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Personality and Emotion for Virtual Characters in Strong-Story Narrative Planning

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PERSONALITY AND EMOTION FOR VIRTUAL CHARACTERS IN STRONG-STORY NARRATIVE PLANNING

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy
in the College of Engineering
at the University of Kentucky

By

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ABSTRACT OF DISSERTATION

PERSONALITY AND EMOTION FOR VIRTUAL CHARACTERS IN STRONG-STORY NARRATIVE PLANNING

Interactive virtual worlds provide an immersive and effective environment for training, education, and entertainment purposes. Virtual characters are an essential part of every interactive narrative. The interaction of rich virtual characters can produce interesting narratives and enhance user experience in virtual environments. I propose models of personality and emotion that are highly domain independent and integrate those models into multi-agent strong-story narrative planning systems. I demonstrate the value of the strong-story properties of the model by generating story conflicts intelligently. My models of emotion and personality enable the narrative generation system to create more opportunities for players to resolve conflicts using certain behavior types. In doing so, the author can encourage the player to adopt and exhibit those behaviors. I conduct multiple human subject and case studies to evaluate these models and show that they enable generating a larger number of stories and character behavior that is preferred and more believable to a human audience.

KEYWORDS: Narrative Planning, Artificial Intelligence, Interactive Narratives, Personality, Emotion, Believable Characters

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PERSONALITY AND EMOTION FOR VIRTUAL CHARACTERS IN STRONG-STORY NARRATIVE PLANNING

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DEDICATION

To my mother who has always been my rock, made so many sacrifices to help me be the man I am today, and always gave me hope to realize the best version of myself. She will always hold a special place in my heart.

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CHAPTER 1. INTRODUCTION

Storytelling has always been prevalent in human culture and various types of media, such as novels, television, and theater. Humans have an inherent ability to describe their experiences in narrative form. This narrative intelligence is central to the cognitive processes employed to tell stories, explain stories, or form expectations regarding a series of events.

Computational systems that reason about narrative intelligence simulate such cognitive processes through different models and algorithms. Although storytelling comes naturally to humans, authoring and creating systems with narrative intelligence poses a significant challenge. This becomes more challenging when the user becomes involved in the story rather than being a mere observer as in watching a movie.

Interactive storytelling or interactive narratives allow users to be a part of a fictional world and influence a dramatic story-line through actions by assuming the role of a character and interacting with non-player characters (NPCs) [Riedl and Bulitko, 2013]. The applications of interactive narratives can be found in education ([Dede; Roussou; Rowe et al., 1995; 2004; 2011]), training ([Thomas and Young; Zook et al.; Garcia et al., 2010; 2012; 2019]), therapy ([Aylett et al.; Dumas et al.; Yannakakis et al., 2007; 2010; 2010]), and entertainment ([Zyda and Sheehan; Levine; Shirvani and Ware, 1997; 2014; 2020]).

Interactive narratives immerse users in a virtual world where they can interact with the world and its characters and feel as an integral part of an unfolding story [Riedl and Bulitko, 2013]. Whether a story is interactive or not, characters are its key component and crucial to its coherence. If we consider the user as one of the characters, character actions and interactions form a major portion of a story. Therefore, I focus mainly on character behavior with the goal of providing the user with an immersive and effective experience.

There are many qualities that make story characters behave in a more consistent and believable manner. The BDI model [Rao et al., 1995] names Beliefs, Intentions, and Desires as three of the core qualities. Characters must have their own individual beliefs about the world they live in, have their own individual goals to achieve, and form intentions to pursue those goals. Other believability models, including those proposed by Loyall (1997), Mateas (1999), and many others, consider personality and emotion as another two important qualities for believable characters. By equipping virtual characters with personality and emotion, we can present a more coherent story with more believable characters whose actions (and how those actions change the world), do not violate the audience's expectations and thus, provide an uninterrupted immersive experience [Young et al., 2013]. In this document, I will build on previous automatic storytelling systems that model agents with goals and beliefs and incorporate emotion and personality into those systems.

1.1 Strong-Story Storytelling

I model personality and emotion in strong-story storytelling. In this section, I will introduce the concept and later, in Chapter 2, provide more details and examples.

Strong-story systems are a class of automatic story generation systems that use a centralized intelligent unit, often referred to as an experience manager [Riedl and Bulitko, 2013], to coordinate the actions of all characters. Strong story is considered an extreme, on the opposite side of the spectrum, from strong autonomy. Storytelling systems often strike a middle ground between strong story and strong autonomy or choose to be closer to end of the spectrum than the other.

Strong autonomy puts their characters first and gives them a high degree of freedom and independence from the experience manager (if there exists one at all). Strong-autonomy systems are often used for entertainment and simulations whose authors have no specific goals but to provide an entertaining and engaging experience. In strong autonomy, each character is an independent intelligent agent that is situated in the world, and the story emerges organically as the characters interact with the world, the player, or other characters. The author can constrain the decision making of each character, but they generally cannot control how they behave in specific situations (or at least without hand-authoring those situations).

Strong-story systems explore the space of all possible stories and choose the best one that matches some constraints. More specifically, the experience manager can foresee and anticipate all events and character interactions to plan ahead the storylines that best fit those constraints. We can even assume that the experience manager is the only intelligent agent as it decides about the actions and behaviors of all story characters, such that they appear to be autonomous and intelligent. Strong story provides authors with more control over the player experience; but it often comes at a high computational cost as story spaces tend to be immense.

Strong-story systems are most suitable for authors who want their players to have a particular type of experience and achieve a certain set of goals in the narrative. For training and educational simulations, they enable authors to teach their players specific lessons, provide them with important information, or help them acquire certain skills. For entertainment, they can personalize the narrative to various types of players or tailor story events to increase player engagement and enjoyment.

Riedl et al. consider narrative planners as strong story systems because they rely on an experience manager to generate a story that satisfies the author goals and then try to explain the actions of non-player characters [Riedl and Bulitko, 2013]. I build on previous multi-agent narrative planners that model agents with their individual goals and beliefs [Riedl and Young; Teutenberg and Porteous; Ware and Young; Teutenberg and Porteous; Shirvani et al., 2004; 2013; 2014; 2015; 2017]. These planners lack of a model of personality and emotion that could make their characters behave more consistently and human-like. To propose a model of personality and emotion, I focus on multi-agent strong-story narrative planning.

1.2 Intelligent Conflict Generation

By using a strong-story model, I enable experience managers to explore the space of all possible stories, reason about different types of stories, and intelligently choose ones that best fit the system's goals. In this document, I will support this idea in practice by using emotion, personality, and the ability of strong-story systems to intelligently create player choices, specifically for conflict resolution.

Many narratologists agree that conflict is an essential part of every story [Brooks and Warren; Abbott; Field, 1979; 2020; 2006]. A conflict can provoke anxiety and suspense, making a character pause to carefully consider their options. A conflict occurs when a character, such as the player, is faced with a choice which could have negative outcomes for them.

In an interactive context, a strong-story narrative planner can search the space of all possible stories and

1. Find all player choices that represent a conflict: the planner can find all character plans and how those plans could threaten to thwart each other. For instance, the planner can identify that the player wants to cross a forest, a bandit living in the forest, and the conflict of the player getting robbed by the bandit.

