence of a clear anticipatory representation of the synthetic characters' intentions, as well as the scene affective context associated with such a representation, prevents the scene from having a deeper emotional meaning to the player watching the interaction or actually interacting with the synthetic characters. In this work, we strive to create a model dynamically supporting such believable and detailed interactions, with the goal of creating more believable scenes for games whose play experience heavily relies on.

1.3 Hypothesis

In this work, we aim at creating an anticipatory and affective behavior model for synthetic characters bridging traditional animation principles with modern affective and anticipatory modeling to allow the creation of more believable interactions and consequently more believable scenes. Our main hypothesis is that by explicitly modeling the traditional split of an action animation into anticipation, action, and follow-through stages, we will be able to communicate both the intentions of a character in a clearer way as well as give a richer emotional context for all the characters involved in the scene, consequently improving the scene's overall believability.

1.4 Contribution

The main contributions of this work are:

- Review of the state of the art on models of emotion and anticipation for synthetic characters;
- Definition of a computational model for synthetic characters communicating through an action split between anticipation, action and follow-through;
- Implementation of the model and a set of scenarios aimed at putting the model to the test;
- Run tests with users to assert the viability of the proposed approach.

1.5 Outline

In the next few sections we'll be start by defining believability and what are believable characters, focusing then on character animation by studying some of the principles of traditional animation. Then we will take a closer look to what is emotion and anticipation and we can computed them, also mentioning what is awareness and situatedness and who it can help on the creation of believable characters. We will also see how to measure believability. Finalizing with a detailed view of the model implementation, complete with illustrative scenarios, testing methodology, results and conclusions.

Chapter 2

Related Work

In this section we'll describe what is a believable character, how we can compute its emotions and how to measure its believability. This will be made by exploring practical and theoretical work in the areas of Psychology and Artificial Intelligence.

2.1 Believability

As described previously this work focuses on creating believable scenes where agents cooperate and fight each other. To do so one could rely on pre-scripted scenes or reactive responses managed by a single entity, instead we'll focus on creating believable characters that act on their own, creating a believable scene without explicit declaration. Therefore, for this work, the working definition of a believable scene is

"A scene is as believable as the characters and the interactions between them."

We'll be letting out the interactions with the environment, has they are not the main focus of this work.

But what is believability? The Oxford dictionary of English defines the verb 'to believe' as "accept that (something) is true, especially without proof"[1], yet there is still no generally agreed or precise definition of believability, instead, there's a "family of related meanings denoted by the same word"[22]. In its more obvious linguistic denotation, believability means that something can be believed by someone. The entertainment industry gradually linked believability with the audience's engagement in a performance, often defining believability as the empathy with the characters emotions and problems. In the context of Artificial Intelligence and video games we can add that something about a character or even the character itself is believed to be real by someone. Togelius, Yannakakis, Karakovskiy and Shaker[22] state that behind this definition there are two broad classes of examples:

- *Player Believability*: "Someone believes that the *player* controlling the character is real, i.e. that a human is playing as that character instead of the character being computer-controlled"[22].
- *Character Believability*: Someone believes that the character itself is real in a certain context.

[1] Oxford Dictionary of English: `http://www.oxforddictionaries.com/`

Player believability assumes the observer knows the character isn't real and that he "believes that a human has an ongoing input to and control over these processes, and that the human's control is interactive in the sense that the human is aware of what the character is doing in the game"[22].

An important group of observers are the experienced players, these have a better knowledge about rules and possible actions in a particular game, or in games in general, also knowing of the patterns of actions exhibited by the artificial intelligence routines in games. What is important to note about experienced players is that, in general, they will have a much easier time distinguishing between a human-controlled and a computer-controlled character.

"Many games become more engaging for players who believe that they are playing against fellow human players"[22], one of those reasons being that humans are less predictable than computers. Even though a Non-Player Character (NPC) with player believability can bring major advantages to a game, this work will not focus on the illusion that a character being controlled by a human.

Character believability as described by Togelius, Yannakakis, Karakovskiy and Shaker[22] implies a very high degree of realism, and therefore impossible to represent in video games, and restricted to the big-budget non-interactive movies. They describe the problem of the *uncanny valley*, where almost, but not completely, real characters tend to be "creepy"[13] and elicit negative emotions in humans. While that is true, there is a difference between something being realistic and something being believable.

The research on character believability is mainly inspired by the roots of two other fields: drama and animation.

When referring to drama we can go back to the ancient Greeks, where, according to Aristotle, a believable character "should be able to (1) capture, (2) represent and (3) project believable states. Whether a believable character possesses any of the properties is irrelevant: it only needs to appear to have them"[12]. Additionally Prendinger and Ishizuka[19] claim that realistic looking characters performance have high expectations from the users, meaning that little deficiencies lead to user irritation and dissatisfaction, as opposed to an obvious synthetic embodiment.

In animation is where the concept of *realism* and *believability* are clearly distinct. Let's take as an example Chuck Jones' Road Runner[9], a cartoon where a coyote (Wily E. Coyote) repeatedly attempts to catch and subsequently eat the Road Runner without success. During a chase when the Road Runner runs off a cliff and Wily E. Coyote follows, they are both able to stop in mid air, but it is only when the coyote looks down, becoming aware of his situation, that he falls. Still the Road Runner can still continue running and escape. "This is the audience's believable world, and the audience will never question the fact that it is not realistic. It is just the way how the world works"[12]. If the rules were broken, believability would be lost and the audience's attention as well: it wouldn't be realistic in the world they created.

Therefore a believable character has to be consistent with its world and also give the illusion of life, "the change of shape shows that a character is thinking, but it is the thinking that gives the illusion of life, and it is life that gives meaning to the expression"[8, 12].

In this work were considering a scene in which the characters will cooperate and fight as the believable world.

2.1.1 Believable Agents

Believable agents are the software embodiment of the believable characters previously mentioned, therefore it is important to define them.

Given the multiple definitions of believability, several authors, from different fields, gave their definition of a believable agent. We'll only consider the ones most relevant to this work:

Bates (CMU, 1992): Believable agents require “only that they not be clearly stupid or unreal”. Such broad, shallow agents must “exhibit some signs of internal goals, reactivity, emotion, natural language ability, and knowledge of agents...as well as of the... micro-world”[1].

Ortony (NWU, 2003): “Believability entails not only that emotions, motivations, and actions fit together in a meaningful and intelligible way at the local (moment-to-moment) level, but also that they cohere at a more global level – across different kinds of situations, and over quite long time periods”[16].

Using this definitions we determine that a believable agent must have its own goals, be reactive and emotional, and be aware of himself and the world he's in, remaining consistent at a local and global level.

2.2 Principles of Traditional Animation

Even after defining believable characters and knowing their components, if they are not properly presented they can lose the audience's attention. In this section we will discuss how that problem was solved in traditional animation.

The principles of traditional animation, first introduced by F. Thomas and O. Johnston in their book *The Illusion of Life: Disney Animation*[8], are based on standardized practices followed by Disney's animators and allow the creation of a more believable animation, both traditional and computer animation[11].

- ***Timing***, or speed of an action, defines how well the idea behind an action will be read by an audience. More importantly timing defines the weight of an object, as in the example “a giant has much weight, more mass, more inertia than a normal man; therefore he moves more slowly. (...) he takes more time to get started and, once moving, takes more time to stop.”[11].

  One can also define the emotional state of a character by it's movement, where the varying speed of an action indicates whether the character is lethargic, excited, nervous or relaxed.

- ***Anticipation*** is the preparation for the action, for example, if a character wishes to grab a cup of coffee he first raises his arm and stares at the cup, broadcasting his intentions, which leads those watching to expect the character to pick up the cup before the action is done. Without anticipation many actions are abrupt, stiff and unnatural.

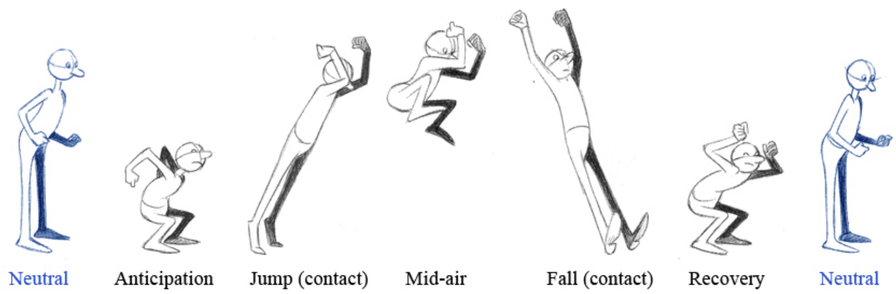


Figure 2.1: Different stages of a jump. Notice the stretching of the arms and legs in the anticipation, preparing the viewer for the jump.

An exaggerated anticipation can also emphasize the heavy weight of an object, when a person has to bends down to be able to pick up a heavy crate, or show a characters emotional state, when one is scared or anxious of doing something he must do.

- ***Staging*** "is the presentation of an idea so it's completely and unmistakably clear"[11]. This principle declares that to clearly stage an idea the audience must be lead to be paying attention exactly to what the creator wants them to, otherwise the idea will be missed.

  When staging an action, it's important that only one action be passed to those watching, to do that there should be a contrast between the object to focus on and the rest of the scene, for example, in a big crowd walking in the side-walk, a person standing still will attract the viewer's attention.

- ***Follow Through and Overlapping Action*** – Most of the times an action does not come to a sudden stop after it is complete, in many movements like a jump there is the termination of the action or Follow Through, for example the recovery in Figure 2.1, where the action is carried past their termination point.

  An Overlapping Action can be variations added to the timing and speed of the loose parts of objects or an action that overlaps the previous one, which makes the objects seem more natural and maintains a continual flow between the phrases of actions.

- ***Exaggeration*** is self-explanatory, but it has to be done with care. It can work with every component, but not in isolation. The exaggeration of various components must be balanced, where some elements are exaggerated and the others are used as natural elements for the viewer to use has comparison, so that the scene remains realistic.

  When animating characters, exaggeration is very important to transmit theirs emotional state. If a character is sad, make him sadder; if he is wild make him frantic.

- ***Secondary Action*** "is an action that results directly from another action"[11]. It is important since it add realistic complexity to the scene, but must always be kept subordinate to the primary action.

  Although secondary, this type of actions will be very important to this work, since we will consider the reply to the primary action, of those characters who watched, to be a secondary actions.

Following the steps of Nuno Costa in his work *Believable Interactions Between Synthetic Characters*[2] where he considers an action as divided in two phases, anticipation and execution, we'll also consider another phase, Follow Through and Overlapping Action. We'll also give special attention to the Secondary Action, has it might help us create a more dynamic system.

There are other principles that were not described above as they are not applicable to this work: **Squash and Stretch** principle defines the rigidity and mass of an object by distorting it's shape during an action, **Straight Ahead Action and Pose-To-Pose Action** are two approaches to the creation of movement, **Slow In and Out** principle that specifies the spacing between frames to achieve subtle movements and timing, **Arc** is a visual path of action for a believable movement, **Appeal** principle describes how to create and action that the audience enjoys watching.

2.3 Emotions and Anticipation

When talking about believable characters it's impossible not to talk about emotions, being one of the major factors that makes a character believable. Unfortunately there isn't an exact definition for emotion, much like what occurs with the definition of believability (see section 2.1). Kleinginna and Kleinginna[10] compiled ninety two disparate definitions for emotions into distinct categories pertaining to the more basic psychological theory they supported (affective, cognitive, physiological, adaptive, and so on...). Although there is no concrete conclusion to the definition of emotion, there is a consensus of the view, that emotion is considered by most theorists,

"as a bounded episode in the life of an organism, characterized as an emergent pattern of component synchronization preparing adaptive action tendencies to relevant events as defined by their behavioural meaning and seeking control precedence over behaviour."[20]

From this one can gather the limited time frame of an emotion, as well as a pattern of behaviour in response to certain stimuli.

What about anticipation? Anticipation and emotions are closely related. One of the emotions' principal function is precisely that of anticipating events, especially when those events involve the well-being of the organism. *"If I am walking in the woods and, suddenly, 'something' ahead on the path lets out a loud roar, my heart races, my muscles tense, I 'feel' afraid and ready to run away"*[12]. In this example the emotions helped reduce the number of possible actions, by eliminating most of the consequences of each from consideration a-priori. Therefore creating an **action tendency** or in other words a desire to behave in select communicative or important actions that are connected to a particular emotion.

Yet the anticipation of an event may also elicit an emotion. Let's rephrase the previous example, *If I am **hunting** in the woods and, suddenly, 'something' ahead on the path lets out a loud roar, my heart races, I found my pray, today I'll feed my family, I am happy*. In this case the emotion was elicited by anticipation. These emotions are often related with expectations, commitment towards important goals, and the validation or invalidation of both expectation and goals. Therefore, the same outcome can lead to a wide range of emotional experiences, based on different types of expectations. "To be prepared for what is to come is a crucial factor in survival"[12].

In the next section it will be described what are the models used to compute emotions, keep in mind that this work will focus on emotions and event's anticipation.

2.4 Computable Emotions

Having the definition of emotion established (Section 2.3), it's important to know how emotions can be computed. Scherer, Banziger and Roesch [20] created five general categories to incorporate different affective models, each category differences themselves in what particularity they wish to convey special relevance or the psychological theory they are backed by. Even though all of the categories are important, for this work we'll be focusing on the Appraisal theory approaches.

2.4.1 Appraisal Theory Approaches

Appraisal theory postulates that "all emotions come mostly from our own interpretations of events"[18], where our appraisal of the situation is the emotional response. The theory is best used in connecting awareness with emotion, focusing on the individual and it's psychological response, where his own judgment of a situation is to blame as the source of his' emotional response.

In the book "The Cognitive Structure of Emotions"[17], Ortony, Collins and Clore describe an emotional classification that states that emotion is structured into the categories of Fortune-of-others, Prospect-based, Well-Being, Attribution and Attraction, or more largely grouped into consequences of events, actions of agents or aspects of objects. This is known as the **OCC Model** and many virtual emotional models that opt for the appraisal theory often base themselves on this model.

The OCC Model attempts to incorporate all emotions, but with no relationship between them other than categorical, but not all models based on the OCC model incorporate all emotions. One good example is the model proposed by Ochs, Sabouret and Corruble[15] which focuses on believability of the NPCs. They attempt to improve the experience by focusing on personality, social relations and roles of the NPCs inside the a game. The emotions modelled, using the OCC, were joy/distress, hope/fear and relief/disappointment. There is also a emotional decay component implemented to revert the emotional state to a neutral state after some time period.

This model focuses on the NPCs and try increasing believability through simulation of social relations. Even though the focus of this work is on the believability of Player and NPCs, it does not focus on their social relations but on their actions and theirs effects.

Another model using the OCC model comes from He, Liu and Xiong[6], it is a fuzzy emotional model for virtual agents. The emotions of events modelled were hope/fear, satisfaction/fear-confirmation and relief/disappointment, and were based on three variables, desirability, "if an event is beneficial to an agent, it is desirable otherwise it is undesirable", importance, "we equate goal's importance with motivation intensity", and likelihood, "we equate likelihood with the possibility of what other virtual agents will do".

This model was created for virtual agents only, having a big decision making component, and not focusing on games. It is good to note “how the model accounts for relations between agents as predictor of behaviour for them”[18], which makes this model a possible candidate for the emotional model of this work.