   By using an emotion model and a player model, the planner can assume the player's goals and how the player <u>fears</u> failing their goals. This fear calls for a player choice that could either end up in the player's <u>fears becoming true</u> or feeling <u>relieved</u> instead.

2. Reason about player expectations of the outcomes of that choice by exploring the possible worlds that could unfold as a result: after identifying the conflict of the player getting robbed, the planner finds player plans that could resolve the conflict. For instance, the player could do nothing, flee, attack, or talk to the bandit. Based on the player's beliefs about the world state, the planner can reason about their expectations: if they do nothing, the bandit will rob them;

if they flee the bandit will follow them, and so on. Using a personality model, the planner can distinguish between these different options, predict what option the player chooses, or determine what type of behavior is encouraged by each option. For instance, attacking the bandit is not agreeable or talking to the bandit is extroverted.

3. Use this information to plan a narrative and coordinate all virtual characters: after the planner has reasoned about player options and expectations, the planner can coordinate the actions of every other character. For instance, the planner may decide that there are no <u>good</u> options to resolve a conflict—here, good is a measure that is often provided by the system's author. For instance, the planner determines that the player believes the only way to avoid getting robbed is to attack the bandit. In that case, the planner never puts the bandit on the player's path to avoid forcing the player to resort to violence.

Using this process, I enable the narrative system to intelligently generate conflicts based on the author's goals. For instance, in training and education, using this model, the author can encourage the player to pursue certain goals and adopt certain personality traits. In entertainment, the author can elicit the player's personality and personalize the narrative for various types of players.

In Chapter 4, I will describe the process of conflict generation in more detail, and in Chapter 5, I will present the experiments used to evaluate this model.

1.3 Evaluation

I hypothesize that, using my models of personality and emotion for strong-story narrative planning, (1) human readers find the generated character behavior to be more believable and consistent, and (2) we can create story conflicts intelligently by distinguishing between different conflicts and reasoning about their usefulness.

I conducted several experiments. To evaluate how my models of emotion and personality contribute to character believability, the stories generated by those models must be presented to a human audience. Without a human audience, it is near impossible to objectively determine that a system improves character believability on its own merit and in comparison to others. Using the crowd sourcing platform, Amazon's Mechanical Turk, I implemented several (interactive) stories using Twine[1] and recruited participants to play those stories and answer questions about them. A summary of my findings are as follows. I will provide detailed descriptions of the experiments and their results in Chapter 6.

- Participants significantly agreed that stories generated by my models of personality and emotion are more believable than those generated by previous systems (with no emotion or personality).
- Participants were able to perceive the personality traits of the story characters and stated that those characters act in a more consistent way than those without a personality.
- My model accurately simulates what a character should feel at different parts of the story according to the expectations of the participants.
- Participants showed more empathy towards characters that expressed emotions than those that did not.

These results show that my models of emotion and personality accurately simulate character behavior in line with the expectations of a human audience, and using these models, a human audience finds the generated behavior more consistent and believable.

To investigate the effectiveness of my models for intelligent conflict generation, I implemented two interactive narratives from two story domains, one in an entertainment context and one in a training simulation context. I simulated a player agent

[1] https://twinery.org/

who played through that narratives. A summary of my findings are as follows. I will provide detailed descriptions of the experiments and their results in Chapter 6.

- On average, the player experienced a smaller number of conflicts when the system generated conflicts intelligently, as it did not allow conflicts that could not be resolved by the intended behavior.

- On average, out of all instances of a player conflict in the two story domains, 28.08% and 30.52% of the conflicts could not be resolved using the author's intended behavior when the system did not generate conflicts intelligently.

- On average, out of all instances of a player conflict in the two story domains, the player chose to resolve a conflict using the author's intended behavior 56.31% and 67.35% of the time when the system generated conflicts intelligently, and 46.48% and 35.14% of the time when it did not.

These results show that my model reduces the number of generated conflicts by removing those that cannot be resolved by the author's intended behaviors. Moreover, by providing a choice to resolve a conflict using the author's intended behaviors, a player is more likely to exhibit those types of behaviors. In short, the proposed model enables us to distinguish which conflicts are useful in the context of a story.

1.4 Outline

The rest of this document is organized as follows. In Chapter 2, I will discuss the related work in generating believable behavior and computational models of emotion and personality. More specifically, I will show what the general consensus is on qualities that make characters believable and how previous storytelling systems have modeled certain key qualities.

In Chapter 3, I will present the fundamental concepts of narrative planning and introduce the models of personality, i.e. the Five Factor Model (FFM) [Goldberg, 1992], and emotion, i.e. OCC [Ortony et al., 1990], in psychology that inspired my models. In Chapter 4, I will provide more formal definitions of narrative planning concepts used by my models, and discuss the adaptation of FFM and OCC into computational models of personality and emotion. I will also explain in detail how the incorporation of those models into strong-story state-space narrative planning changes the previous definitions, allows generating more stories, and can be used for intelligent conflict generation in interactive contexts.

Chapter 5 focuses on the investigation and evaluation of the proposed models via multiple experiments. Using several human-subject studies, I will first show how the stories generated by my models improve a human audience's perceived believability of the story characters. Next, I will evaluate the use of personality and emotion in conflict generation by generating multiple interactive narratives and having a simulation agent play through them. Finally, Chapter 6 will present the conclusions and future work.

CHAPTER 2. RELATED WORK

2.1 Believable Characters

The concept of believability has long been studied in animation, theater, and other media. In their work on Walt Disney animation, Thomas and Johnston describe how Disney animations attempt to make the audience believe in their characters, to laugh, and to cry with those characters' adventures and misfortunes [Johnston and Thomas, 1981]. They elaborate on the notion of the illusion of life as a special ingredient in their animated characters that make them appear to think and act of their own volition.

According to Bates et al., believability is the illusion of life that permits suspension of disbelief where the audience accepts the story even though what they perceive contradicts with what they think is real [Bates et al., 1992]. Suspension of disbelief does not mean the audience believes everything they perceive but that they won't reject the story for the sake of enjoyment [Lee and Heeter, 2015].

In fact, suspension of disbelief is a common ground shared by many definitions of believable characters. Mateas defines a believable character as one who seems life-like, whose actions make sense, and allows for suspension of disbelief [Mateas, 1999]. Loyall considers a character believable when it allows suspension of disbelief and provides a convincing portrayal of personality [Loyall, 1997].

2.1.1 Believable Characters vs. Realistic Characters

Believable characters do not necessarily have to be realistic [Loyall, 1997] but they must be real in the context of their environment [Mateas, 1999]. As was mentioned, believable characters enable the audience to willingly suspend their disbelief even if those characters are fictional and unrealistic.

Clear examples of the difference between realism and believability can be found in Disney animations. In fact, they have shown that believability does not require human form [Loyall, 1997]. They animated their characters to only resemble what that type of animal looks like, while exhibiting human-like expressions and reactions.

2.1.2 Believable Characters vs. Believable Agents

Computer Scientists and Artificial Intelligence researchers have borrowed the practices of early animators to create believable agents. In other words, believable agents are personality-rich autonomous agents with properties of believable characters [Loyall, 1997]. As with the illusion of life in believable characters, believable agents may give the illusion of being controlled by a human [Tencé et al., 2010].