Using a partial OCC model implementation, the work of Jacobs, Broekens and Jonker[7] focuses on the importance of the link between reward/punishment and an emotional response. They propose the use of an emotion label system that converts each agent’s state transition an initial joy/distress mapping that converts into a hope/fear mapping over time, related to the agent’s previous knowledge, hopefully allowing the gathering of useful information for planning and decision making of the agent.

This model’s objective is focused on the modelling of the agent behaviour, but is important to note how the modelling anticipatory behaviour improved the tested agent’s performance. This model is a good candidate for this work’s emotional model having a good anticipatory model, yet it can be too specific and don’t allow for a wider range of emotions.

FatiMA[4] offers a interesting appraisal theory application, where the OCC model is implemented by storing appraisals (valence based) in a numeral intensity value (-10;10). This model acting along with goal mechanisms and perceived events, models the complete range of emotions inside the OCC, being able to give individual personalities and coping mechanism to deal with specific goals.

Unfortunately this model does not take into account anticipation, an important part of this work.

In **Emotivector**[12], sensations can be dynamically modelled to incorporate both anticipation and expectation. This approach splits the sensorial input into several categories, according to expectation and valence: an increase in a positive sensation or a better reward than expected leads towards excitement, a decrease of a positive sensation or a worse reward than expected leads towards discontentment; a stronger punishment than expected leads towards depression and a lower punishment leads to pleasure. Other categories can be made, such as expecting a reward and receiving a punishment can lead to sadness and frustration.

Since this approach offers a appraisal model for virtual agents based on anticipation and it’s relation with emotions, it is the best candidate to the emotional model.

The appraisal theory approach show potential when used in a more static NPC or Environment emotional association, which is are relevant for this work, giving a simpler and robust emotional model to the in-game interactions.

2.4.2 Anatomical Approaches

This approach tries to emulate the neural structure that is behind an emotional response. They tend to specialize on a single emotion, since they emotions as separate entities with their own systems, giving great importance to the systems that create the emotion.

Although a very detailed approach, they focus on a more raw and basic emotional response and tend specialize on a single emotion, limiting this model, that will make use of several emotions for it’s characters.

2.4.3 Rational Approaches

Rational approaches “ponder what adaptive function does emotion serve”[18], attempting to incorporate an abstract version of this from its implementation in humans into a model of intelligence. This approach is typically associated with artificial intelligence research, where models using this approach are usually used to further develop machine intelligence’s theories, not being appropriate for this model.

2.4.4 Communicative Approaches

The theories behind the communicative approaches focuses on the social component of emotion, that “serves an empathic objective to aid in communication and to transmit non-verbal cues”[18]. This approach is more usually used in social studies, crowd dynamics and multi-agent systems, focusing on the outward emotional display, often disregarding internal work for creating and emotion.

These approaches are a viable solution to implement emotions in this model, but because they are strongly intertwined with a social component that, although important, is not the main focus of this work, we’ll not be using these type of approaches.

2.4.5 Dimensional Theory Approaches

Nowlis and Nowlis in their work *The Description And Analysis Of Mood*[14] analysed and concluded that there were between six and twelve independent affective states (ie. sadness, anger, anxiety, etc.) to the human psyche, introducing the concept that all complex affective states could be broken down to a simpler list. Later Schlosberg[21] hinted that emotions shouldn’t be viewed as discreet and unrelated but as an end product of a system of undisclosed variables. The dimension theory approaches focuses on this view, where affective states are connected and their origins is an n-dimensional vector.

Even though “a big advantage of the dimensional approach is one can attempt to code the seemingly complex nature of human emotions as a combination of simpler internal factors”[18], it can still be quite complex, increasing focus and resources needed in more important sections of this model.

2.5 Awareness and Situatedness

It’s impossible to have a believable scene and characters without the concept of awareness, “the ability to perceive, to feel, or to be conscious of events, objects, thoughts, emotions, or sensory patterns”[2]. Implying that the agents in an environment must be aware of it’s surroundings and act with that in mind.

In movies and books, the authors choose what the characters and the audience are aware of, being able to surprise the audience with unforeseen events. In video games and other interactive media, the awareness of an agent is determined by other factors, since the author has no control over the agents

[2] Merriam-Webster Online Dictionary: `http://www.merriam-webster.com`

actions in run-time. If a bandit is moving slowly behind a guard, with his knees bent and his head low, it's expected that the guard is unaware of his presence, otherwise the believability of the scene would be broken. On the other hand, it should be clear to the audience when an agent becomes aware of another agent's presence, let's take for example Mickey Mouse and his dog Pluto. Whilst Pluto is napping on the carpet, Mickey comes back home, slamming the door and entering. Hearing the familiar sounds, but with no intention of getting up, Pluto raises his head and acknowledges Mickey's presence, returning to his sleep. If Pluto hadn't lifted his head the audience would lose focus, breaking the scenes believability.

It's important to this work to have an awareness system implemented, even if it's simple, this way improving character believability and subsequently improving the scenes believability.

As for situatedness, Mathew Costelo[3] defines it as "a theoretical position that posits that the mind is ontologically and functionally intertwined within environmental, social, and cultural factors", meaning that an agent's mind is not anchored in interiority, but rather an expression of the interaction between the agent and the environment.

To have a believable scene, its characters not only must be aware of the environment they are in, but also they must act and think regarding their social, and cultural factors. If a funny colleague, that is known to always be jumping around and dancing, is in a class room, where everyone is silently listening to the teacher, he will be quiet and calm, otherwise the scene would not be believable.

One must behave accordingly to where he is. For this work is important that the actions taken in a scene are correct, approving situatedness and increasing believability.

2.6 Believable Interactions Between Synthetic Characters

The title of this section refers to the work of Nuno Costa[2]. Costa proposes a new clearer approach to agent communication and cooperation. His approach will be the basis for this work, being therefore important to describe his work and why we chose it.

The core of his approach consists on dividing an action in two stages, anticipation and execution, following part of the principles of the traditional animation (Section 2.2).

The anticipation stage serves a purpose of broadcasting the intent of an agent, so that every other "is expecting it and can prepare accordingly". After the broadcast, the agent may choose to either execute or cancel his action, based on the other agents replies. If the agent chooses to execute the action it the enters the execution stage.

The stages may overlap at any time and different agents may be at different stages in a given time. Additionally the agents must be aware of each others current state of the action, so they can effectively cooperate.

2.6.1 Confidence

Confidence is one of the more interesting components in this work. For each action, each agent has a confidence value, that anticipates if the agent's action will be successful. When the agent broadcasts his intention to perform an action, his confidence will increase or decrease depending on the other agents' reactions. If the confidence value is below a certain threshold, then the agent cancels the action, feels frustrated, and the process starts all over again.

The confidence's threshold is dependent on the agent's personality. "Just as feedback impacts different people differently in the real world, it should impact different agents differently". Additionally the outcome of the action can also influence the confidence associated with future intents, creating an very dynamic agent.

Even though some components will be changed or even removed, this approach gives a good foundation to build upon, incorporating from base the notion of a multi-staged action and the broadcast of intentions.

2.7 Measuring Believability

2.7.1 User Testing

To evaluate this work's believable characters, it requires user validation in some form of quantifiable metrics. We'll be using a set of metrics defined by Gomes *et al*[5] with the goal of measuring believability. This metrics, or believable dimensions, are the following:

- **behavior coherence:** The audience will evaluate the coherence of a character's behavior, which is one key aspect of believability[17].
- **change with experience:** In the context of interactive narrative, it represents how an agent changed because of a story event, a significant change in a life value of a character.
- **awareness:** The audience should perceive the agent as being aware of his surroundings.
- **behavior understandability:** The audience must understand the agent's behavior, therefore the agent must express itself in a way that it's thoughts and motivations are clearly understood.
- **personality:** The agent should be perceive as an unique individual. It's behavior should suggest unique personality traits.
- **emotional expressiveness:** The agent should be able to express it's emotions so that the audience can perceive them correctly.
- **social:** The audience must be able to acknowledge a social relationship between the agents.
- **visual impact:** "The agent should draw the attention of the participant."[2]
- **predictability:** An agent's behavior must be moderately predictable to the audience, meaning that a very predictable agent will harm believability as much as a unpredictable one, affecting behavior coherence[17]. The extremes should be avoided.

The audience's perception is asserted using Likert scales, one scale per dimension. The templates for the phrases to be rated, except for emotional expressiveness, by the subjects are:

- awareness: <***X***> perceives the world around him/her.
- behavior understandability: It is easy to understand what <***X***> is thinking about.
- personality: <***X***> has a personality.
- visual impact: <***X***>'s behavior draws my attention.
- predictability: <***X***>'s behavior is predictable.
- behavior coherence: <***X***>'s behavior is coherent.
- change with experience: <***X***>'s behavior changes according to experience.
- social: <***X***> interacts socially with other characters.

As for emotional expressiveness, participates are asked what emotions are displayed by the agent in specific moments, such as joyfulness or sadness. If the participant's answer matches the emotion the system was trying to reproduce, this dimension would score higher, lowering if the answers did not match.

2.8 Summary

This section began with a study of what is believability, dividing it in player believability and character believability. Focusing on the latter, we talked of its origin, drama and animation, taking from them what is a believable character. Following this line of thought, we went deeper on the concept of animation and described some of its traditional principles, like Anticipation or Timing, which help create a believable character. From there we discussed emotions in believable characters and how they act on or react the agent's anticipation, and specified what are the computational models for applying emotions and anticipation to agents.

We also talked about concepts of awareness and situatedness and how they help on believability of the characters and the scene, followed by an overview of the work made by Nuno Costa[2] that will be the basis of this work. Concluding with a study on how to measure believability to be able to correctly create tests for this work.

Chapter 3

Implementation

We based this approach on the work of Costa[2] and improve upon it. We'll divide an action in three stages: **anticipation**, **action** and **follow through**.

As in Costa's work the anticipation stage "serves the purpose of communicating the intent so every other agent (...) is expecting it and can prepare for it accordingly". This stage allows an agent to broadcast its intention and receive input from other agents. In Costa's work the input received from other agents was considered either positive or negative. In this work, the agent replies with an emotion (Confidence, Fear, Apprehension, Confusion, etc.), allowing the receiving agent to interpret the emotion as it sees fit.

We also subdivided the anticipation stage in two sub-stages, interruptible and uninterruptible, this allows for a single action to be more detailed. The interruptible stage, as the name suggests, is a stage that can be interrupted, follow the example in figure 3.1 where an agent throws a ball, while it has the ball in its hand it can always stop the action from developing, but in the moment it releases the ball, we enter the uninterruptible stage, where the action is not finished, but the agent can create an expectation about its end. In the example, the agent could expect the ball to hit the target, even though the ball is still flying. The uninterruptible stage is optional, since not all actions go through this step, walking, for example, is always interruptible.

The action stage is instantaneous, meaning it only exists in a conceptual view and is not implemented, that is because we consider this stage as the moment where the action gets its resolve, changing the state of the world. In the previous example, this moment would occur right after the ball hits (or misses) the target.

After the action is resolved, we enter the follow through stage, where we broadcast the result of the action, validating or invalidating the agents' expectations. This is a new stage compared to Costa's work, where previously the agent would just update its information about the event, either increase or decrease the action's confidence value, now the agent also expresses its emotions to others, allowing them to feel sorry for it, for example.

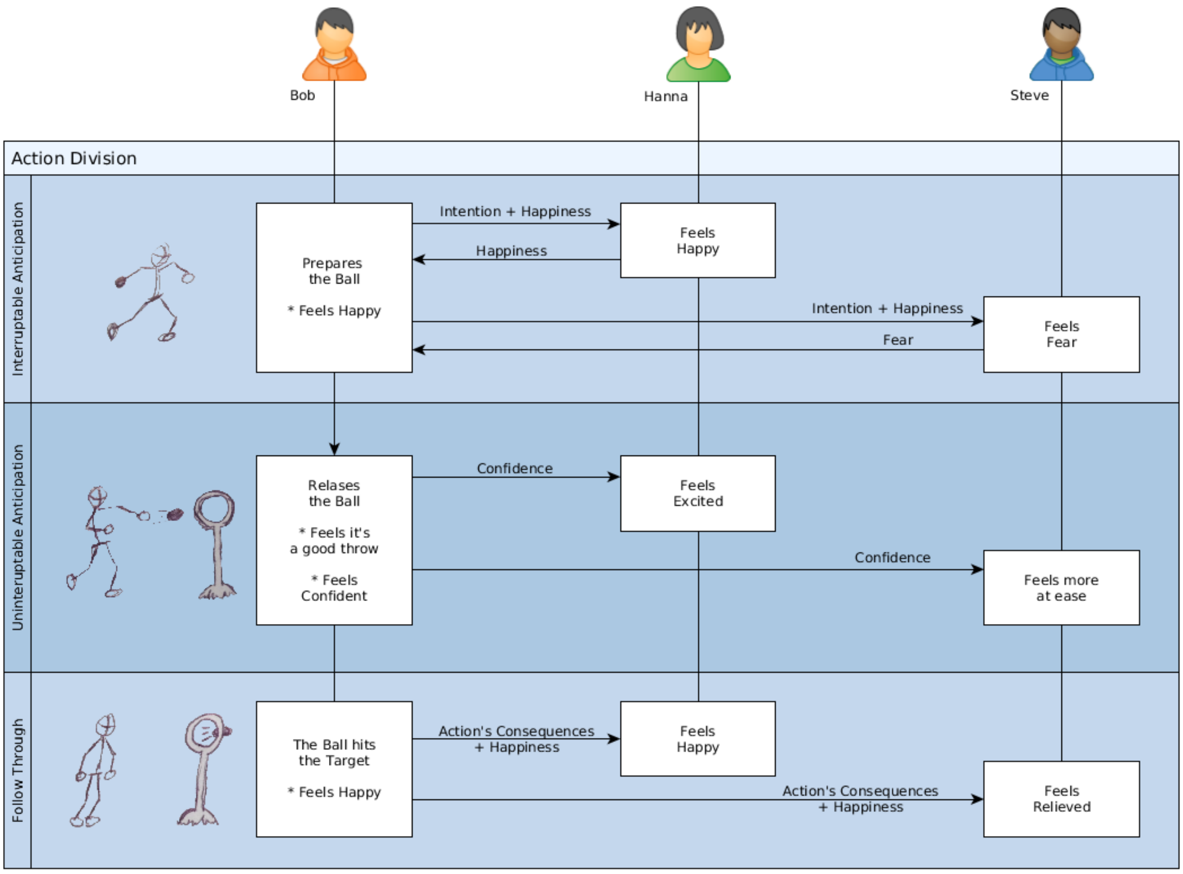


Figure 3.1: Example of an agent through a ball.

3.1 Architecture

We'll start by giving an overview over the agent's architecture and then detail certain features that we considered important to reference. See Appendix A to see the full system architecture.

3.1.1 Overview

The agent is composed of a emotional module, a decision making module and a action execution module. An agent's behavior can be described in four steps: Perceive, React, Decide and Perform. The agent perceives changes in the world, then reacts upon them, using the emotional model, decides what to do, regarding the changes and its emotion, using the decision making module, and then perform its action, using the action execution module (see Figure 3.2).

The *Emotional* module selects the emotion the agent is feeling using Emotivector[12] approach, where for each action they will expect a reward or a punishment, with this approach the agent can create expectations regarding the action's success and react upon them. This module will be called throughout the execution of an action, allow an agent to feel different emotions in the course of a single action, allowing the creation of a more believable agent. While important, the emotional module is not the focus of this work, therefore, was emulated by a script. The script only selects what emotions the agent feels at a given time, allowing us to create believable scenes while correctly simulating the emotional module.

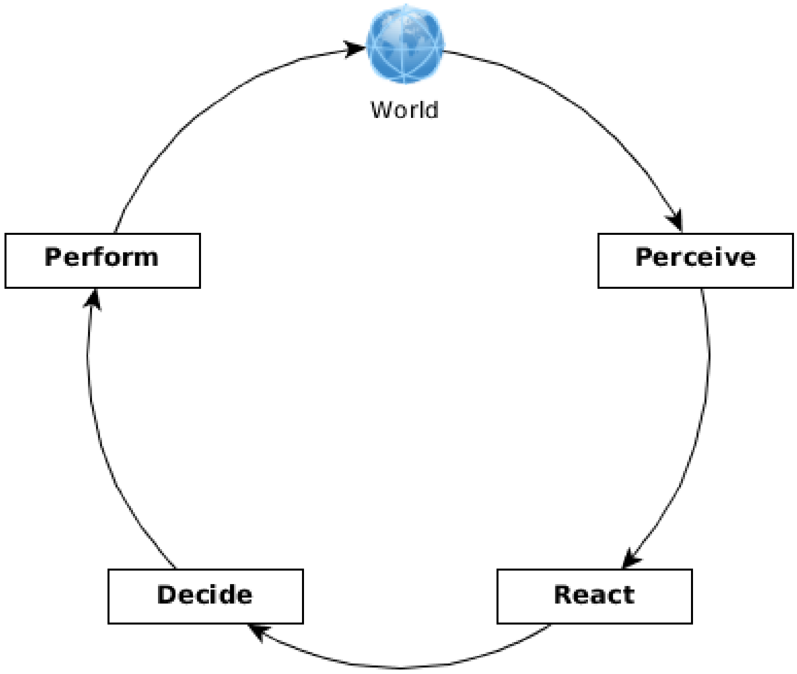


Figure 3.2: Agent behavior cycle.

The *Decision Making* module selects an *action* according to the agent's *Beliefs* and *Desires*, as in the BDI architecture[1]. The agent stores information regarding the action possible success, such has the amount of times the action succeeded. The action may contain additional information, for example, what is the target when performing an attack, and is then sent to the action execution module. While important, the decision making module is not the focus of this work, therefore, was emulated by a script. The script only selects what actions to execute at what time, allowing us to create believable scenes while correctly simulating the decision making module.

The action execution module allows the separation and stepped execution of an action, dividing it in its different stages. It's important to note that in each stage information is sent, regarding the stage itself and the agent's emotion at that moment, to those aware of the action's unfolding.

As previously described, when an action starts being performed it enters the interruptible anticipation stage, where after the information is sent, the agents aware of the action can reply with emotions. In this stage the agent may choose to cancel the action, allowing it to change its mind after receiving input from other agents. It's also important to note the in the current implementation the agent can not only react to the emotions but also to the actions the other agent's perform, for example, if an agent is starting to walk and expects another to follow, the agent can cancel its action if its partner does not follow.

If the action proceeds, it enters the uninterruptible anticipation stage, where the emotional information sent is regarding his expectation over the outcome of the action (see example in Figure 3.1). This stage is sometimes skipped, because it is not applicable to every action.

The action continues and is resolved, applying the changes to the world and entering the follow

[1] Belief-Desire-Intention Architecture, created by Michael Bratman: `https://en.wikipedia.org/wiki/Belief%E2%80%93desire%E2%80%93intention_software_model`

through stage, where those changes are disseminated to the agents aware of the ongoing action, with the changes, the emotion of the performing agent is also sent, broadcasting the end of the action and it's consequences.

When an action is canceled it does not automatically stop, this is mainly because it is not believable or even real, an action always takes some time to stop. This way, when an agent cancels an action it enters a canceling stage, where it stays until the action finishes, only then can the agent start another action. This stage also sends information to other agents and with this it's possible to create more believable scenes.

Regarding emotion expression, in this model emotions contain information about who is expressing them and if it is a reply or not. Additionally, emotions can be considered a single stage action, meaning that expressing an emotion can take time, it's not instantaneous, and can be correlated with action execution, one agent can be doing an action and expressing an emotion at the same time.

3.1.2 Mental State

Each agent has its own mental state, in there it stores information about itself and other agents.

For itself, it stores what it is doing, what it is feeling, what it can do, a list of available actions, what it can feel, and a list of available emotions. This information allows the agent to act and feel, but it is as important as the information of other agents.

For other agents, it store information about what action they are performing and what stage are they in, and what emotions are they feeling. This way, an agent can predict certain behavior or express emotions to other agents depending not only on itself. More importantly, it can create knowledge gaps, where if an agent is not aware of a certain action it can act differently then if it knew.

3.1.3 World

The world where the agents are inserted in is the one that propagate events, but before describing events, lets look back at Figure 3.2, representing the behavior cycle the world and the agents obey. The creation of this cycle comes from a problem that emerges when propagating events, let's say an agent emits an event, when should the world transmit the event to other agents? If it is transmitted as soon as it is received, the other agents will have an advantage over the emitting agent, where he would be unable to perceive them before they perceive it. To solve this issue the world only performs each stage, after all agents have performed the previous one, and only transmits new events at the start of new cycles.

In short, the world sends any new events to all the agents, then all that agents perceive, only after all agents have perceived, does all of them start reacting and so on. This way, we guaranty that all agents behave correctly and that one does not have advantages over another.

3.1.4 Events

In this model, events are an important piece for allowing the information to be broadcast. There are currently two types of events, action and emotion events, and as the names suggest, they carry information about a change in an agent's state, either telling about a new action, a change in a stage of an action or the feeling of a new emotion.

An agent uses events to send and receive information about other agents, therefore updating their mental representation of the other agents. Without events the spreading of information would be impossible.

3.1.5 Perception

What about perceiving an event? Agents could perceive an event as soon as it sent to them, but that is not believable, nor realistic, since humans and animals take some milliseconds to process new information, where they have seen it, but their brains have not yet reacted to it, because of this we implemented a small delay that makes the agents wait until they can completely perceive what happened.

But the different times of sending and perceiving events lead to yet another interesting situation, where for example an agent perceives that another is performing an action, but has not yet perceived its emotion. These types of situation lead us to create a timer system, allowing agents to wait for a given time until something happens or until the time runs out to do an action, therefore emulating human behavior, where not only do we not react instantaneously, but we also wait to see things unfold until we act.

3.2 Illustrative Scenario

Given the complexity of the model it's important to exemplify how the model works. In this section we will illustrate how agents act in a scene using this model.

Let's take the scene in Figure 3.3 as our example, where Hanna and Bob are about to cross a bridge. The boxes in white represent the action stage and emotion an agent is feeling at a given time, the arrows represent events being passed to the other agent (a simplified version of the event broadcasting).

Bob confidently starts crossing the bridge, broadcasting his intention and emotion, some time later Hanna perceives the event and shows apprehension, but decides to follow Bob, showing fear in crossing the bridge. To this event Bob replies with confidence, maybe to try and calm Hanna down. Up to this point the actions haven't left the interruptible anticipation stage and the agents could have canceled the action, but decided not to. It's important to note that in most systems, where the anticipation stage is not considered, this important non-verbal messages are completely ignored.

The first to reach the end of the bridge is Bob, showing happiness. Hanna is relieved that everything went fine and breaths out, and a little time later, she also reaches the end of the bridge is next to Bob showing happiness, for which Bob replies with the same emotion.

Although with just two actions, this scene can be complex and help create more believable scenarios just by using this model.

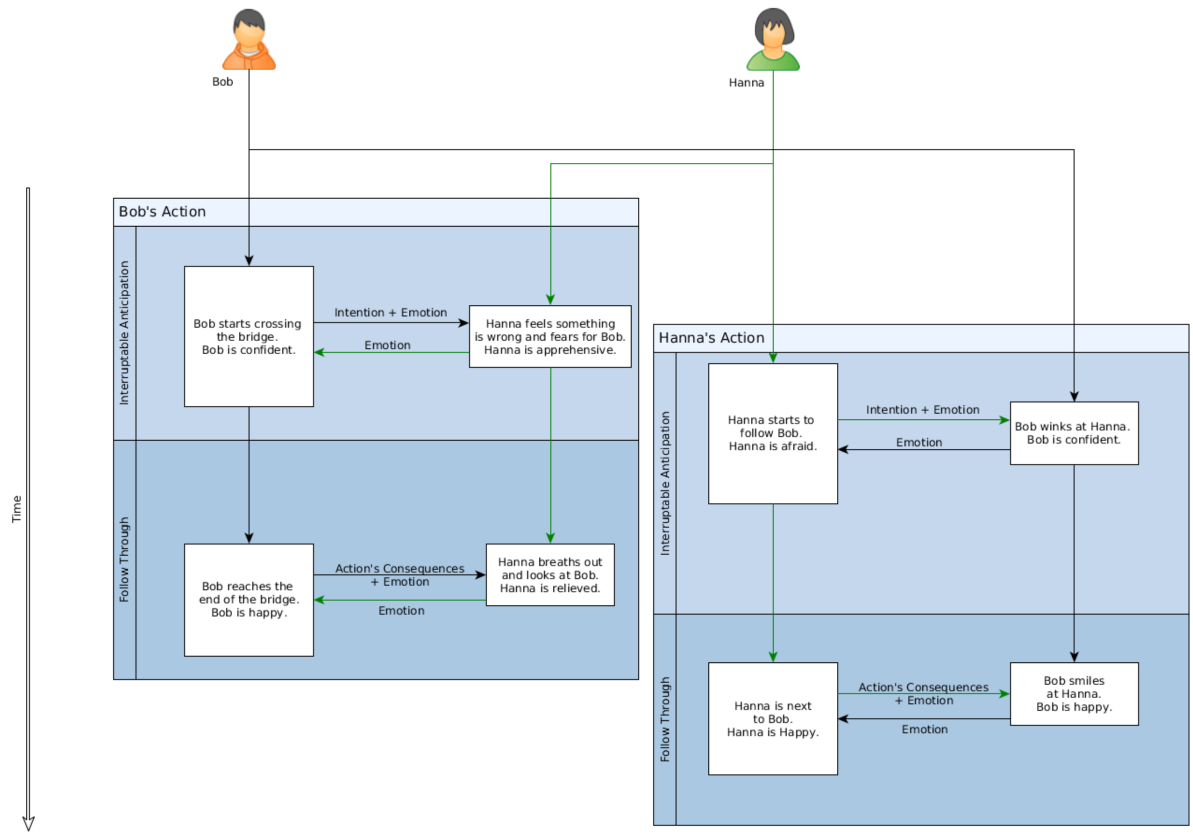


Figure 3.3: Illustrative scenario where agents cross a bridge.

3.3 Development Tools

This model was implemented using C++ and Qt, a framework for creating cross-platform applications with Graphical User Interfaces (GUIs). Although originally the intent was to create a console based application, where some prototypes were made, the portability and ease-of-use of Qt made us rethink our approach.

To allow for a better use of the model, it was created within a C++ library and Qt was used as an example of how to use the library. This approach allows for the library to be imported into other projects with ease and to be used in Unreal Engine[2] for example.

Regarding the interface, it was important to let the users understand what was happening. The events in the scene were unfolding and the way we showed it was by using text and progress bars (Figure 3.4). When the action started to unfold a message would appear informing the user about what was happening and, beside it, would appear a progress bar, informing the user of how long a stage had progressed, in a video game progression could be an animation being played. When a stage was complete or was canceled the progress bar changed its color from red to gray, symbolizing that stage's end.

After having a way to express the progress of a stage, we needed a way to express the progress of a scene. We created two ways to solve that issue, the *Log* view (Figure 3.5(a)) and the *Detail* view (Figure

[2]Unreal Engine is a C++ game engine developed by Epic Games: `https://www.unrealengine.com/`

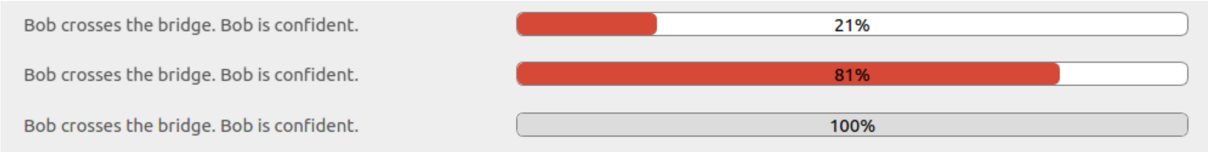
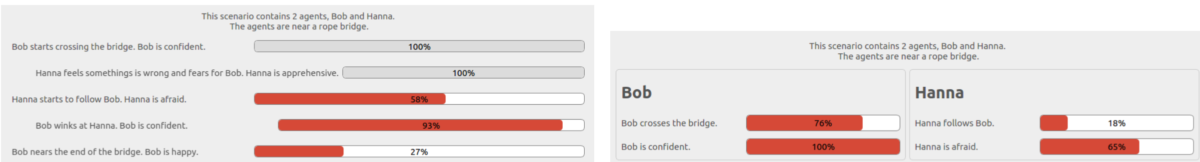


Figure 3.4: Progress of a stage of an action.

3.5(b)), in both scenes an introduction is shown at the top, informing them of the scene and its agents.

In the first view, all new stages are placed below the previous stage, creating a log of what has happened and allowing the user to view the current state of the actions, where only the ones in red are active. In this view, replies to an action stage are placed below it with an indentation, creating a visual bond, without explicitly naming it, that indentation can be seen in Figure 3.6.

The latter view shows all the agents in the scene and shows what they are doing and how they are feeling, this allows the user more easily see the state of every agent in the scene. In the view the new action or emotion stages replace the previous one. Replies on this view are represented as the emotions they carry, where the only difference is the text describing, instead of the stating the emotion ("Bob is confident"), it has more information ("Bob winks at Hanna. Bob is confident").



(a) New stages are shown below the previous.

(b) New stages replace the agent's previous stage.

Figure 3.5: Ways of expressing a scene with progress bars.

After some informal tests with a couple of users, it was decided that the *Log* view as the one best suited for expressing a scene, mainly because this view allows users to see what happened earlier and more easily recall previous events.

3.4 Summary

In this section we presented our solution to create more believable characters through the sub-division of actions and using non-verbal communication. We divided an action in three stages: anticipation stage, action stage and follow through stage. The anticipation stage could be subdivided into interruptible and uninterruptible sub-stages, as an improvement to Costa's work, this model contributes to the previous work by no longer restricting communication to be of approval or disapproval, allowing for a range of emotions to be passed, by introducing interruptible and uninterruptible sub-stages of anticipation, which

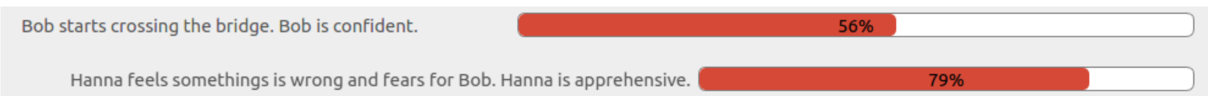


Figure 3.6: Indentation to the text, creates a visual bond to the previous message.

deepens the possible interactions in a single action and finally by adding a stage after the action gets resolved, the follow through stage, where the reactions to what happened are broadcast, allowing for a bigger emotional involvement of the agents.

Later we described the architecture, where we explained that each agent has emotional, decision making and action execution modules. Additionally an agent also possesses a mental state, where it stores information about itself and other agents. We also explained how events work and how they are broadcast by the world.

After explaining the architecture, we jumped to a illustrative scenario where we see how to model works and some of its improvements compared with models that don't consider anticipation.