In this document, I will use believable characters and agents interchangeably. However, one of their major differences is that believable agents are interactive or more specifically, the interactions with their audience are bidirectional which makes their creation even more difficult [Loyall, 1997].

2.1.3 Believability vs. Intelligence

As AI researchers searched for essential qualities to create the illusion of life, they gravitated more towards reasoning, problem-solving, and other qualities associated with intelligence. Bates attributes this trend to the fact that intelligence is a quality of a scientist and thus, valued by the AI and computer science community [Bates et al., 1992].

However, the central requirement for believable agents is not intelligence [Loyall, 1997], but rather personality [Loyall; Mateas, 1997; 1999] and emotions [Bates et al.; Ortony, 1992; 2002]. In fact, one could say that flaws and dysfunctionalities of an agent might add to their believability [Lisetti and Hudlicka, 2015] and a general competence for routine physical activities and social interactions is enough to create believable agents [Loyall, 1997].

Table 2.1 presents a comparison between AI research focused on intelligent and believable agents [Mateas, 1999]. Many definitions of believability include personality as one of the key qualities. In contrast to intelligent agents motivated by optimally

Table 2.1: A Comparison of Intelligent and Believable Agents

	Believable Agents	Intelligent Agents
Focus	Personality	Competence
Goal	Believability	Realism
Design	Specificity	Generality
Evaluation	Audience Perception	Objective Measurement

solving complex problems and tasks, a believable character could be smart or stupid depending on its personality.

Each believable character has its own specific personality as intended by the author, whereas intelligent agents follow a general set of principles to solve a universal problem. A fictional character like Sherlock Holmes is not a solution to a general problem but plays a specific role in the context of its story.

A believable character is an artistic abstraction of reality [Mateas, 1999]. They are designed to exist in virtual worlds however they are imagined by the artist or the author. In contrast, Intelligent agents function in settings that best simulate, perhaps constrained, real world scenarios. For instance, face recognition algorithms aim to identify or verify a person in the real world from a digital image or video frame.

Finally, the success of an intelligent agent is objectively measured by its accuracy, efficiency, the number of problems it can solve, and so on. This cannot be applied to assess believable agents without involving an audience. For believable agents, an audience is required to evaluate them based on their perception of the agents, i.e. whether the audience finds those agents believable and to what extent.

2.1.4 Qualities of Believable Characters

There are many qualities that make characters believable. There has been extensive research on those qualities and there are several key ones that many researchers came to agree on. Since these qualities are well established in the literature, I do not further investigate their effect on character believability. Instead I attempt to extend existing narrative systems equipped with some qualities to incorporate ones they lack,

Table 2.2: Believability Qualities Present in Various Models

Quality\Present in model	1	2	3	4	5
Personality	Y	Y	Y	Y	Y
Emotions	Y	Y	Y	Y	Y
Change	Y	Y	Y	N	Y
Illusion of Life (IoL)	Y	Y	N	N	Y
IoL: Goals	Y	Y	N	Y	Y
IoL: Social Context	Y	Y	Y	Y	Y
IoL: Awareness and Responsiveness	Y	Y	Y	Y	Y
IoL: Appearance and Capabilities	Y	Y	Y	Y	Y

1. [Loyall, 1997]
2. [Mateas, 1999]
3. [Gomes et al., 2013]
4. [Lee and Heeter, 2015]
5. [Bogdanovych et al., 2016]

specifically personality and emotions. In this section, I focus on five believability models to show the importance of the three major qualities of believable characters, personality, emotions, and illusion of life. Table 2.2 presents these qualities and the models that consider them important.

Personality

"A personality trait is an enduring personal characteristic that reveals itself in a particular pattern of behavior in different situations" [Poznanski and Thagard, 2005]. Personality is the unique and consistent pattern of traits over situation and time [Guilford; Pervin and John, 1959; 1999]. Such unique way of doing things makes characters more interesting [Mateas, 1999]. For virtual characters, personality can contribute to coherency, consistency, and predictability of their reactions and responses [Ortony, 2002]. As Table 2.2 shows, many researchers agree that having characters with noticeable individual personalities is one of the qualities that improve believability.

Emotions

As shown in Table 2.2 and by many other researchers, the ability to process and express emotions is another quality of believable agents [Hayes-Roth and Doyle; Bates et al.; Reilly and Bates; Romano and Wong, 1998; 1992; 1995; 2004]. According to Loyall, a character should not only appear to think, but also must show emotions of their own [Loyall, 1997]. In case of virtual characters, artificial emotions are labels for states that may not exactly replicate human feelings, but are intended to initiate behavior that we would expect from someone in that state [Picard, 1997].

Change

Change, specially in the protagonist, can contribute to believability if used in certain genres. A character's behavior can change with experience [Gomes et al., 2013] and in line with their personality [Loyall, 1997]. Bogdanovych et al. define change as learning and describe it as the ability of agents to change their behavior to adapt to the changes in their environment [Bogdanovych et al., 2016]. Samsonovich et al. describe character arc as the evolution of a character and its goals in a story. By their definition, a character's beliefs, goals, and intentions are a function of time [Samsonovich and Aha, 2015].

Illusion of Life

Loyall (1997) defines illusion of life as several requirements for believability as described in the following sections. These requirements are mainly overlooked by artists that create believable characters because they are taken for granted since, for instance, in theater, the actor naturally brings them to life. However, this is not something that believable virtual agents can afford to ignore.

All the mentioned models in Table 2.2 consider illusion of life as a quality of believable characters. More specifically, two models directly reference Loyall's definition [Lee and Heeter; Mateas, 2015; 1999]. Although the other two models define their own qualities, their descriptions are very similar to the definition of certain requirements of illusion of life [Bogdanovych et al.; Gomes et al., 2016; 2013].

Illusion of Life: Goals

Illusion of life requires agents to appear to have goals and be able to pursue them at the same time. In fact, goals, motivations, or desires are the main focus of many narrative systems for generating believable behavior [Riedl and Young; Ware and Young; Teutenberg and Porteous, 2010; 2011; 2013].

Riedl and Young address this requirement by proposing <u>intentional agents</u> [Riedl and Young, 2004]. Intentional agents choose to take an action only if it serves at least one of their goals, which are defined by an author.

Illusion of Life: Social Context

Characters must exist in a social context and understand the social conventions and other aspects of the culture and world [Loyall, 1997]. Although the author accepts responsibility for creating and describing the culture and conventions, characters may choose to oblige or defy those conventions based on their personality. Since social conventions are highly domain dependent, it is very challenging to provide a general model for this aspect of social context.

In a social context, characters' interactions must be consistent with their relationships. Such interactions not only reveal [Loyall, 1997] but also change their relationships [Mateas, 1999].

Illusion of Life: Awareness and Responsiveness

Believable agents are <u>situated</u> and <u>reactive</u>. According to Loyall (1997), agents not only react to events in a timely manner, they also change what they are doing and how they are doing it in response to their observations.

Another interpretation of these two qualities is mostly referred to as <u>awareness</u>. Agents with awareness can perceive the world around them [Gomes et al., 2013] or their context and state within the environment [Bogdanovych et al., 2016].

Illusion of Life: Appearance and Capabilities

Agents must be broadly capable, e.g. talking, walking, emoting, and yet be resource bounded. In other words, believable agents are not omniscient beings and even characters such as Superman have certain physical and mental limitations. Belief Models are an example of addressing this requirement by limiting what agents could know about the world and other agents at any given time [Teutenberg and Porteous; Eger and Martens; Shirvani et al., 2015; 2017; 2017].