Finishing up, it was discussed the development tools used to create the model, where we saw that by creating the model in a library we could reuse it in other projects and that mixing text with progress bar and using a Log view we could create a believable scene easy to understand.

Chapter 4

Evaluation

In this chapter we will show what was the evaluation process used to validate our approach, starting by describing three scenarios we designed to portrait the same scene with slightly different agents. Next we will describe the though process used to create the questionnaires and how they were distributed, ending with the presentation of the results taken from the questionnaires.

4.1 Problem Description

The objective was to test the believability of the scenes created in this model, to that end we used questionnaires and videos to show our model at work.

As previously stated this model currently used scripted decision making and emotional modules, this makes the scenes believable, but always behave in the same way. Because of this, we decided to tape videos to show to users instead of making them run the program in their own computers. Using videos also allowed us to reach more people that uses mobile devices and could not run the program in those devices.

The questionnaires asks some questions about each of the three videos using the model. The questionnaire takes about 15 to 20 minutes to fill. In order to avoid bias regarding the order of the videos, three versions of the questionnaire were made, each presenting the videos in a different sequence, also assuring they do not repeat the same position in any questionnaire. To better explain this procedure let's assume we have three videos named Anticipation (A), No Anticipation (NA) and Random (R) (these three denominations will be explained in Section 4.1.1) in Table 4.1, where each line represents a version of the questionnaire and each column represents the order by which the videos are presented. In this table we can see that Anticipation never repeats its position, guaranteeing non-bias results.

To distribute the questionnaires correctly, we created a script that, when opening a link, would redirect the page to one of version of the questionnaire. The version it redirected to followed a linear pattern, A, B, C, A, B, C, and so on, this way all the versions have the same number of replies.

Unfortunately this method could not account for the case where a questionnaire was opened, but not filled, creating inconsistencies in the number of replies in each version. Although the number of replies

	1st	2nd	3rd
Version A	A	NA	R
Version B	R	A	NA
Version C	NA	R	A

Table 4.1: Questionnaire ordering. Lines represent a version of the questionnaire and the columns represent the order by which the videos are presented.

are almost the same in any version of the questionnaire.

4.1.1 Videos

We developed three videos to represent the same scene. In this scene two agents, Bob and Hanna, cross a bridge, what differs in each videos is how the modules are used. The scene is represented using the Log view described in Section 3.3.

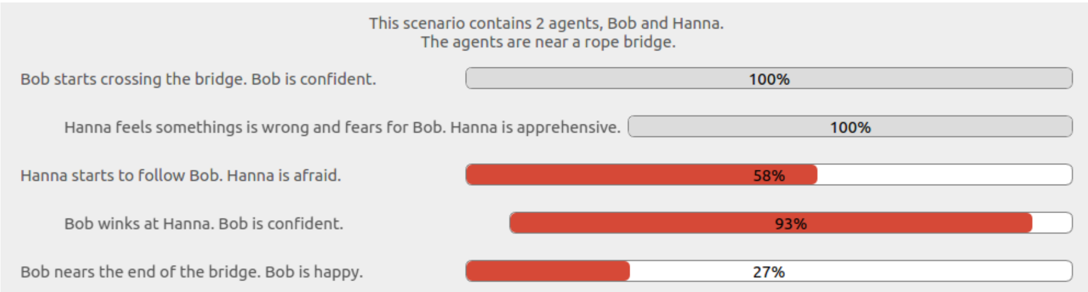


Figure 4.1: Screen capture of the Anticipation video.

We named the videos **Anticipation**[1], **No Anticipation**[2] and **Random**[3].

In the *Anticipation* video a scene is shown where the agents correctly uses our model, meaning that the agents reply with the correct timing and emotion. Since this video represents the correct usage of the model, we expected this to be the one containing a more believable scene.

In the *No Anticipation* video the same scene is shown, but the agents don't use the anticipation module, simulating the approach used in most models. This video represents models that neglect anticipation, but have a system to spread information when an action is complete, similar to the follow through module, while ignoring the emotion sent by the agent. We expected this video to represent a believable scene, but not has much as the previous one.

Last but not least, the *Random* video shows a scene where the agents behave using the anticipation model, but failing on timings and emotions, confusing the ones watching the video. We expect this video to be the least believable. This video was created to fight the idea that more is better, since the *No Anticipation* video contains less information that the *Anticipation* video, proving that information needs to be shown at the right time with the right content.

[1] To view the Anticipation video follow this link: `https://youtu.be/_ZLP-wv2yUo`
[2] To view the No Anticipation video follow this link: `https://youtu.be/0NBGq8cpQR0`
[3] To view the Random video follow this link: `https://youtu.be/_rQ-gHsRIGY`

4.2 Questionnaires

The questionnaires were developed using Google Forms[4], which offered a responsive layout and video integration (see Appendix B).

In our questionnaires, we started by asking the participant questions about himself, which may help us better understand each participant, if needed.

After these questions, we presented three videos (described previously in Section 4.1.1 in an order described in Section 4.1), after each video we asked the participants to express how they felt about statements regarding their perception of the agents and how the agents perceived other agents. It's important to note that in the questionnaire agents are referred to as characters, as such we can consider them synonyms in this context.

- From your (the participant) point of view:
  - I understood what the characters were doing.
  - I could predict the characters' actions.
  - I understood what the characters were feeling.
  - I could predict the characters' feelings.
  - I understood the characters' intentions.
- From the characters point of view:
  - The characters were aware of each other.
  - The characters were aware of each other's actions.
  - The characters could predict each others' actions.
  - The characters were aware of each other's feelings.
  - The characters could predict each others' feelings.
  - The characters were aware of each other's intentions.

The participant could express how they felt by using Likert scales that went from *1 - Strongly Disagree* to *5 - Strongly Agree*. The statements refer to the measuring of a character's believability using some metrics defined by Gomes *et al*[5] (see Section 2.7), which includes awareness, behavior understandability, predictability, behavior coherency, change with experience and social metrics, but also measures the ability of a character to perceive and interact with other characters.

After these statements, the participant is asked to express how believable was the scene by using a Likert scale with the same values as the previous statements. This measure helps us to understand what the participant thought was the most believable scene overall.

The participant is also asked to write a description of what happened in the scene, allowing us to better understand if the scene was or not transmitting the correct content to the user.

[4]Google Forms, by Google: `https://www.google.com/forms/about/`

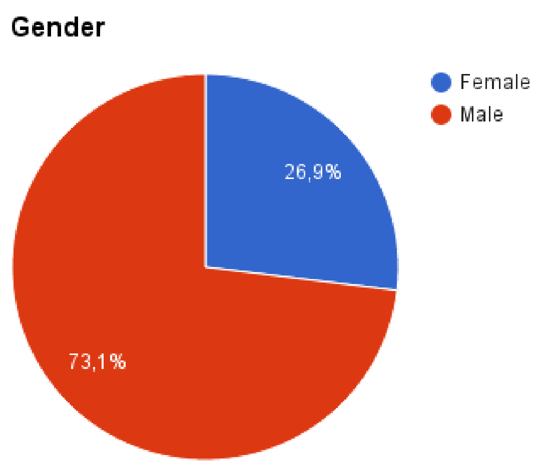
4.3 Results

Testing involved a sample of a total of 52 participants. In order to analyze the results, we ported the data to IBM's SPSS. The resulting tests, like Shapiro-Wilk and Friedman, are present in Appendix C. Recalling Section 4.1, we have three version of the questionnaire, A, B and C, with the videos in different others in the referred section, we will use these version naming during this section for simplicity.

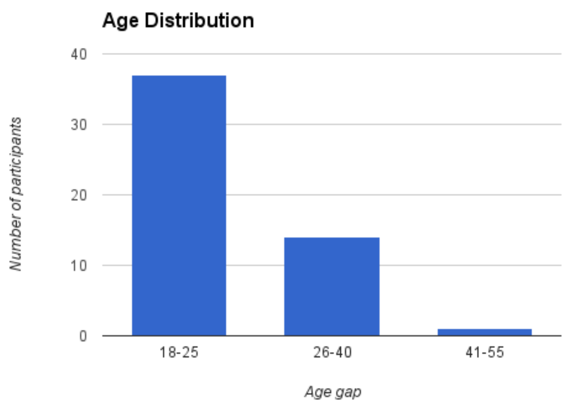
4.3.1 Sample Analysis

Of the 52 participants that filled the questionnaire, 18 participants replied version A, 18 participants replied version B and 16 replied version C.

Regarding their gender, around 27 percent of the participants were female and 73 percent of male participates (see Figure 4.2(a)). As for their age, 37 participants were in the age between 18 and 25 years old, 14 where in the age between 26 and 40 years old and only one participant was between 41 and 55 years old (see Figure 4.2(b)).



(a) Gender Distribution.



(b) Age Distribution.

Figure 4.2: Gender and Age of participants.

We also recorded some habits from the participants, how frequently they play video games (Figure 4.3(a)), how frequently they watch animation movies (Figure 4.3(b)), how many games have they played where they had to interact with non-playable characters (NPCs) (Figure 4.3(c)) and how important was the interactions with NPCs in games for them (Figure 4.3(d)).

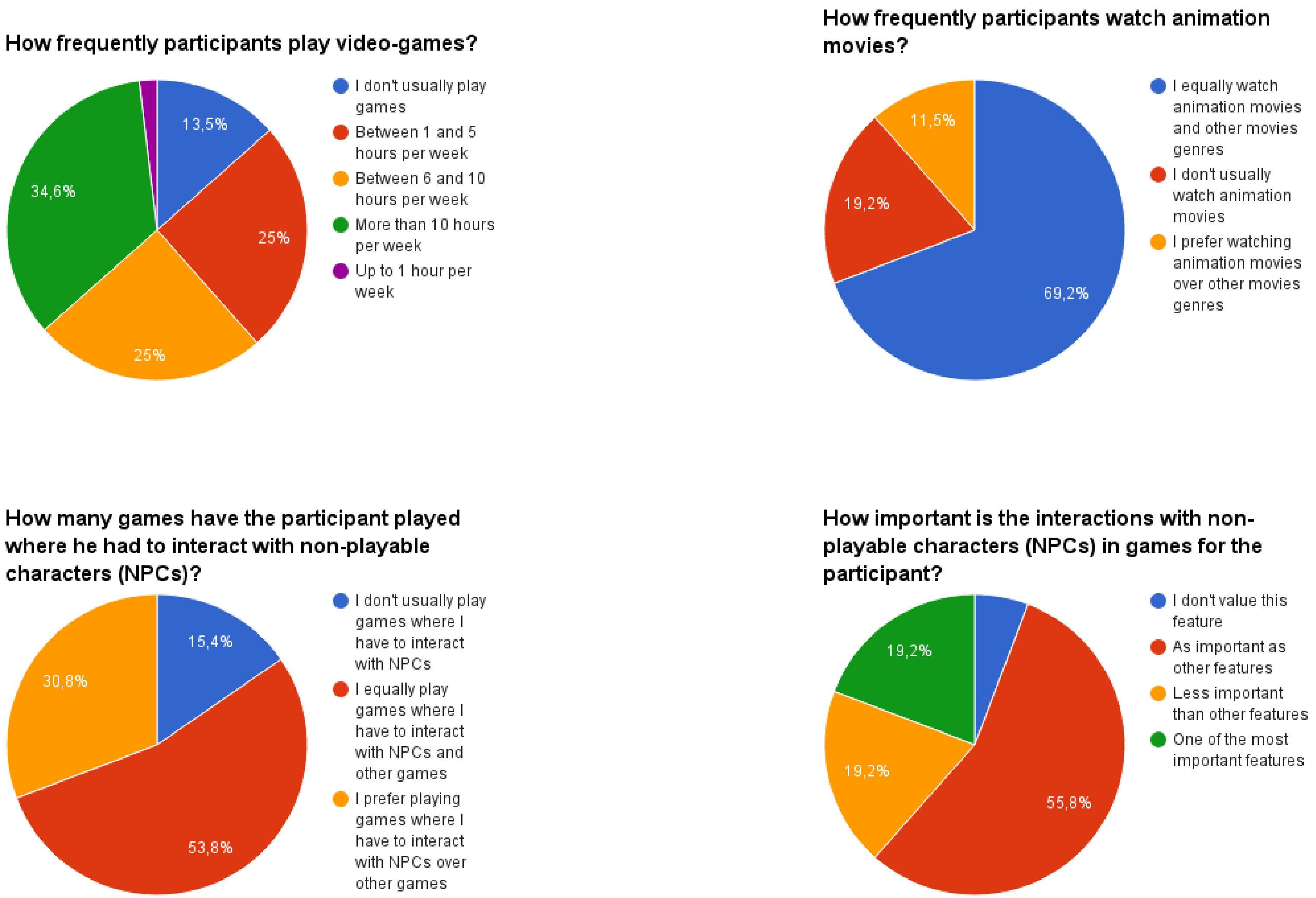


Figure 4.3: Information regarding participants habits.

4.3.2 Video Analysis

In this section we will analyze in detail the results from the videos statements. Each statement was shown as a Likert scale, which values ranged from *1 - Strongly Disagree* to *5 - Strongly Agree*, we'll consider these values as belonging to scale ranging from 1 to 5. It's important to note that when referring to statement's data sets we are referring to the answers given to the same statement in each video, Anticipation, No Anticipation and Random, as previously described (see Section 4.1.1).

Using Shapiro-Wilk test we determined that none of the data sets were normally distributed and we are therefore only able to use non-parametric tests on our data (see Appendix C.1). We then applied the Friedman test on each statement data set, this way determining if the answers for all the videos were or not correlated (see Appendix C.2).

For fine-grain, we proceeded to use the Wilcoxon signed rank test, which allowed us to compare how the answer to a statement in two different videos correlate (see Appendix C.3).

Next we will analyze each statement individually.

I understood what the characters were doing.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 4.440$, $s = 0.752$
- No Anticipation: $\bar{x} = 4.190$, $s = 0.841$
- Random: $\bar{x} = 3.560$, $s = 1.274$

Using Friedman test we found that there was a statistically significant difference in the way the participant understood what the characters were doing depending on the video, $\chi^2(2) = 28.055$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was no statistically significant correlation between any of the videos. Comparing Anticipation with No Anticipation we have $Z = -2.275$, $p = 0.023$, for Anticipation with Random we have $Z = -4.423$, $p = 0.000$ and for No Anticipation with Random we have $Z = -3.623$, $p = 0.000$.

We concluded that the participant better understood what the characters were doing in the Anticipation video, followed by the No Anticipation video and the least understood was the Random video.

I could predict the characters' actions.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 3.190$, $s = 1.011$
- No Anticipation: $\bar{x} = 3.120$, $s = 1.096$
- Random: $\bar{x} = 2.620$, $s = 1.140$

Using Friedman test we found that there was a statistically significant difference in the way the participant could predict the characters' actions depending on the video, $\chi^2(2) = 14.744$, $p = 0.001$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the Anticipation and the No Anticipation videos ($Z = -0.469$, $p = 0.639$). Comparing Anticipation with Random we have $Z = -3.819$, $p = 0.000$ and for No Anticipation with Random we have $Z = -3.198$, $p = 0.001$.

We concluded that the Anticipation and No Anticipation allowed the participant to predict the characters's action in equal manner and better than Random video. This result was expected since although No Anticipation video does not use the anticipation module, one can still predict the agent's actions.

I understood what the characters were feeling.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 4.330$, $s = 0.760$
- No Anticipation: $\bar{x} = 3.920$, $s = 1.007$
- Random: $\bar{x} = 3.350$, $s = 1.297$

Using Friedman test we found that there was a statistically significant difference in the way the participant understood what the characters were feeling depending on the video, $\chi^2(2) = 26.255$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was no statistically significant correlation between any of the videos. Comparing Anticipation with No Anticipation we have $Z = -2.839$, $p = 0.005$, for Anticipation with Random we have $Z = -4.454$, $p = 0.000$ and for No Anticipation with Random we have $Z = -2.799$, $p = 0.005$.

We concluded that the participant better understood what the characters were feeling in the Anticipation video, followed by the No Anticipation video and the least understood was the Random video.

I could predict the characters' feelings.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 3.310$, $s = 0.961$
- No Anticipation: $\bar{x} = 3.170$, $s = 1.043$
- Random: $\bar{x} = 2.560$, $s = 1.195$

Using Friedman test we found that there was a statistically significant difference in the way the participant could predict the characters' feelings depending on the video, $\chi^2(2) = 26.000$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the Anticipation and the No Anticipation videos ($Z = -1.009$, $p = 0.313$). Comparing Anticipation with Random we have $Z = -4.395$, $p = 0.000$ and for No Anticipation and Random we have $Z = -3.477$, $p = 0.001$.

We concluded that the Anticipation and No Anticipation allowed the participant to predict the characters's feelings in equal manner and better than Random video. We had hopped this result to favor Anticipation video, since it contains more information about the upcoming events and emotions.

I understood the characters' intentions.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 3.880$, $s = 0.943$
- No Anticipation: $\bar{x} = 3.750$, $s = 1.046$
- Random: $\bar{x} = 3.480$, $s = 1.291$

Using Friedman test we found that there was no statistically significant difference in the way the participant understood the characters's intentions depending on the video, $\chi^2(2) = 3.823$, $p = 0.148$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation between the Anticipation and the No Anticipation videos ($Z = -1.009$, $p = 0.313$) and between No Anticipation and Random videos ($Z = -3.477$, $p = 0.001$). Comparing Anticipation with Random we have $Z = -4.395$, $p = 0.000$.

Because of the statistically significant similarities revealed in the Friedman test, we conclude that the participants understood the character's intentions in all of the videos with no statistically significant difference, but from Wilcoxon signed-rank test we can conclude that the Anticipation video is statistically significantly different from Random video, which lead us to conclude that even though Anticipation video is statistically similar to No Anticipation video, it is better that Random video.

The characters were aware of each other.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 4.600$, $s = 0.569$
- No Anticipation: $\bar{x} = 4.270$, $s = 0.630$
- Random: $\bar{x} = 4.120$, $s = 1.022$

Using Friedman test we found that there was a statistically significant difference in the way the participant perceived that the agents were aware of each other depending on the video, $\chi^2(2) = 15.540$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the No Anticipation and the Random videos ($Z = -1.102$, $p = 0.271$). Comparing Anticipation with No Anticipation we have $Z = -3.392$, $p = 0.001$ and for Anticipation and Random we have $Z = -3.407$, $p = 0.001$.

We conclude that the participant perceived that the characters were aware of each other better in the Anticipation video, than the other two videos.

The characters were aware of each other's actions.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 4.370$, $s = 0.687$
- No Anticipation: $\bar{x} = 3.960$, $s = 0.791$
- Random: $\bar{x} = 3.830$, $s = 1.024$

Using Friedman test we found that there was a statistically significant difference in the way the participant perceived that the agents were aware of each other's actions depending on the video, $\chi^2(2) = 13.520$, $p = 0.001$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the No Anticipation and the Random videos ($Z = -0.975$, $p = 0.330$). Comparing Anticipation with No Anticipation we have $Z = -3.500$, $p = 0.000$ and for Anticipation and Random we have $Z = -3.405$, $p = 0.001$.

We conclude that the participant perceived that the characters were aware of each other's actions better in the Anticipation video, than the other two videos.

The characters could predict each others' actions.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 3.830$, $s = 1.024$
- No Anticipation: $\bar{x} = 3.000$, $s = 0.886$
- Random: $\bar{x} = 2.940$, $s = 0.802$

Using Friedman test we found that there was a statistically significant difference in the way the participant perceived that the agents were able to perceive each other's actions depending on the video, $\chi^2(2) = 34.503$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the No Anticipation and the Random videos ($Z = -0.475$, $p = 0.635$). Comparing Anticipation with No Anticipation we have $Z = -4.014$, $p = 0.000$ and for Anticipation and Random we have $Z = -4.774$, $p = 0.000$.

We conclude that the participant perceived that the characters could predict each other's actions better in the Anticipation video, than the other two videos.

The characters were aware of each other's feelings.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 4.080$, $s = 0.860$

- No Anticipation: $\bar{x} = 3.380$, $s = 1.013$

- Random: $\bar{x} = 3.40$, $s = 1.107$

Using Friedman test we found that there was a statistically significant difference in the way the participant perceived that the agents were aware of each other's feelings depending on the video, $\chi^2(2) = 22.872$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the No Anticipation and the Random videos ($Z = -0.309$, $p = 0.757$). Comparing Anticipation with No Anticipation we have $Z = -3.449$, $p = 0.001$ and for Anticipation and Random we have $Z = -3.634$, $p = 0.000$.

We conclude that the participant perceived that the characters were aware of each other's feelings better in the Anticipation video, than the other two videos.

The characters could predict each others' feelings.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 3.350$, $s = 1.083$

- No Anticipation: $\bar{x} = 2.900$, $s = 0.975$

- Random: $\bar{x} = 2.920$, $s = 0.947$

Using Friedman test we found that there was a statistically significant difference in the way the participant perceived that the agents were able to perceive each other's feelings depending on the video, $\chi^2(2) = 8.879$, $p = 0.012$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the No Anticipation and the Random videos ($Z = -0.173$, $p = 0.862$). Comparing Anticipation with No Anticipation we have $Z = -2.424$, $p = 0.015$ and for Anticipation and Random we have $Z = -2.658$, $p = 0.008$.

We conclude that the participant perceived that the characters could predict each other's feelings better in the Anticipation video, than the other two videos.

The characters were aware of each other's intentions.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 3.960$, $s = 0.862$

- No Anticipation: $\bar{x} = 3.540$, $s = 0.896$

- Random: $\bar{x} = 3.480$, $s = 0.960$

Using Friedman test we found that there was a statistically significant difference in the way the participant perceived that the agents were aware of each other's intentions depending on the video, $\chi^2(2) = 18.198$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was statistically significant correlation only between the No Anticipation and the Random videos ($Z = -0.546$, $p = 0.585$). Comparing Anticipation with No Anticipation we have $Z = -3.300$, $p = 0.001$ and for Anticipation and Random we have $Z = -3.148$, $p = 0.002$.

We conclude that the participant perceived that the characters were aware of each other's intentions better in the Anticipation video, than the other two videos.

The interaction between characters in this scene was believable.

In this statement, the mean and standard deviation values for each video are:

- Anticipation: $\bar{x} = 4.230$, $s = 0.854$
- No Anticipation: $\bar{x} = 3.810$, $s = 0.951$
- Random: $\bar{x} = 3.310$, $s = 1.408$

Using Friedman test we found that there was a statistically significant difference in the way the participant classifies the degree of believability in each video, $\chi^2(2) = 21.798$, $p = 0.000$.

Going in detail, a Wilcoxon signed-rank test showed that for this statement there was no statistically significant correlation between any of the videos. Comparing Anticipation with No Anticipation we have $Z = -3.111$, $p = 0.002$, for Anticipation with Random we have $Z = -4.274$, $p = 0.000$ and for No Anticipation with Random we have $Z = -2.611$, $p = 0.009$.

We concluded that the participants rated the Anticipation video as the most believable, followed by the No Anticipation video and the least believable was the Random video. This results confirmed our prospects, as we expected that the scene using our model would be the most believable.

4.4 Discussion

The analysis of the collected data led us to conclude that the Anticipation video (the video that correctly uses the model, paying attention to timing) ranked higher in almost every statement, meaning that participants perceived this video to contain the most believable scene.

The statements regarding the participant's perception of the agents was were we expected to see more similarities between the Anticipation and the No Anticipation videos. The expectations were confirmed and statements as "I could predict the characters' actions." were similar in values between these two videos. A broken expectation was that of the statement "I could predict the characters' feelings.", where we hoped the new information given by the anticipation module would allow participants to more easily predict the agent's emotions.

A weird phenomenon happen in the statement “I understood the characters’ intentions.” where the three videos were not statically significantly different. One can suppose that the intentions of the agents are easy to perceive in any of the videos or even that after watching the video the intentions were made clear. Other possible supposition is that the participants meant that they were capable of perceiving that the intentions had not change.

The statements regarding the agent’s perception of other agents and their actions, feelings and intentions gave results that always favored the Anticipation video, indicating that in fact the correct usage of the model improves believability.

Although the Anticipation video’s scene is favored, we were expecting the No Anticipation video’s scene to be statistically significantly different from the Random video, which was not the case. Probably the addition of new information in the Random video still made participants consider the agent’s aware of each other and therefore similar to the No Anticipation video.

Chapter 5

Conclusions

We started by saying that although there are models to create believable characters, interactions with or between characters are generally not the focus of such works. With this we wanted to create a model that focused on interactions and that could possibly leave the Academia and be used in commercial products.

The model we created uses decision making and emotional modules, but the main focus was the subdivision of an action and non-verbal communication.

The subdivision of actions takes inspiration from the principles of traditional animation, where an action can be divided into stages such as the anticipation stage and the follow through. With the usage of these new stages we hoped to increase believability in characters and in scenes.

These stages also allow for the transmission of non-verbal communication, by which we mean, the expression of emotions as a way of communicate.

After creating these features, we needed to implement them. By using a text and progress bar based GUI, we created a visual guideline that users could watch to see actions take place. The text offered the information about what an agent was doing and feeling and the progress bars offered the notion of how the action stage was developing.

To test this model and to see if it really helped to create more believable characters, we created questionnaires where we asked participants to answer some questions regarding three videos containing different agents in the same scene.

In one version they used the model with correct timed anticipation and expressing the correct emotions.

In the second version the agents did not use anticipation and ignored all the emotional feedback from other agents. This version simulated how most model work (with no anticipation and no non-verbal communication).

Last but not least, the third version presented agents using the model incorrectly, which means that the anticipation responses were ill timed and the emotions sent were erroneous. This version helped to prove that to make a more believable character or scene one can not just add more information.

After the analysis of the questionnaires we concluded that this model helps create more believable characters that a model that does not consider the subdivision of an action and non-verbal communication.

With this model we hope to be able to bring to commercial products and to other developers an easy way of creating more believable and detailed interactions.

5.1 Future Work

In the current state of the model there is still many untapped treasures, take for example the moment when an agent is aware that other is starting to perform an action, but is unaware of that agent's emotional state. In situations like this it's important to study not only what should the agent do, but also compare that to what a human would do. The study of these situations could lead to more interesting believable scenes than those we have now.

Other important step to take is to implement fully functional decision making and emotional modules, replacing the scripts currently implemented. As proposed in my work one possible decision making module could be implemented using a BDI architecture, for example. A similar example applies to the emotional module and a Emotivector architecture, which would surely create some interesting scenes.

An also important step to take would be to put this model to use in a big project, for example a video game. This type of usage would improve the model and see how one could use it out of the Academia.

Prior to the previous step, it is important to try to incorporate the model into a game engine or an AI experience. Given the complexity of the graphics engines seen today, the model would need to be tested and modified before it can be used.

Regarding the results, given the limited amount of time, it was impossible to explore some tests that correlated types of people with certain habits to the results, for example determining if those who play more videos games have a more distinct set of answer, the same applies to those who watch animation movies more often.

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Appendix A

System Architecture

The figure bellow portraits the system architecture. Although not including every class used in the model, it contains the main ones.

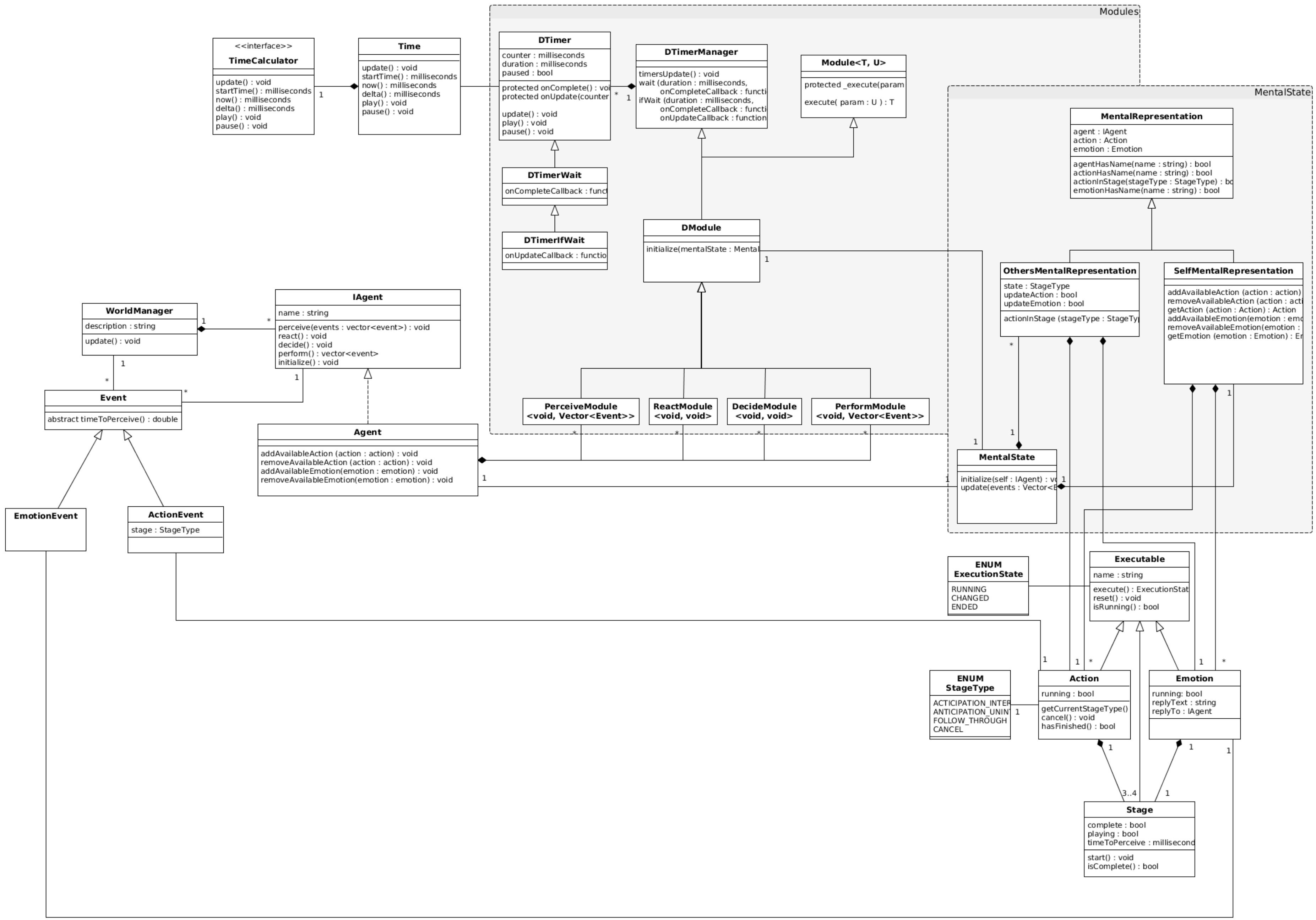
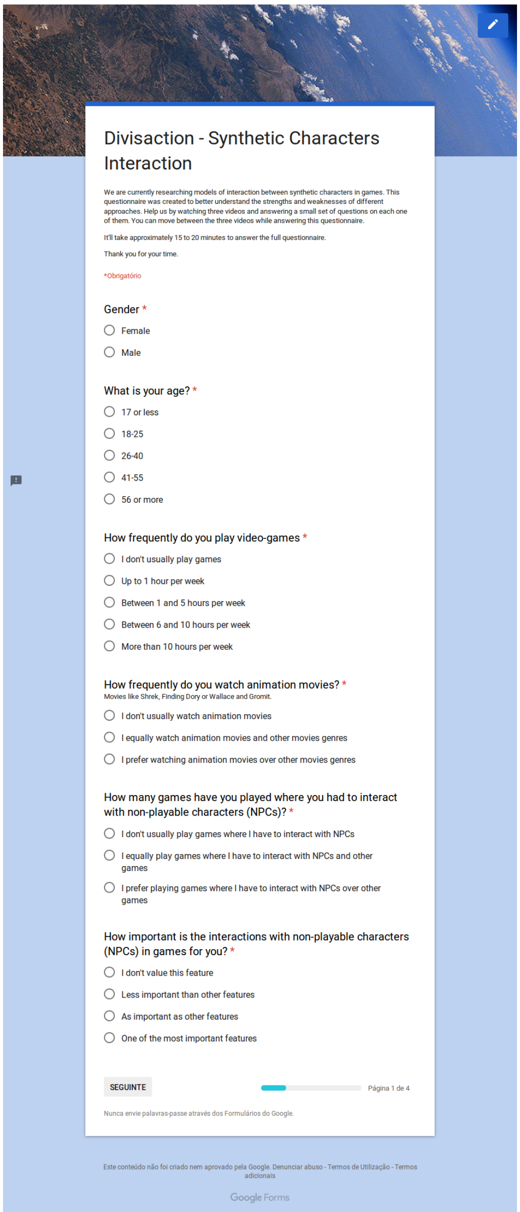


Figure A.1: System Architecture.