Believable agents must also be able to integrate those capabilities. For instance, an animated agent must smoothly transition between different actions instead of resetting to idle or stopping before switching to the next animation.

The integration requirement is similar to appearance described by Lee and Heeter [Lee and Heeter, 2015] and visual impact defined by Gomes et al. [Gomes et al., 2013]. Appearance describes all visually perceivable qualities, such as gender, age, height, as well as any details that attract the attention of the audience without their distraction [Lester and Stone, 1997]. For instance, when an animated character is idle, their chest moves to simulate breathing. Another example is verbal and non-verbal behaviors described as liveness by Bogdanovych et al [Bogdanovych et al., 2016].

2.1.5 Defining a Scope in Adapting Believability Qualities

Personality and Emotion

Many stories can immensely benefit from characters with personalities and emotions. My main focus is to propose a model of personality and emotion to equip virtual agents with those qualities. In order to do so, I draw from widely-known and already-validated models of personality and emotion is psychology. I do not investigate the validity of those models; instead, I focus on operationalizing and adapting them into computational models.

Social Context

There have been narrative systems, e.g. [McCoy et al.; McCoy et al., 2012; 2014], that focus on the social dynamics of characters in virtual worlds. Most of those systems sacrifice domain independence for providing a model of social context, e.g. through defining a set of rules to portray social conventions, social cues, etc. I believe that a highly domain-independent model that incorporates social context in interactive narratives will ignore many important aspects of social dynamics. I will not address social context in this document and only ensure that my proposed models can be extended to include it in the future.

As a future direction, a model of character relationships can be incorporated into my models of personality and emotion. For instance, making another character feel positive or negative emotions can improve or deteriorate their relationship and characters can consider their relationships when making choices based on their personality.

Change

Although there are no explicit constraints on story length, I assume interactive stories generated by my model are not long enough to benefit from character changes. As mentioned, change manifests itself over time and such quality may better suit novels or plays, rather than a relatively short interactive narrative.

As a future direction, my model of personality can be extended to include change by allowing character personalities to change as a direct consequence of the dynamic between triggered emotions and character choices. For instance, if an agreeable character always makes benevolent choices but feels resentment and disappointment for it, its personality may be shifted towards making less agreeable choices in the future.

Appearance

Appearance is determined by the presentation, e.g. how virtual characters are embodied or animated in 2D or 3D rendered formats. In the context of this document, I need to distinguish between appearance in my model of emotion and my model of

Figure 2.1: Facial Expression and Gestures in Camelot

personality. For personality, I solely focus on its impacts on external behavior, more specifically making character choices. For emotion, although, my focus is again on its effects on character behavior, I also consider its manifestation as visual cues.

For example, in my text-based experiments, I express character emotions through emotional keywords, such as “hopes to”, “fears”, “is disappointed by”. I have also integrated my model of emotion into my 3D game engine, Camelot, developed over the course of my Ph.D. Camelot is a modular customizable virtual environment that can be fully controlled by an external, independent experience manager and acts as its presentation layer [Shirvani and Ware, 2020]. Camelot provides a set of characters with different body types, outfits, skin colors, and hair styles. An experience manager can also choose to express the emotions of those characters via their facial expression and idle animations, i.e. the character’s pose and gesture while standing still. Figure 2.1 presents some examples of these expressions. I will discuss more details of how Camelot works and how I integrated my models in Camelot in Appendix 1.

Despite how I have integrated my model into these contexts to provide a visualization for a human audience, the focus of my research is not on the physiological manifestations of emotion and personality. I leave the detailed investigation of this believability quality to the research focusing on physiological manifestations [Allbeck and Badler; Kasap et al.; Arellano et al., 2002; 2009; 2008].

Goals

Riedl and Young's narrative planner addresses character goals and motivations [Riedl and Young, 2004], and has been extensively researched and evaluated [Niehaus and Young; Ware; Teutenberg and Porteous; Ware and Young, 2009; 2012; 2013; 2011]. I will continue to build on my previous work that extended their planner to combine intentionality and belief, and explain how characters take actions they believe will help them to achieve their goals [Shirvani et al., 2017].

Broadly Capable but Resource Limited

In narrative planning and specifically this research, agents are limited only to the actions defined by the author. They are only as capable and limited as the author allows them to be.

In my previous work, I proposed a model of belief that prevents agents from being omniscient [Shirvani et al., 2017]. This limits their knowledge about the world and other agents to their observations. Agents are aware of their own state, goals, and have (possibly wrong) beliefs about the state of the world and other agents. They update this information after they take actions themselves or observe actions performed by others.

Being Situated and Reactive

Although I do not focus on situatedness and reactiveness, these two requirements are implicitly addressed in how agents execute their plans in pursuit of their goals. More specifically, when an agent observes an event in the world, they reevaluate their current plan and may switch to a different one if a better plan is found.

2.2 Computational Models of Believable Characters

In this section, I will break down the previous work on systems that generate believable behavior based on how they differ from my work:

- I incorporate personality and emotion into strong-story narrative planners.

- My model of emotion is proactive in addition to being reactive.
- I consider the effect of personality on agent behavior without focusing only on a specific subset of the five factors.
- I choose to prioritize domain independence over expressiveness. In other words, I strive to minimize hand-authored information, even though they enable characters to be more expressive in specific story domains.
- My models are applicable to multi-character narratives rather than single-agent simulations such as virtual humans.
- I focus on communicating personality via higher-granularity actions rather than natural language dialog or fine-grained physiological manifestations, such as facial expressions and gestures.
- I consider the direct effect of personality on reasoning and external behavior rather than using it to express the emotional state.

2.2.1 Strong Story vs. Strong Autonomy

One categorization of automatic story generation systems divides them into strong story and strong-autonomy systems. In strong-story systems, characters only act with the permission and guidance of a centralized reasoning process, often referred to as the experience manager [Riedl and Bulitko, 2013].

An experience manager is an intelligent, omniscient, and disembodied agent that drives the narrative forward by intervening in the fictional world through coordination of non-player characters (NPCs) and the environment [Riedl and Bulitko, 2013]. Based on the NPCs' degree of autonomy from the experience manager, narrative generation systems fall on a spectrum from strong story to strong autonomy. Figure 2.2 presents some examples of previous narrative systems and how they are situated on the strong story / strong autonomy spectrum.