Appendix B

Questionnaires



Divisaction - Synthetic Characters Interaction

We are currently researching models of interaction between synthetic characters in games. This questionnaire was created to better understand the strengths and weaknesses of different approaches. Help us by watching three videos and answering a small set of questions on each one of them. You can move between the three videos while answering this questionnaire.

It'll take approximately 15 to 20 minutes to answer the full questionnaire.

Thank you for your time.

*Obrigatório

Gender *

- Female
- Male

What is your age? *

- 17 or less
- 18-25
- 26-40
- 41-55
- 56 or more

How frequently do you play video-games *

- I don't usually play games
- Up to 1 hour per week
- Between 1 and 5 hours per week
- Between 6 and 10 hours per week
- More than 10 hours per week

How frequently do you watch animation movies? *

Movies like Shrek, Finding Dory or Wallace and Gromit.

- I don't usually watch animation movies
- I equally watch animation movies and other movies genres
- I prefer watching animation movies over other movies genres

How many games have you played where you had to interact with non-playable characters (NPCs)? *

- I don't usually play games where I have to interact with NPCs
- I equally play games where I have to interact with NPCs and other games
- I prefer playing games where I have to interact with NPCs over other games

How important is the interactions with non-playable characters (NPCs) in games for you? *

- I don't value this feature
- Less important than other features
- As important as other features
- One of the most important features

SEGUINTE

Página 1 de 4

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Figure B.1: First page of every questionnaire.

Figure B.2: Anticipation Video questionnaire page.

Figure B.3: No Anticipation Video questionnaire page.

Divisaction - Synthetic Characters Interaction

*Obrigatório

Video C

It's important to understand what the video is about and what is happening at what time, so please feel free to replay, pause and rewind the video whenever you see fit.

If the video is too small you can view it here: https://youtu.be/_rQ-gHsRIGY

Divisaction S

This scenario contains 2 agents, Bob and Hanna.
The agents are near a rope bridge.

From your point of view... *
Select the column below that best represents how you feel about each statement.

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I understood what the characters were doing.	○	○	○	○	○
I could predict the characters' actions.	○	○	○	○	○
I understood what the characters were feeling.	○	○	○	○	○
I could predict the characters' feelings.	○	○	○	○	○
I understood the characters' intentions.	○	○	○	○	○

From the characters point of view... *
Select the column below that best represents how you feel about each statement.

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
The characters were aware of each other.	○	○	○	○	○
The characters were aware of each other's actions.	○	○	○	○	○
The characters could predict each others' actions	○	○	○	○	○
The characters were aware of each other's feelings	○	○	○	○	○
The characters could predict each others' feelings	○	○	○	○	○
The characters were aware of each other's intentions.	○	○	○	○	○

The interaction between characters in this scene was believable. *
Select the column below that best represents how you feel about each statement.

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Describe what happened in this scene. *
This answer will allow us to better understand how you perceived what happened in the scene.

A sua resposta

ANTERIOR SUBMETER Página 4 de 4

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Google Forms

Figure B.4: Random Video questionnaire page.

Appendix C

Test Results

C.1 Statement Information and Normality Tests

Explore: I understood what the characters were doing.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
UnderstoodCharacters_A	52	100.0%	0	0.0%	52	100.0%
UnderstoodCharacters_NA	52	100.0%	0	0.0%	52	100.0%
UnderstoodCharacters_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
UnderstoodCharacters_A	Mean		4.44	.104
	95% Confidence Interval for Mean	Lower Bound	4.23	
		Upper Bound	4.65	
	5% Trimmed Mean		4.53	
	Median		5.00	
	Variance		.565	
	Std. Deviation		.752	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-2.099	.330
	Kurtosis		7.349	.650
UnderstoodCharacters_NA	Mean		4.19	.117
	95% Confidence Interval for Mean	Lower Bound	3.96	
		Upper Bound	4.43	
	5% Trimmed Mean		4.28	
	Median		4.00	
	Variance		.707	
	Std. Deviation		.841	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-1.412	.330
	Kurtosis		3.233	.650
UnderstoodCharacters_R	Mean		3.56	.177

Descriptives

			Statistic	Std. Error
	95% Confidence Interval for Mean	Lower Bound	3.20	
		Upper Bound	3.91	
	5% Trimmed Mean		3.62	
	Median		4.00	
	Variance		1.624	
	Std. Deviation		1.274	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.814	.330
	Kurtosis		-.344	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
UnderstoodCharacters_A	.309	52	.000	.670	52	.000
UnderstoodCharacters_NA	.275	52	.000	.771	52	.000
UnderstoodCharacters_R	.290	52	.000	.841	52	.000

a. Lilliefors Significance Correction

Explore: I could predict the characters' actions.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
PredictCharacters_A	52	100.0%	0	0.0%	52	100.0%
PredictCharacters_NA	52	100.0%	0	0.0%	52	100.0%
PredictCharacters_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
PredictCharacters_A	Mean		3.19	.140
	95% Confidence Interval for Mean	Lower Bound	2.91	
		Upper Bound	3.47	
	5% Trimmed Mean		3.20	
	Median		3.00	
	Variance		1.021	
	Std. Deviation		1.011	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.166	.330
	Kurtosis		-.629	.650
PredictCharacters_NA	Mean		3.12	.152
	95% Confidence Interval for Mean	Lower Bound	2.81	
		Upper Bound	3.42	
	5% Trimmed Mean		3.13	
	Median		3.00	
	Variance		1.202	
	Std. Deviation		1.096	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.051	.330
	Kurtosis		-.825	.650
PredictCharacters_R	Mean		2.62	.158
	95% Confidence Interval for Mean	Lower Bound	2.30	
		Upper Bound	2.93	
	5% Trimmed Mean		2.57	
	Median		2.00	
	Variance		1.300	
	Std. Deviation		1.140	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		.488	.330
	Kurtosis		-.411	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PredictCharacters_A	.211	52	.000	.903	52	.000
PredictCharacters_NA	.194	52	.000	.909	52	.001
PredictCharacters_R	.225	52	.000	.898	52	.000

a. Lilliefors Significance Correction

Explore: I understood what the characters were feeling.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
UndersCharFeel_A	52	100.0%	0	0.0%	52	100.0%
UndersCharFeel_NA	52	100.0%	0	0.0%	52	100.0%
UndersCharFeel_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
UndersCharFeel_A	Mean		4.33	.105
	95% Confidence Interval for Mean	Lower Bound	4.12	
		Upper Bound	4.54	
	5% Trimmed Mean		4.41	
	Median		4.00	
	Variance		.577	
	Std. Deviation		.760	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-1.752	.330
	Kurtosis		5.870	.650
UndersCharFeel_NA	Mean		3.92	.140
	95% Confidence Interval for Mean	Lower Bound	3.64	
		Upper Bound	4.20	
	5% Trimmed Mean		3.99	
	Median		4.00	
	Variance		1.014	
	Std. Deviation		1.007	
	Minimum		1	

Descriptives

			Statistic	Std. Error
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-1.040	.330
	Kurtosis		.640	.650
UndersCharFeel_R	Mean		3.35	.180
	95% Confidence Interval for Mean	Lower Bound	2.99	
		Upper Bound	3.71	
	5% Trimmed Mean		3.38	
	Median		4.00	
	Variance		1.682	
	Std. Deviation		1.297	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.348	.330
	Kurtosis		-1.055	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
UndersCharFeel_A	.257	52	.000	.713	52	.000
UndersCharFeel_NA	.319	52	.000	.808	52	.000
UndersCharFeel_R	.231	52	.000	.887	52	.000

a. Lilliefors Significance Correction

Explore: I could predict the characters' feelings.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
PredictCharFeel_A	52	100.0%	0	0.0%	52	100.0%
PredictCharFeel_NA	52	100.0%	0	0.0%	52	100.0%
PredictCharFeel_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
PredictCharFeel_A	Mean		3.31	.133
	95% Confidence Interval for Mean	Lower Bound	3.04	
		Upper Bound	3.58	
	5% Trimmed Mean		3.33	
	Median		3.00	
	Variance		.923	
	Std. Deviation		.961	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.390	.330
	Kurtosis		-.139	.650
PredictCharFeel_NA	Mean		3.17	.145
	95% Confidence Interval for Mean	Lower Bound	2.88	
		Upper Bound	3.46	
	5% Trimmed Mean		3.19	
	Median		3.00	
	Variance		1.087	
	Std. Deviation		1.043	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.361	.330
	Kurtosis		-.705	.650
PredictCharFeel_R	Mean		2.56	.166
	95% Confidence Interval for Mean	Lower Bound	2.23	
		Upper Bound	2.89	
	5% Trimmed Mean		2.51	
	Median		2.50	
	Variance		1.428	
	Std. Deviation		1.195	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		.288	.330
	Kurtosis		-.824	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PredictCharFeel_A	.226	52	.000	.895	52	.000
PredictCharFeel_NA	.248	52	.000	.885	52	.000
PredictCharFeel_R	.180	52	.000	.902	52	.000

a. Lilliefors Significance Correction

Explore: I understood the characters' intentions.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
UndersCharIntentions_A	52	100.0%	0	0.0%	52	100.0%
UndersCharIntentions_NA	52	100.0%	0	0.0%	52	100.0%
UndersCharIntentions_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
UndersCharIntentions_A	Mean		3.88	.131
	95% Confidence Interval for Mean	Lower Bound	3.62	
		Upper Bound	4.15	
	5% Trimmed Mean		3.97	
	Median		4.00	
	Variance		.888	
	Std. Deviation		.943	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		0	
	Skewness		-1.223	.330
	Kurtosis		2.046	.650
UndersCharIntentions_NA	Mean		3.75	.145
	95% Confidence Interval for Mean	Lower Bound	3.46	
		Upper Bound	4.04	
	5% Trimmed Mean		3.82	
	Median		4.00	
	Variance		1.093	
	Std. Deviation		1.046	
	Minimum		1	

Descriptives

			Statistic	Std. Error
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.970	.330
	Kurtosis		.498	.650
UndersCharIntentions_R	Mean		3.48	.179
	95% Confidence Interval for Mean	Lower Bound	3.12	
		Upper Bound	3.84	
	5% Trimmed Mean		3.53	
	Median		4.00	
	Variance		1.666	
	Std. Deviation		1.291	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		3	
	Skewness		-.297	.330
	Kurtosis		-1.178	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
UndersCharIntentions_A	.318	52	.000	.806	52	.000
UndersCharIntentions_NA	.325	52	.000	.827	52	.000
UndersCharIntentions_R	.195	52	.000	.876	52	.000

a. Lilliefors Significance Correction

Explore: The characters were aware of each other.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
CharAwareEach_A	52	100.0%	0	0.0%	52	100.0%
CharAwareEach_NA	52	100.0%	0	0.0%	52	100.0%
CharAwareEach_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
CharAwareEach_A	Mean		4.60	.079
	95% Confidence Interval for Mean	Lower Bound	4.44	
		Upper Bound	4.75	
	5% Trimmed Mean		4.65	
	Median		5.00	
	Variance		.324	
	Std. Deviation		.569	
	Minimum		3	
	Maximum		5	
	Range		2	
	Interquartile Range		1	
	Skewness		-1.058	.330
	Kurtosis		.180	.650
CharAwareEach_NA	Mean		4.27	.087
	95% Confidence Interval for Mean	Lower Bound	4.09	
		Upper Bound	4.44	
	5% Trimmed Mean		4.30	
	Median		4.00	
	Variance		.397	
	Std. Deviation		.630	
	Minimum		3	
	Maximum		5	
	Range		2	
	Interquartile Range		1	
	Skewness		-.274	.330
	Kurtosis		-.586	.650
CharAwareEach_R	Mean		4.12	.142
	95% Confidence Interval for Mean	Lower Bound	3.83	
		Upper Bound	4.40	
	5% Trimmed Mean		4.21	
	Median		4.00	
	Variance		1.045	
	Std. Deviation		1.022	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-1.041	.330
	Kurtosis		.508	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CharAwareEach_A	.396	52	.000	.668	52	.000
CharAwareEach_NA	.300	52	.000	.769	52	.000
CharAwareEach_R	.268	52	.000	.804	52	.000

a. Lilliefors Significance Correction

Explore: The characters were aware of each other's actions.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
CharAwareEachActions_A	52	100.0%	0	0.0%	52	100.0%
CharAwareEachActions_NA	52	100.0%	0	0.0%	52	100.0%
CharAwareEachActions_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
CharAwareEachActions_A	Mean		4.37	.095
	95% Confidence Interval for Mean	Lower Bound	4.17	
		Upper Bound	4.56	
	5% Trimmed Mean		4.41	
	Median		4.00	
	Variance		.472	
	Std. Deviation		.687	
	Minimum		3	
	Maximum		5	
	Range		2	
	Interquartile Range		1	
	Skewness		-.624	.330
	Kurtosis		-.679	.650
CharAwareEachActions_NA	Mean		3.96	.110
	95% Confidence Interval for Mean	Lower Bound	3.74	
		Upper Bound	4.18	
	5% Trimmed Mean		4.00	
	Median		4.00	
	Variance		.626	
	Std. Deviation		.791	

Descriptives

			Statistic	Std. Error
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		2	
	Skewness		-.425	.330
	Kurtosis		-.138	.650
CharAwareEachActions_R	Mean		3.83	.142
	95% Confidence Interval for Mean	Lower Bound	3.54	
		Upper Bound	4.11	
	5% Trimmed Mean		3.88	
	Median		4.00	
	Variance		1.048	
	Std. Deviation		1.024	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.665	.330
	Kurtosis		-.109	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CharAwareEachActions_A	.303	52	.000	.761	52	.000
CharAwareEachActions_NA	.269	52	.000	.845	52	.000
CharAwareEachActions_R	.240	52	.000	.869	52	.000

a. Lilliefors Significance Correction

Explore: The characters could predict each others' actions

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
CharPredictEachActions_A	52	100.0%	0	0.0%	52	100.0%
CharPredictEachActions_NA	52	100.0%	0	0.0%	52	100.0%
CharPredictEachActions_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
CharPredictEachActions_A	Mean		3.83	.142
	95% Confidence Interval for Mean	Lower Bound	3.54	
		Upper Bound	4.11	
	5% Trimmed Mean		3.88	
	Median		4.00	
	Variance		1.048	
	Std. Deviation		1.024	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.665	.330
	Kurtosis		-.109	.650
CharPredictEachActions_NA	Mean		3.00	.123
	95% Confidence Interval for Mean	Lower Bound	2.75	
		Upper Bound	3.25	
	5% Trimmed Mean		2.98	
	Median		3.00	
	Variance		.784	
	Std. Deviation		.886	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		.176	.330
	Kurtosis		-.460	.650
CharPredictEachActions_R	Mean		2.94	.111
	95% Confidence Interval for Mean	Lower Bound	2.72	
		Upper Bound	3.17	
	5% Trimmed Mean		2.90	
	Median		3.00	
	Variance		.644	

Descriptives

		Statistic	Std. Error
	Std. Deviation	.802	
	Minimum	1	
	Maximum	5	
	Range	4	
	Interquartile Range	1	
	Skewness	.580	.330
	Kurtosis	1.273	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CharPredictEachActions_A	.240	52	.000	.869	52	.000
CharPredictEachActions_NA	.212	52	.000	.886	52	.000
CharPredictEachActions_R	.317	52	.000	.820	52	.000

a. Lilliefors Significance Correction

Explore: The characters were aware of each other's feelings

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
CharAwareEachFeelings_A	52	100.0%	0	0.0%	52	100.0%
CharAwareEachFeelings_NA	52	100.0%	0	0.0%	52	100.0%
CharAwareEachFeelings_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
CharAwareEachFeelings_A	Mean		4.08	.119
	95% Confidence Interval for Mean	Lower Bound	3.84	
		Upper Bound	4.32	
	5% Trimmed Mean		4.14	
	Median		4.00	
	Variance		.739	
	Std. Deviation		.860	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		-.729	.330
	Kurtosis		.032	.650
CharAwareEachFeelings_NA	Mean		3.38	.140
	95% Confidence Interval for Mean	Lower Bound	3.10	
		Upper Bound	3.67	
	5% Trimmed Mean		3.37	
	Median		3.00	
	Variance		1.026	
	Std. Deviation		1.013	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		.210	.330
	Kurtosis		-1.004	.650
CharAwareEachFeelings_R	Mean		3.40	.154
	95% Confidence Interval for Mean	Lower Bound	3.10	
		Upper Bound	3.71	
	5% Trimmed Mean		3.45	
	Median		3.00	
	Variance		1.226	
	Std. Deviation		1.107	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.333	.330
	Kurtosis		-.422	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CharAwareEachFeelings_A	.253	52	.000	.828	52	.000
CharAwareEachFeelings_NA	.225	52	.000	.873	52	.000
CharAwareEachFeelings_R	.186	52	.000	.907	52	.001

a. Lilliefors Significance Correction

Explore: The characters could predict each others' feelings

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
CharPredictEachFeelings_A	52	100.0%	0	0.0%	52	100.0%
CharPredictEachFeelings_NA	52	100.0%	0	0.0%	52	100.0%
CharPredictEachFeelings_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
CharPredictEachFeelings_A	Mean		3.35	.150
	95% Confidence Interval for Mean	Lower Bound	3.04	
		Upper Bound	3.65	
	5% Trimmed Mean		3.37	
	Median		3.00	
	Variance		1.172	
	Std. Deviation		1.083	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.068	.330
	Kurtosis		-.613	.650
CharPredictEachFeelings_NA	Mean		2.90	.135
	95% Confidence Interval for Mean	Lower Bound	2.63	
		Upper Bound	3.18	
	5% Trimmed Mean		2.88	
	Median		3.00	
	Variance		.951	
	Std. Deviation		.975	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		.462	.330
	Kurtosis		-.105	.650
CharPredictEachFeelings_R	Mean		2.92	.131
	95% Confidence Interval for Mean	Lower Bound	2.66	
		Upper Bound	3.19	
	5% Trimmed Mean		2.93	
	Median		3.00	
	Variance		.896	
	Std. Deviation		.947	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.131	.330
	Kurtosis		-.033	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CharPredictEachFeelings_A	.202	52	.000	.908	52	.001
CharPredictEachFeelings_NA	.230	52	.000	.887	52	.000
CharPredictEachFeelings_R	.244	52	.000	.899	52	.000

a. Lilliefors Significance Correction

Explore: The characters were aware of each other's intentions

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
CharAwareEachIntentions_A	52	100.0%	0	0.0%	52	100.0%
CharAwareEachIntentions_NA	52	100.0%	0	0.0%	52	100.0%
CharAwareEachIntentions_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
CharAwareEachIntentions_A	Mean		3.96	.120
	95% Confidence Interval for Mean	Lower Bound	3.72	
		Upper Bound	4.20	
	5% Trimmed Mean		4.01	
	Median		4.00	
	Variance		.744	
	Std. Deviation		.862	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		2	
	Skewness		-.497	.330
	Kurtosis		-.342	.650
CharAwareEachIntentions_NA	Mean		3.54	.124
	95% Confidence Interval for Mean	Lower Bound	3.29	
		Upper Bound	3.79	
	5% Trimmed Mean		3.54	
	Median		4.00	
	Variance		.802	
	Std. Deviation		.896	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		-.290	.330
	Kurtosis		-.634	.650
CharAwareEachIntentions_R	Mean		3.48	.133
	95% Confidence Interval for Mean	Lower Bound	3.21	
		Upper Bound	3.75	
	5% Trimmed Mean		3.52	
	Median		4.00	
	Variance		.921	
	Std. Deviation		.960	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.566	.330
	Kurtosis		.305	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CharAwareEachIntentions_A	.249	52	.000	.851	52	.000
CharAwareEachIntentions_NA	.274	52	.000	.862	52	.000
CharAwareEachIntentions_R	.244	52	.000	.884	52	.000

a. Lilliefors Significance Correction

Explore: The interaction between characters in this scene was believable

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
InteractionBelievable_A	52	100.0%	0	0.0%	52	100.0%
InteractionBelievable_NA	52	100.0%	0	0.0%	52	100.0%
InteractionBelievable_R	52	100.0%	0	0.0%	52	100.0%

Descriptives

			Statistic	Std. Error
InteractionBelievable_A	Mean		4.23	.118
	95% Confidence Interval for Mean	Lower Bound	3.99	
		Upper Bound	4.47	
	5% Trimmed Mean		4.33	
	Median		4.00	
	Variance		.730	
	Std. Deviation		.854	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-1.648	.330
	Kurtosis		3.872	.650
InteractionBelievable_NA	Mean		3.81	.132
	95% Confidence Interval for Mean	Lower Bound	3.54	
		Upper Bound	4.07	
	5% Trimmed Mean		3.86	
	Median		4.00	
	Variance		.903	
	Std. Deviation		.951	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.737	.330
	Kurtosis		.431	.650
InteractionBelievable_R	Mean		3.31	.195
	95% Confidence Interval for Mean	Lower Bound	2.92	
		Upper Bound	3.70	
	5% Trimmed Mean		3.34	
	Median		4.00	
	Variance		1.982	
	Std. Deviation		1.408	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.444	.330
	Kurtosis		-1.079	.650

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
InteractionBelievable_A	.297	52	.000	.729	52	.000
InteractionBelievable_NA	.272	52	.000	.864	52	.000
InteractionBelievable_R	.227	52	.000	.868	52	.000

a. Lilliefors Significance Correction

C.2 Friedman Tests

NPar Tests: I understood what the characters were doing.

Friedman Test

Ranks

	Mean Rank
UnderstoodCharacters_A	2.33
UnderstoodCharacters_NA	2.09
UnderstoodCharacters_R	1.59

Test Statistics[a]

N	52
Chi-Square	28.055
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: I could predict the characters' actions.

Friedman Test

Ranks

	Mean Rank
PredictCharacters_A	2.21
PredictCharacters_NA	2.12
PredictCharacters_R	1.67

Test Statistics[a]

N	52
Chi-Square	14.744
df	2
Asymp. Sig.	.001

a. Friedman Test

NPar Tests: I understood what the characters were feeling.

Friedman Test

Ranks

	Mean Rank
UndersCharFeel_A	2.37
UndersCharFeel_NA	2.00
UndersCharFeel_R	1.63

Test Statistics[a]

N	52
Chi-Square	26.255
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: I could predict the characters' feelings.

Friedman Test

Ranks

	Mean Rank
PredictCharFeel_A	2.27
PredictCharFeel_NA	2.17
PredictCharFeel_R	1.56

Test Statistics[a]

N	52
Chi-Square	26.000
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: I understood the characters' intentions.

Friedman Test

Ranks

	Mean Rank
UndersCharIntentions_A	2.13
UndersCharIntentions_NA	2.04
UndersCharIntentions_R	1.84

Test Statistics[a]

N	52
Chi-Square	3.823
df	2
Asymp. Sig.	.148

a. Friedman Test

NPar Tests: The characters were aware of each other.

Friedman Test

Ranks

	Mean Rank
CharAwareEach_A	2.29
CharAwareEach_NA	1.87
CharAwareEach_R	1.85

Test Statistics[a]

N	52
Chi-Square	15.540
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: The characters were aware of each other's actions.

Friedman Test

Ranks

	Mean Rank
CharAwareEachActions_A	2.29
CharAwareEachActions_NA	1.87
CharAwareEachActions_R	1.85

Test Statistics[a]

N	52
Chi-Square	13.520
df	2
Asymp. Sig.	.001

a. Friedman Test

NPar Tests: The characters could predict each others' actions

Friedman Test

Ranks

	Mean Rank
CharPredictEachActions_A	2.55
CharPredictEachActions_NA	1.78
CharPredictEachActions_R	1.67

Test Statistics[a]

N	52
Chi-Square	34.503
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: The characters were aware of each other's feelings

Friedman Test

Ranks

	Mean Rank
CharAwareEachFeelings_A	2.43
CharAwareEachFeelings_NA	1.77
CharAwareEachFeelings_R	1.80

Test Statistics[a]

N	52
Chi-Square	22.872
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: The characters could predict each others' feelings

Friedman Test

Ranks

	Mean Rank
CharPredictEachFeelings_A	2.24
CharPredictEachFeelings_NA	1.86
CharPredictEachFeelings_R	1.90

Test Statistics[a]

N	52
Chi-Square	8.879
df	2
Asymp. Sig.	.012

a. Friedman Test

NPar Tests: The characters were aware of each other's intentions.

Friedman Test

Ranks

	Mean Rank
CharAwareEachIntentions_A	2.34
CharAwareEachIntentions_NA	1.84
CharAwareEachIntentions_R	1.83

Test Statistics[a]

N	52
Chi-Square	18.198
df	2
Asymp. Sig.	.000

a. Friedman Test

NPar Tests: The interaction between characters in this scene was believable

Friedman Test

Ranks

	Mean Rank
InteractionBelievable_A	2.38
InteractionBelievable_NA	1.93
InteractionBelievable_R	1.69

Test Statistics[a]

N	52
Chi-Square	21.798
df	2
Asymp. Sig.	.000

a. Friedman Test

C.3 Wilcoxon signed rank Tests

NPar Tests: I understood what the characters were doing.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
UnderstoodCharacters_NA - UnderstoodCharacters_A	Negative Ranks	14[a]	10.54	147.50
	Positive Ranks	5[b]	8.50	42.50
	Ties	33[c]		
	Total	52		
UnderstoodCharacters_R - UnderstoodCharacters_A	Negative Ranks	27[d]	15.37	415.00
	Positive Ranks	2[e]	10.00	20.00
	Ties	23[f]		
	Total	52		
UnderstoodCharacters_R - UnderstoodCharacters_NA	Negative Ranks	23[g]	15.48	356.00
	Positive Ranks	5[h]	10.00	50.00
	Ties	24[i]		
	Total	52		

a. UnderstoodCharacters_NA < UnderstoodCharacters_A

b. UnderstoodCharacters_NA > UnderstoodCharacters_A

c. UnderstoodCharacters_NA = UnderstoodCharacters_A

d. UnderstoodCharacters_R < UnderstoodCharacters_A

e. UnderstoodCharacters_R > UnderstoodCharacters_A

f. UnderstoodCharacters_R = UnderstoodCharacters_A

g. UnderstoodCharacters_R < UnderstoodCharacters_NA

h. UnderstoodCharacters_R > UnderstoodCharacters_NA

i. UnderstoodCharacters_R = UnderstoodCharacters_NA

Test Statistics[a]

	UnderstoodCharacters_NA - UnderstoodCharacters_A	UnderstoodCharacters_R - UnderstoodCharacters_A	UnderstoodCharacters_R - UnderstoodCharacters_NA
Z	-2.275[b]	-4.423[b]	-3.623[b]
Asymp. Sig. (2-tailed)	.023	.000	.000

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: I could predict the characters' actions.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
PredictCharacters_NA - PredictCharacters_A	Negative Ranks	15[a]	14.83	222.50
	Positive Ranks	13[b]	14.12	183.50
	Ties	24[c]		
	Total	52		
PredictCharacters_R - PredictCharacters_A	Negative Ranks	25[d]	16.40	410.00
	Positive Ranks	5[e]	11.00	55.00
	Ties	22[f]		
	Total	52		
PredictCharacters_R - PredictCharacters_NA	Negative Ranks	20[g]	14.85	297.00
	Positive Ranks	6[h]	9.00	54.00
	Ties	26[i]		
	Total	52		

a. PredictCharacters_NA < PredictCharacters_A

b. PredictCharacters_NA > PredictCharacters_A

c. PredictCharacters_NA = PredictCharacters_A

d. PredictCharacters_R < PredictCharacters_A

e. PredictCharacters_R > PredictCharacters_A

f. PredictCharacters_R = PredictCharacters_A

g. PredictCharacters_R < PredictCharacters_NA

h. PredictCharacters_R > PredictCharacters_NA

i. PredictCharacters_R = PredictCharacters_NA

Test Statistics[a]

	PredictCharacters_NA - PredictCharacters_A	PredictCharacters_R - PredictCharacters_A	PredictCharacters_R - PredictCharacters_NA
Z	-.469[b]	-3.819[b]	-3.198[b]
Asymp. Sig. (2-tailed)	.639	.000	.001

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: I understood what the characters were feeling.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
UndersCharFeel_NA - UndersCharFeel_A	Negative Ranks	15[a]	8.97	134.50
	Positive Ranks	2[b]	9.25	18.50
	Ties	35[c]		
	Total	52		
UndersCharFeel_R - UndersCharFeel_A	Negative Ranks	26[d]	14.31	372.00
	Positive Ranks	1[e]	6.00	6.00
	Ties	25[f]		
	Total	52		
UndersCharFeel_R - UndersCharFeel_NA	Negative Ranks	22[g]	17.64	388.00
	Positive Ranks	9[h]	12.00	108.00
	Ties	21[i]		
	Total	52		

a. UndersCharFeel_NA < UndersCharFeel_A

b. UndersCharFeel_NA > UndersCharFeel_A

c. UndersCharFeel_NA = UndersCharFeel_A

d. UndersCharFeel_R < UndersCharFeel_A

e. UndersCharFeel_R > UndersCharFeel_A

f. UndersCharFeel_R = UndersCharFeel_A

g. UndersCharFeel_R < UndersCharFeel_NA

h. UndersCharFeel_R > UndersCharFeel_NA

i. UndersCharFeel_R = UndersCharFeel_NA

Test Statistics[a]