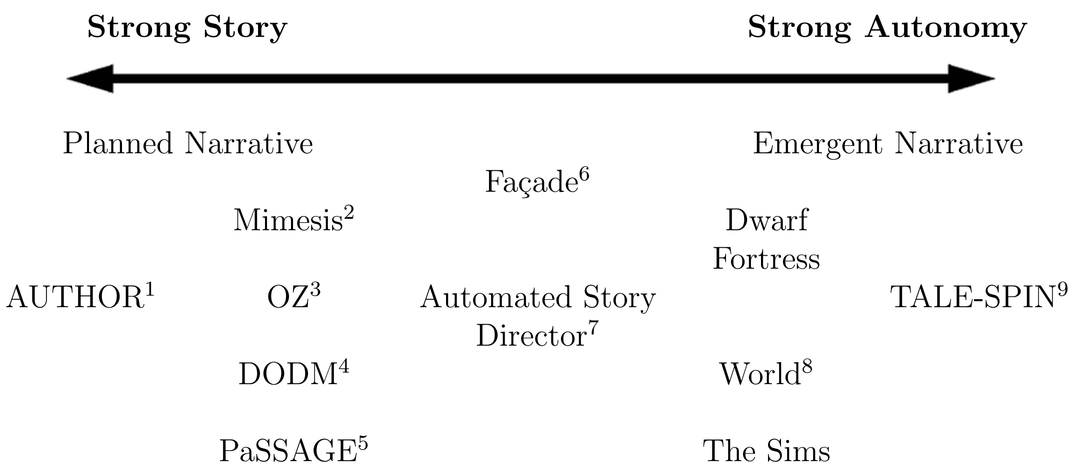


Figure 2.2: Examples of Strong Story vs. Strong Autonomy

1. [Dehn, 1981]
2. [Saretto and Young, 2001]
3. [Mateas, 1999]
4. [Nelson et al., 2006]
5. [Thue et al., 2008]
6. [Mateas and Stern, 2003]
7. [Riedl et al., 2005]
8. [Ryan, 2018]
9. [Meehan, 1977]

In strong-autonomy systems, NPCs are unaware of the overarching narrative and independently decide about their actions. Since the user's experience is driven by the uncoordinated actions of the NPCs and their own actions, the product of strong-autonomy systems are often referred to as emergent narrative [Aylett, 1999]. An extreme example of strong autonomy is TALE-SPIN, which generates simple stories where human-like animals take action to achieve their goals [Meehan, 1977].

While the raw transpiring of a simulation can be interpreted as a narrative, it will almost always lack story structure [Ryan, 2018]. There are ways however, to filter events from the simulation to find interesting stories. For instance, a story sifter sifts through raw simulated material to extract narrative artifacts with discernible story structure [Ryan, 2018]. Nevertheless, in strong autonomy, we are limited to the material offered by a simulation, and may often miss out on a, possibly more interesting, subset of the space of all possible stories.

These characteristics make strong-autonomy systems suitable for simulation games and exploratory learning environments where it is not always necessary to guide the user's experience towards a particular conclusion [Riedl and Bulitko, 2013]. The author does not necessarily want to constrain the emergent narrative and only need it to be interesting or engaging. For instance, Dwarf Fortress is a simulation game that generates unique game worlds for the player to experience through procedural content generation (PCG)[1]. The Sims is a sandbox game, in that it lacks any defined goals. The player creates virtual people called Sims, places them in houses, and helps direct their moods and satisfy their desires. World models a virtual world occupied by procedurally generated virtual people that give rise to many emergent narratives.

In contrast, in strong story, the author almost always wants to steer the plot in a specific direction and satisfy a specific set of goals. In order to do so, the experience manager is given full control over the world and its NPCs to ensure achieving the

[1]Bay 12 Games: Dwarf Fortress, url="https://www.bay12games.com/dwarves/", Last Accessed: 6/28/2021

author goals. The experience manager explores the space of all possible stories prioritizing author constraints and ensuring that all NPCs are acting consistently with their own character.

AUTHOR is on the opposite side of the spectrum as TALE-SPIN. AUTHOR simulates an author's mind rather than the world in which events take place [Dehn, 1981]. In doing so, characters may take actions that served the author's goals, even though they were out of character or contradicted with their goals.

The OZ drama manager controls a story at the level of plot points, a series of events such as a scene [Mateas, 1999]. At a high level of granularity, the OZ drama manager controls the narrative by altering the ordering and permutations of plot points. This helps to achieve some level of plot coherence, but at the same time, limits the system's control over lower level granularities, such as individual character actions.

Mimesis uses planning to determine player actions that could threaten the world's storyline and how the storyline could be rewritten to accommodate those actions. If the storyline cannot be effectively rewritten, the system finds a realistic way of preventing that action [Saretto and Young, 2001].

Declarative Optimization-based Drama Management (DODM) abstracts possible drama manager interventions as a set of DM actions. An optimization method chooses DM actions to maximize story quality [Nelson et al., 2006] based on a function that is provided by the author.

PaSSAGE[2] automatically learns player preferences by observing their behavior and utilizes those preferences to dynamically choose the events of an interactive narrative [Thue et al., 2007]. More specifically, PaSSAGE annotates player actions to build a model of their preferred styles of play, and then compares that model to author-provided play-style annotations on possible story events to decide what should happen next in the story.

[2]Player-Specific Stories via Automatically Generated Events

By having the ability to reason and intervene in all user interactions, strong story provides the author with the highest degree of leverage over their narrative structure. This is particularly important, for instance, for educational and training purposes that have a clear set of pedagogical goals. Strong-story systems are also not limited to a subset of all possible stories, as strong autonomy often would be, since they search through the space of all possible events to plan for the best narrative. This, however, comes at a higher computational cost.

Many narrative systems attempt to strike a middle ground between strong story and strong autonomy. Façade breaks down the narrative into high-level plot units. An experience manager provides coherence by coordinating the plot units and characters are autonomous to the extent that they can independently decide about realizing each plot unit [Mateas and Stern, 2003]. In Automated Story Director, characters behave autonomously until directed by an experience manager, at which point they must seamlessly transition between their autonomous and required behaviors [Riedl et al., 2005].

My proposed models are not purely strong story, as they ensure author goals are satisfied and, at the same time, all character actions can be explained in terms of character goals. For brevity, I will refer to them as being strong story since they are on the strong-story side of the spectrum. My models can use all the leverage of a strong-story system, while still having the ability to reason about emotion and personality like a strong-autonomy system. In other words, they bring the improved believability that was previously mostly found in strong-autonomy systems into strong-story systems.

I build directly on previous strong-story narrative planners that equipped NPCs with goals [Riedl and Young, 2004] and beliefs [Shirvani et al., 2017], and I improve believability by giving those planners information on personality and emotion to work with. In doing so, I also strengthen the strong story nature of the planner by giving it more stories to explore. The more stories a planner can find, the more leverage it has to tell the story it needs.

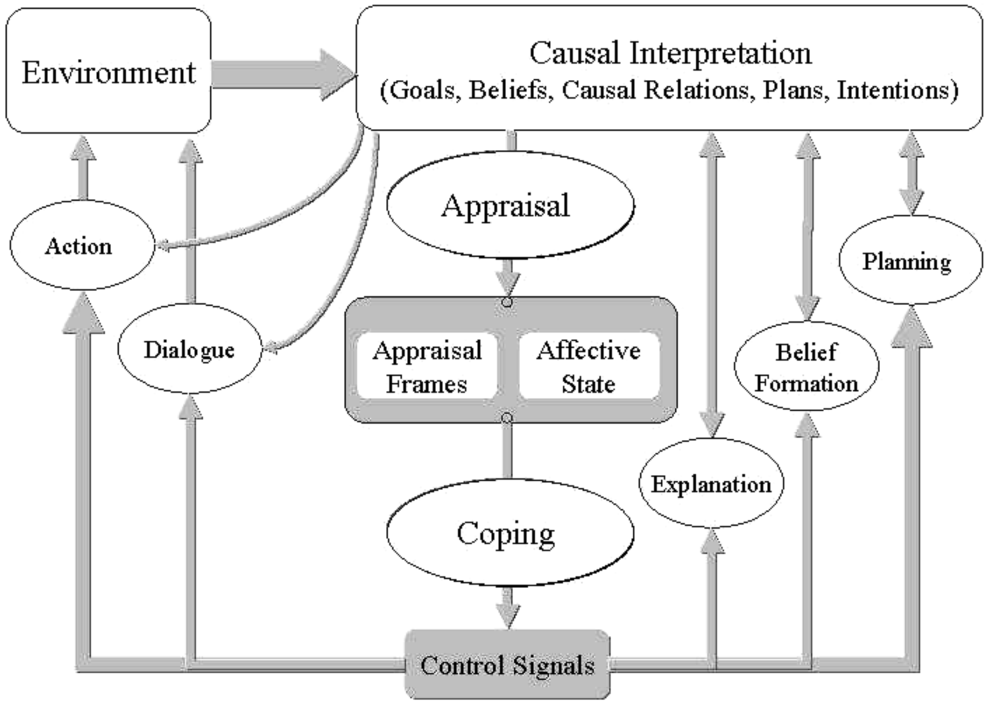
Reactive vs. Proactive

The Appraisal Theory is one of the most widely known and validated models of emotion [Lazarus and Lazarus, 1991]. An appraisal characterizes the relationship between a person and their physical and social environment, referred to as the person-environment relationship. “Changes to this relationship may induce new emotional responses, resulting in a cycle of change in the person’s relation to the environment [Marsella and Gratch, 2009].” EMA is one of the most notable computational models of emotion that adopts the appraisal theory to generate believable agents [Marsella and Gratch, 2009]. Figure 2.3 presents EMA’s architecture.

EMA builds and maintains a causal interpretation of world events in terms of beliefs, desires, and intentions. It then characterizes features of the causal interpretation using appraisals, and maps each appraisal to individual instances of emotion. Emotion instances are then aggreagated into a current emotional state and overall mood, and a coping strategy is selected in response to the current emotional state. Coping alters the person-environment relationship by motivating actions that change the environment (problem-focused coping) or by motivating changes to the interpretation of this relationship (emotion-focused coping) [Marsella and Gratch, 2009].

There are two main differences between story generation systems using EMA and my model of emotion. First, I choose to implement emotion types based on the OCC theory of emotion [Ortony et al., 1990] rather than Lazarus’s appraisal theory. Second, EMA is mainly reactive and my system is proactive as well as reactive. Through the process described above, EMA determines the emotional state of an agent based on appraisals and enables agents to react, mainly through coping mechanisms. With proactive reasoning, a strong-story system can explore the space of all possible stories and foresee many, if not all, sequences of events that will trigger different emotions for different characters. Using this information, the system can plan ahead to cre-

Figure 2.3: EMA's Cognitive-Motivational-Emotive System



ate specific emotional situations for both the player and the NPCs. That is a type of reasoning that EMA-based story generation systems do not attempt to do. Not only does my model determine what triggers an emotion and how characters react emotionally to events, but it also integrates reasoning about emotions into story generation. This proactive reasoning enables notable opportunities for story generation. As I will show later, we can use proactive reasoning to foresee narrative paths that cause positive and negative emotions in the player and use them to guide the player's experience.

Domain-Independent vs Expressive

To generate believable behavior, systems strike a middle ground between domain independence and expressiveness. By providing more details about the domain, such as the particular set of possible actions, we can model character actions on a finer level of detail and enable them to be more expressive. The more domain specific a system becomes, the more it relies on the system's author to provide more information and, in turn, makes it more difficult to apply the system to other story domains. I choose to prioritize high domain independence over expressiveness to provide a more general tool for automatic story generation. The following are some examples of systems that, in contrast, are more expressive but less domain independent.

The Playground is one of the extensions of the OZ project that used a rather strong-autonomy approach to introduce a model of emotion and personality [Reilly; Neal Reilly, 1996; 1997]. The authors model personality by considering the following characteristics into each behavior: personality quirks, competence, emotions, relationships, attitudes, norms, roles, other goals of the agent, and robustness. These aspects are meant to provide artists (authors) with a concrete methodology for creating personality-rich characters. This methodology, however, is highly domain specific. Indeed, each of the decisions about how to incorporate personality must be made separately for each character [Reilly, 1996]. It is also interesting how this work uses emotion to model personality, rather than vice versa as seen in many other models, such as [Mehrabian; Lisetti; Gebhard, 1996; 2002; 2005]. Similar to EMA, the methodology for maintaining the characters' emotional states is reactive in nature.

Versu is a text-based interactive drama that tells an interactive story using hand-authored episodes [Evans and Short, 2013]. Versu is strong autonomy as in each character chooses his next action based on their own individual beliefs and desires, as well as hand-authored social practices. Social practices describe a type of recurring social situation, such as a greeting, and the actions that the agents can do in those situations, e.g. how to greet or how to respond to a greeting. A practice provides the agent with a set of suggested actions, but it is up to the agent himself to decide which action to perform and the system takes no further measures to control these decisions. Versu creates more expressive characters by using a domain-dependent model of emotion and personality. For instance, to express personality through text, instead of saying walk, characters with different personalities may swagger, walks ponderously, stride, or hobble. I consider Versu relatively highly domain dependent as it needs a considerable amount of hand-authoring to provide the script for different episodes.

FEARNOT! is another example of strong autonomy as it focuses on the emergent narratives in an anti-bullying interactive drama [Aylett et al., 2007]. FEARNOT! simulates scenarios in which children could explore what happens in bullying in a non-threatening environment. The system determines a set of behaviors that the character would perform as a coping mechanism in response to their emotional state [Lazarus and Lazarus, 1991]. For instance, the bullying victim would cry not because it was their goal to cry but because crying a reaction to a distressed emotional state. As the events leading to the emotional state and the corresponding coping mechanisms are hand-authored specific to the bullying scenario.

Riedl and Young enable authors to label operators with recommendations of which personality traits characters should have to perform those actions [Riedl and Young, 2006]. These recommendations are not based on a specific personality model and relegate the responsibility to the authors to define them as they please. The planner uses a heuristic function that favors plans in which more recommendations are satisfied. It is possible for the planner to ignore the recommendations when necessary, which could be interpreted as characters acting "out of character". I believe that one advantage of my model of personality is that it does not ask authors to manually label actions when authoring a new story domain.

SPOT trains a neural network on a hand-authored set of rules based on known behavioral predispositions of the Big Five and common sense about human behaviors [Poznanski and Thagard, 2005]. For instance, crying is the response of a highly neurotic personality in a stressful situation and a bad mood.

Chang et al. develops a planning tool that enables an NPC agent to involve other characters in its plan by changing their minds [Chang and Soo, 2009]. The authors define a set of personality traits as domain-dependent rules. For instance, greed is represented by "one will pick up precious things at their location," or vanity is represented as "a woman will love a man who gives her something precious".

Overlooking vs. Oversimplifying

Due to the complex nature of human personality and emotions, it is almost impossible to propose computational models that adapt every personality trait and every emotion type into a single system. Some computational models focus on certain parts to implement them with as much detail as possible but, in turn, intentionally disregard certain other parts. Other systems try to involve as many parts as possible but it comes at the cost of simplifying each single part.