	UndersCharFeel_NA - UndersCharFeel_A	UndersCharFeel_R - UndersCharFeel_A	UndersCharFeel_R - UndersCharFeel_NA
Z	-2.839[b]	-4.454[b]	-2.799[b]
Asymp. Sig. (2-tailed)	.005	.000	.005

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: I could predict the characters' feelings.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
PredictCharFeel_NA - PredictCharFeel_A	Negative Ranks	15[a]	15.30	229.50
	Positive Ranks	12[b]	12.38	148.50
	Ties	25[c]		
	Total	52		
PredictCharFeel_R - PredictCharFeel_A	Negative Ranks	28[d]	16.59	464.50
	Positive Ranks	3[e]	10.50	31.50
	Ties	21[f]		
	Total	52		
PredictCharFeel_R - PredictCharFeel_NA	Negative Ranks	25[g]	14.96	374.00
	Positive Ranks	4[h]	15.25	61.00
	Ties	23[i]		
	Total	52		

a. PredictCharFeel_NA < PredictCharFeel_A

b. PredictCharFeel_NA > PredictCharFeel_A

c. PredictCharFeel_NA = PredictCharFeel_A

d. PredictCharFeel_R < PredictCharFeel_A

e. PredictCharFeel_R > PredictCharFeel_A

f. PredictCharFeel_R = PredictCharFeel_A

g. PredictCharFeel_R < PredictCharFeel_NA

h. PredictCharFeel_R > PredictCharFeel_NA

i. PredictCharFeel_R = PredictCharFeel_NA

Test Statistics[a]

	PredictCharFeel_NA - PredictCharFeel_A	PredictCharFeel_R - PredictCharFeel_A	PredictCharFeel_R - PredictCharFeel_NA
Z	-1.009[b]	-4.395[b]	-3.477[b]
Asymp. Sig. (2-tailed)	.313	.000	.001

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: I understood the characters' intentions.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
UndersCharIntentions_NA - UndersCharIntentions_A	Negative Ranks	13[a]	11.85	154.00
	Positive Ranks	9[b]	11.00	99.00
	Ties	30[c]		
	Total	52		
UndersCharIntentions_R - UndersCharIntentions_A	Negative Ranks	21[d]	19.43	408.00
	Positive Ranks	12[e]	12.75	153.00
	Ties	19[f]		
	Total	52		
UndersCharIntentions_R - UndersCharIntentions_NA	Negative Ranks	19[g]	16.26	309.00
	Positive Ranks	11[h]	14.18	156.00
	Ties	22[i]		
	Total	52		

a. UndersCharIntentions_NA < UndersCharIntentions_A

b. UndersCharIntentions_NA > UndersCharIntentions_A

c. UndersCharIntentions_NA = UndersCharIntentions_A

d. UndersCharIntentions_R < UndersCharIntentions_A

e. UndersCharIntentions_R > UndersCharIntentions_A

f. UndersCharIntentions_R = UndersCharIntentions_A

g. UndersCharIntentions_R < UndersCharIntentions_NA

h. UndersCharIntentions_R > UndersCharIntentions_NA

i. UndersCharIntentions_R = UndersCharIntentions_NA

Test Statistics[a]

	UndersCharIntentions_NA - UndersCharIntentions_A	UndersCharIntentions_R - UndersCharIntentions_A	UndersCharIntentions_R - UndersCharIntentions_NA
Z	-.924[b]	-2.368[b]	-1.627[b]
Asymp. Sig. (2-tailed)	.355	.018	.104

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: The characters were aware of each other.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
CharAwareEach_NA - CharAwareEach_A	Negative Ranks	17[a]	10.12	172.00
	Positive Ranks	2[b]	9.00	18.00
	Ties	33[c]		
	Total	52		
CharAwareEach_R - CharAwareEach_A	Negative Ranks	17[d]	10.41	177.00
	Positive Ranks	2[e]	6.50	13.00
	Ties	33[f]		
	Total	52		
CharAwareEach_R - CharAwareEach_NA	Negative Ranks	11[g]	13.27	146.00
	Positive Ranks	10[h]	8.50	85.00
	Ties	31[i]		
	Total	52		

a. CharAwareEach_NA < CharAwareEach_A

b. CharAwareEach_NA > CharAwareEach_A

c. CharAwareEach_NA = CharAwareEach_A

d. CharAwareEach_R < CharAwareEach_A

e. CharAwareEach_R > CharAwareEach_A

f. CharAwareEach_R = CharAwareEach_A

g. CharAwareEach_R < CharAwareEach_NA

h. CharAwareEach_R > CharAwareEach_NA

i. CharAwareEach_R = CharAwareEach_NA

Test Statistics[a]

	CharAwareEach_NA - CharAwareEach_A	CharAwareEach_R - CharAwareEach_A	CharAwareEach_R - CharAwareEach_NA
Z	-3.392[b]	-3.407[b]	-1.102[b]
Asymp. Sig. (2-tailed)	.001	.001	.271

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: The characters were aware of each other's actions.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
CharAwareEachActions_NA - CharAwareEachActions_A	Negative Ranks	18[a]	10.72	193.00
	Positive Ranks	2[b]	8.50	17.00
	Ties	32[c]		
	Total	52		
CharAwareEachActions_R - CharAwareEachActions_A	Negative Ranks	18[d]	12.72	229.00
	Positive Ranks	4[e]	6.00	24.00
	Ties	30[f]		
	Total	52		
CharAwareEachActions_R - CharAwareEachActions_NA	Negative Ranks	15[g]	16.30	244.50
	Positive Ranks	13[h]	12.42	161.50
	Ties	24[i]		
	Total	52		

a. CharAwareEachActions_NA < CharAwareEachActions_A

b. CharAwareEachActions_NA > CharAwareEachActions_A

c. CharAwareEachActions_NA = CharAwareEachActions_A

d. CharAwareEachActions_R < CharAwareEachActions_A

e. CharAwareEachActions_R > CharAwareEachActions_A

f. CharAwareEachActions_R = CharAwareEachActions_A

g. CharAwareEachActions_R < CharAwareEachActions_NA

h. CharAwareEachActions_R > CharAwareEachActions_NA

i. CharAwareEachActions_R = CharAwareEachActions_NA

Test Statistics[a]

	CharAwareEachActions_NA - CharAwareEachActions_A	CharAwareEachActions_R - CharAwareEachActions_A	CharAwareEachActions_R - CharAwareEachActions_NA
Z	-3.500[b]	-3.405[b]	-.975[b]
Asymp. Sig. (2-tailed)	.000	.001	.330

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: The characters could predict each others' actions

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
CharPredictEachActions_NA - CharPredictEachActions_A	Negative Ranks	32[a]	20.95	670.50
	Positive Ranks	7[b]	15.64	109.50
	Ties	13[c]		
	Total	52		
CharPredictEachActions_R - CharPredictEachActions_A	Negative Ranks	33[d]	17.23	568.50
	Positive Ranks	1[e]	26.50	26.50
	Ties	18[f]		
	Total	52		
CharPredictEachActions_R - CharPredictEachActions_NA	Negative Ranks	14[g]	13.79	193.00
	Positive Ranks	12[h]	13.17	158.00
	Ties	26[i]		
	Total	52		

a. CharPredictEachActions_NA < CharPredictEachActions_A

b. CharPredictEachActions_NA > CharPredictEachActions_A

c. CharPredictEachActions_NA = CharPredictEachActions_A

d. CharPredictEachActions_R < CharPredictEachActions_A

e. CharPredictEachActions_R > CharPredictEachActions_A

f. CharPredictEachActions_R = CharPredictEachActions_A

g. CharPredictEachActions_R < CharPredictEachActions_NA

h. CharPredictEachActions_R > CharPredictEachActions_NA

i. CharPredictEachActions_R = CharPredictEachActions_NA

Test Statistics[a]

	CharPredictEachActions_NA - CharPredictEachActions_A	CharPredictEachActions_R - CharPredictEachActions_A	CharPredictEachActions_R - CharPredictEachActions_NA
Z	-4.014[b]	-4.774[b]	-.475[b]
Asymp. Sig. (2-tailed)	.000	.000	.635

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: The characters were aware of each other's feelings

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
CharAwareEachFeelings_NA - CharAwareEachFeelings_A	Negative Ranks	26[a]	15.25	396.50
	Positive Ranks	4[b]	17.13	68.50
	Ties	22[c]		
	Total	52		
CharAwareEachFeelings_R - CharAwareEachFeelings_A	Negative Ranks	28[d]	17.05	477.50
	Positive Ranks	5[e]	16.70	83.50
	Ties	19[f]		
	Total	52		
CharAwareEachFeelings_R - CharAwareEachFeelings_NA	Negative Ranks	14[g]	15.57	218.00
	Positive Ranks	16[h]	15.44	247.00
	Ties	22[i]		
	Total	52		

a. CharAwareEachFeelings_NA < CharAwareEachFeelings_A

b. CharAwareEachFeelings_NA > CharAwareEachFeelings_A

c. CharAwareEachFeelings_NA = CharAwareEachFeelings_A

d. CharAwareEachFeelings_R < CharAwareEachFeelings_A

e. CharAwareEachFeelings_R > CharAwareEachFeelings_A

f. CharAwareEachFeelings_R = CharAwareEachFeelings_A

g. CharAwareEachFeelings_R < CharAwareEachFeelings_NA

h. CharAwareEachFeelings_R > CharAwareEachFeelings_NA

i. CharAwareEachFeelings_R = CharAwareEachFeelings_NA

Test Statistics[a]

	CharAwareEachFeelings_NA - CharAwareEachFeelings_A	CharAwareEachFeelings_R - CharAwareEachFeelings_A	CharAwareEachFeelings_R - CharAwareEachFeelings_NA
Z	-3.449[b]	-3.634[b]	-.309[c]
Asymp. Sig. (2-tailed)	.001	.000	.757

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

NPar Tests: The characters could predict each others' feelings

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
CharPredictEachFeelings_NA - CharPredictEachFeelings_A	Negative Ranks	20[a]	14.38	287.50
	Positive Ranks	7[b]	12.93	90.50
	Ties	25[c]		
	Total	52		
CharPredictEachFeelings_R - CharPredictEachFeelings_A	Negative Ranks	19[d]	14.55	276.50
	Positive Ranks	7[e]	10.64	74.50
	Ties	26[f]		
	Total	52		
CharPredictEachFeelings_R - CharPredictEachFeelings_NA	Negative Ranks	9[g]	11.17	100.50
	Positive Ranks	11[h]	9.95	109.50
	Ties	32[i]		
	Total	52		

a. CharPredictEachFeelings_NA < CharPredictEachFeelings_A

b. CharPredictEachFeelings_NA > CharPredictEachFeelings_A

c. CharPredictEachFeelings_NA = CharPredictEachFeelings_A

d. CharPredictEachFeelings_R < CharPredictEachFeelings_A

e. CharPredictEachFeelings_R > CharPredictEachFeelings_A

f. CharPredictEachFeelings_R = CharPredictEachFeelings_A

g. CharPredictEachFeelings_R < CharPredictEachFeelings_NA

h. CharPredictEachFeelings_R > CharPredictEachFeelings_NA

i. CharPredictEachFeelings_R = CharPredictEachFeelings_NA

Test Statistics[a]

	CharPredictEachFeelings_NA - CharPredictEachFeelings_A	CharPredictEachFeelings_R - CharPredictEachFeelings_A	CharPredictEachFeelings_R - CharPredictEachFeelings_NA
Z	-2.424[b]	-2.658[b]	-.173[c]
Asymp. Sig. (2-tailed)	.015	.008	.862

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

NPar Tests: The characters were aware of each other's intentions.

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
CharAwareEachIntentions_NA - CharAwareEachIntentions_A	Negative Ranks	21[a]	12.31	258.50
	Positive Ranks	3[b]	13.83	41.50
	Ties	28[c]		
	Total	52		
CharAwareEachIntentions_R - CharAwareEachIntentions_A	Negative Ranks	22[d]	14.25	313.50
	Positive Ranks	5[e]	12.90	64.50
	Ties	25[f]		
	Total	52		
CharAwareEachIntentions_R - CharAwareEachIntentions_NA	Negative Ranks	10[g]	10.80	108.00
	Positive Ranks	9[h]	9.11	82.00
	Ties	33[i]		
	Total	52		

a. CharAwareEachIntentions_NA < CharAwareEachIntentions_A

b. CharAwareEachIntentions_NA > CharAwareEachIntentions_A

c. CharAwareEachIntentions_NA = CharAwareEachIntentions_A

d. CharAwareEachIntentions_R < CharAwareEachIntentions_A

e. CharAwareEachIntentions_R > CharAwareEachIntentions_A

f. CharAwareEachIntentions_R = CharAwareEachIntentions_A

g. CharAwareEachIntentions_R < CharAwareEachIntentions_NA

h. CharAwareEachIntentions_R > CharAwareEachIntentions_NA

i. CharAwareEachIntentions_R = CharAwareEachIntentions_NA

Test Statistics[a]

	CharAwareEachIntentions_NA - CharAwareEachIntentions_A	CharAwareEachIntentions_R - CharAwareEachIntentions_A	CharAwareEachIntentions_R - CharAwareEachIntentions_NA
Z	-3.300[b]	-3.148[b]	-.546[b]
Asymp. Sig. (2-tailed)	.001	.002	.585

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

NPar Tests: The interaction between characters in this scene was believable

Wilcoxon Signed Ranks Test

Ranks

		N	Mean Rank	Sum of Ranks
InteractionBelievable_NA - InteractionBelievable_A	Negative Ranks	19[a]	11.50	218.50
	Positive Ranks	3[b]	11.50	34.50
	Ties	30[c]		
	Total	52		
InteractionBelievable_R - InteractionBelievable_A	Negative Ranks	27[d]	17.11	462.00
	Positive Ranks	4[e]	8.50	34.00
	Ties	21[f]		
	Total	52		
InteractionBelievable_R - InteractionBelievable_NA	Negative Ranks	19[g]	17.68	336.00
	Positive Ranks	10[h]	9.90	99.00
	Ties	23[i]		
	Total	52		

a. InteractionBelievable_NA < InteractionBelievable_A

b. InteractionBelievable_NA > InteractionBelievable_A

c. InteractionBelievable_NA = InteractionBelievable_A

d. InteractionBelievable_R < InteractionBelievable_A

e. InteractionBelievable_R > InteractionBelievable_A

f. InteractionBelievable_R = InteractionBelievable_A

g. InteractionBelievable_R < InteractionBelievable_NA

h. InteractionBelievable_R > InteractionBelievable_NA

i. InteractionBelievable_R = InteractionBelievable_NA

Test Statistics[a]

	InteractionBelievable_NA - InteractionBelievable_A	InteractionBelievable_R - InteractionBelievable_A	InteractionBelievable_R - InteractionBelievable_NA
Z	-3.111[b]	-4.274[b]	-2.611[b]
Asymp. Sig. (2-tailed)	.002	.000	.009

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.