For instance, André et al. propose an affective agent-user interface based on FFM that only models Extroversion and Agreeableness, to focus on social interactions, and Neuroticism, to control the influence of character emotions [André et al., 1999]. Kasap et al. apply the Neuroticism value to how they update agent relationships and emotion decays [Kasap et al., 2009]. For more neurotic people, positive / negative emotions disappear more quickly / slowly. Bahamon and Young define a mapping between Agreeableness and planning actions as a highly domain independent knowledge base [Bahamón and Young, 2017]. Elgarf considers Extroversion to investigate the process of matching the personality of the user with the virtual character through body language and its impacts of on the likability of the character and the information recall of the story [Elgarf and Peters, 2019]. Paradeda et al. evaluate the effect of the level of assertiveness in virtual agents on the participants' decision-making process and game experience [Paradeda et al., 2019].

In my work, I try to strike a middle ground in implementing my models of emotion and personality. For personality, I choose to model all five factors but to simplify them into a small number of planning features. For emotion, I choose to model 12 emotions out of the 22 emotions defined by the OCC model to maintain a high level of domain independence.

Single-Agent vs. Multi-Agent

Researchers at Institute for Creative Technologies at the University of Southern California have dedicated a long time of research on generating believable behavior in form of virtual humans. Virtual humans are one of the widely researched applications of emotions and personality. "Virtual humans, software entities that look and act like people, but live in simulated graphical environments and can freely interact with humans immersed in the environment" [Gratch, 2002]. They are designed to perceive, understand, and interact with real-world humans [Gratch et al., 2013]. Virtual humans range from the more complex cognitive agents to question response agents.

Some notable systems that model virtual humans are MRE [Rickel et al., 2002], SASO-ST [Swartout et al., 2006], or Virtual Patient [Kenny et al., 2007b]. In addition to a model of emotion, based on EMA, these systems also include higher level components, such as speech recognition, natural language understanding, non-verbal behavior, rhetorical text-to-speech output, gaze / gesture tracking, etc. These systems are another example of prioritizing expressiveness over domain independence. I speculate that the main reason for this decision is that they provide specific simulations for particular applications in the military and medical fields.

The research in virtual humans typically models a single agent that communicates directly with the user. Virtual humans have been used as a patient interviewed by real medical students [Johnsen et al., 2007], as a suspect in a bombing accident for tactical-questioning [Kenny et al., 2007a], as a role-playing subordinate for interpersonal skills training of naval officers [Hays et al., 2012], and as an interviewer in clinical interviews [Lucas et al., 2014].

As shown by the examples above, virtual human applications typically have a particular goal and simulate agents in a specific scenario. This leads to one major difficulty of virtual human simulations, the ability to design and author different scenarios, since setting up a new scenario is no easy task [Kenny et al., 2007a]. While there have been virtual human applications that simulate multiple agents, many simulate scenarios which need not more than a single agent. Systems that do not address the interactions between different agents, for instance in forms of cooperation or conflict, cannot be easily applied to simulate multiple virtual humans in a same scenario.

Physiological Manifestations vs. External Behavior

Moving past the single or multi-agent aspect, a large portion of the previous research on emotion and personality focus solely on physiological manifestations. This includes facial expressions [Kasap et al.; Arellano et al.; Egges et al.; Allbeck and Badler; Egges et al., 2009; 2008; 2003; 2002; 2004], body movement and non-verbal behavior [Pham and Wardhani, 2005], and generally visual features of 3D animated agents.

Bartneck discusses the possibilities and issue of integrating OCC emotions to embodied agents [Bartneck, 2002]. The authors state that an important issue is that not all 22 emotions can be communicated through animations. For instance, the animations for Gratification and Gratitude would look very similar even though they have different trigger conditions.

Egges et al. define a relationship between FFM and goals, standards, and attitudes to generate dialog [Egges et al., 2004]. For instance, Highly Conscientious agents are less likely to abandon their goals or highly Open agents are more likely to change their standards in new situations.

The research focusing on physiological expressions of emotion and personality rarely consider their effects on reasoning and decision making. In other words, their focus is how agent behavior is presented to the user rather than what actions constitute such behavior.

2.3 Summary

In this section, I provided an outline for previous work in believable character models in automatic storytelling. I discussed what believable agents are, how they are different from intelligent agents, and what qualities make them believable. I also identified personality and emotion as two of such important qualities.

In sum, the key differences between previous relevant research and my proposed models of emotion and personality are as follows.

- I adapt personality and emotion into strong story, not strong autonomy, to leverage the strengths of such systems.

- I do not overlook any of the five factors of personality, even though this may come at the cost of oversimplifying the original psychology model.

- I rely on existing narrative structures to model emotion and personality in order to minimize the author burden and improve the models' reusability for various story domains.

- My models account for interactions between different characters and their expectations about each other, which makes it more effective in multi-agent simulations.

- I provide models for character personality and emotion that manifest through their external behavior and not natural language dialog or physiology, such as facial expressions and gestures.

CHAPTER 3. METHODOLOGY

3.1 Narrative Planning

One similarity between AI and narrative research is that both reason about actions and plans. Both model characters / agents that form plans and take actions to achieve their goals. Where AI planning systems seek to find a plan to achieve a goal, narrative planning systems generate plans for a collection of characters to represent how they plan to succeed, thwart, or overcome. In this section, I will introduce and informally discuss the concepts and processes used in narrative planning. I will provide the formal definitions of these concepts later in Chapter 4.

3.1.1 Example Story Domain

I use the following example throughout this paper. I will refer to this example as Tom's Tale. Tom is sick and needs medicine. He has two coins and he wants to acquire the medicine while spending the least number of coins. He could either go to a nearby town and spend one coin to buy the medicine from a Merchant or he could go to a nearby forest and make it using herbs that grow there. Although he believes that he could do the latter, in reality, there are no herbs in forest that he could use to make the medicine.

Tom also knows that there is a Bandit in the forest that could steal all his coins. Tom can buy a sword from the merchant that prevents the bandit from robbing him. Having a sword also gives Tom the option to steal the medicine from the merchant. Both the bandit and the merchant want to have as many coins as they can.

3.1.2 Narrative Planning Problems

A planning problem is typically described by specifying an initial state of the world and some author-defined goals that the system is meant to achieve. In classical planning, the initial state represents a complete description of the world. I use Helmert's definition of logical propositions to represent an initial state [Helmert, 2006]. The story world is comprised of a set of variables, and a proposition is the assignment of a value to a variable. For instance, in Tom's Tale, we could represent the initial state as follows:

$$at(Tom) = Home \wedge at(Merchant) = Town \wedge at(Bandit) = Forest \wedge$$
$$at(Medicine) = Merchant \wedge at(Sword) = Merchant \wedge$$
$$at(Coin1) = Tom \wedge at(Coin2) = Tom$$

Here, the $\wedge$ symbol represents the AND operator. These propositions state that Tom is at his home, the merchant is at the town, the bandit is at the forest, the merchant has the medicine and a sword, and Tom has two coins.

Author goals are defined as a set of logical propositions that must hold at the end of a story. For example, the author goals in Tom's tale can be represented by the following propositions:

$$\{at(Medicine) = Tom, at(Coin1) = Bandit\}$$

The author wants his stories to end in Tom acquiring the medicine or the bandit robbing Tom.

In contrast to previous narrative planners [Riedl and Young; Ware and Young; Shirvani et al., 2004; 2011; 2017], I represent the author goals using utility functions. A utility function is a function that receives a state and produces a number. Higher numbers indicate better consequences. I represent a utility function by a sequence of conditionals that are evaluated in order. If none of the conditions hold, the function returns 0[1]. The author goals stated above are translated into the following function:

$$U(s) = \left\langle \begin{array}{c} at(Medicine) = Tom \rightarrow 1, \\ at(Coin1) = Bandit \rightarrow 1, \end{array} \right\rangle$$

[1]I will provide a formal definition in Chapter 4.

action	Go(Character c*, Place to)
PRE:	$True$
EFF:	$at(c) = to$
action	Buy(Character $c1$*, Character $c2$*, Item i, Place p)
PRE	$at(c1) = p \wedge at(c2) = p \wedge at(i) = c2 \wedge at(Coin1) = c1$
EFF	$at(i) = c1 \wedge at(Coin1) = c2$
action	Rob(Character $c1$*, Character $c2$, Place p)
PRE	$at(c1) = p \wedge at(c2) = p \wedge at(Coin1) = c2 \wedge at(Coin2) = c2$
EFF	$at(Coin1) = c1 \wedge at(Coin2) = c1$
action	Steal(Character $c1$*, Character $c2$, Item i, Place p)
PRE	$at(c1) = p \wedge at(c2) = p \wedge at(i) = c2 \wedge at(Sword) = c1$
EFF	$at(i) = c1$

Figure 3.1: Actions in the Tom's Tale Domain

The argument s is the state in which we calculate the value of the utility function. For instance, in the initial state, the author's utility function is 0. If Tom acquires the medicine or the bandit robs Tom, the author's utility function is increased by 1.

A planning problem is defined in the context of a story domain. A story domain consists of a set of types, a set of constants, and a set of all possible actions. The set of types represent the possible types for each object in the world, e.g. Character, Place, Location. The set of constants represent each object in the world and their corresponding type. For instance, constants Tom, Merchant, and Bandit are constants of type Character, while Medicine, Herbs, and Sword are constants of type Item, and Home, Town, and Forest are constants of type Place.

Actions are similar to STRIPS operators [Fikes and Nilsson, 1971]. Each action has three main specifications, the agents / objects that are involved, a precondition that must hold for that action to be possible, and an effect that specifies how the world changes as a result of that action. Figure 3.1 presents the actions of the Tom's Tale domain.

For instance, action Buy has three arguments, $c1$ and $c2$ of type Character and i of type Item. If $c1$ and $c2$ are in the same place, $c2$ has i, and $c1$ has $Coin1$, $c1$ can buy i from $c2$ for it. As a result of the action, $c1$ will have i and $c2$ will have $Coin1$.

A solution to a classical planning problem is a sequence of actions that achieves the author goals if taken from the initial state. For instance,

$$\langle Go(Tom, Town), Buy(Tom, Merchant, Medicine) \rangle$$

and

$$\langle Go(Tom, Forest), Rob(Bandit, Tom) \rangle$$

are both solutions to the Tom's Tale planning problem.

In narrative planning, each character also has a set of goals [Riedl and Young, 2004]. I also represent the goals of a character via a utility function. For instance, The merchant and the bandit's utility functions are equal to the number of coins they have and Tom's utility function is as follows:

$$U(Tom, s) = \left\langle \begin{array}{c} at(Medicine) = Tom \rightarrow 4 \\ at(Coin1) = Tom \wedge at(Coin2) = Tom \rightarrow 2, \\ at(Coin1) = Tom \rightarrow 1, \\ at(Coin2) = Tom \rightarrow 1, \end{array} \right\rangle$$

This shows that having each coin increases Tom's utility by 1 and having the medicine sets it to 4, showing that Tom values the medicine more than each coin. It is reasonable for him to spend a coin to buy the medicine.

Narrative planners introduce an additional constraint to classical planning; a character consents to taking an action only if it is in service of one of their goals [Riedl and Young, 2004] (it helps increase that character's utility). In that case, we say that an action is explained for that character. In Figure 3.1, the consenting characters of each action is specified by a star symbol next to the corresponding argument. For instance, both characters must consent to action *Buy* in order to trade an item for a coin. However, only the robber needs to consent to action *Rob* and the victim is not a consenting character of that action.

A solution to a narrative planning problem is a sequence of actions that increases the authors utility from the initial state and every action in that sequence is explained for its consenting characters. Here,

$$\langle Go(Tom, Town), Buy(Tom, Merchant, Medicine)\rangle$$

and

$$\langle Go(Tom, Forest), Rob(Bandit, Tom)\rangle$$

are also solutions to the Tom's Tale narrative planning problem, since they both increase the author's utility and contain only actions that are explained for their consenting characters. The following is not a solution to a narrative planning problem, as it achieves the author goal but is not explained for Tom.

$$\langle Go(Tom, Forest), Give(Tom, Bandit, Coin1)\rangle$$

3.1.3 State-Space Narrative Planners

State-space planners are a type of planners that search through the space of all possible world states to find a solution to a planning problem. The space of all possible world states is represented by a directed graph, called the search space, in which each edge represents an action and each node represents a state. There is a directed edge for action a from state s_1 to state s_2 if the precondition of a holds in s_1 and applying the effects of a to s_1 results in s_2. Figure 3.2 presents a portion of the Tom's Tale state space.

3.1.4 Narrative Planners with a Model of Belief

In state-space narrative planning, a state space is a set of temporally possible worlds in which states are connected by temporal edges. For example, Figure 3.2 represents

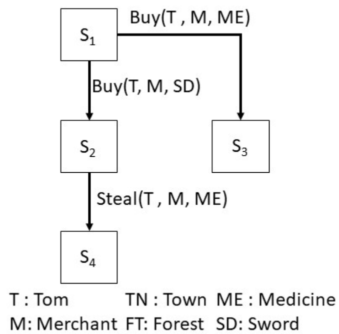


Figure 3.2: A Portion of the State Space of Tom's Tale

two possible worlds in which Tom could go to the town and buy the medicine (states s_1 and s_3) or buy a sword and steal the medicine (states s_1, s_2, and s_4).

Narrative planners that don't reason about belief [Ware and Young; Riedl and Young; Riedl and Young; Ware and Young, 2011; 2004; 2010; 2014], assume their characters are omniscient. In other words, when a proposition becomes True or False, all characters become aware of its value. Using those planners, Tom will always know that there are no herbs in the forest. In order to tell a story in which he wrongly believes that there are herbs in the forest, we need to extend those planners to include a model of belief.

I enable previous state spaces to also account for epistemically possible worlds [Shirvani et al., 2017]. Using epistemic edges, we can model what each character believes about the state of the world, as well the what they believe other characters believe and so on.

Figure 3.3 shows an example of epistemically possible worlds that only shows Tom's beliefs in the initial state. As you can see, in contrast to temporal edges, the label of epistemic edges are characters not actions. Following an epistemic edge for character c from state s_1 to state s_2 means that when the world state is s_1, character c believes the world state is s_2. In a full search space, I define that from each state, there is one and only one epistemic edge for each character. This means that every character always commits to what they believe and there is no uncertainty about those beliefs [Shirvani

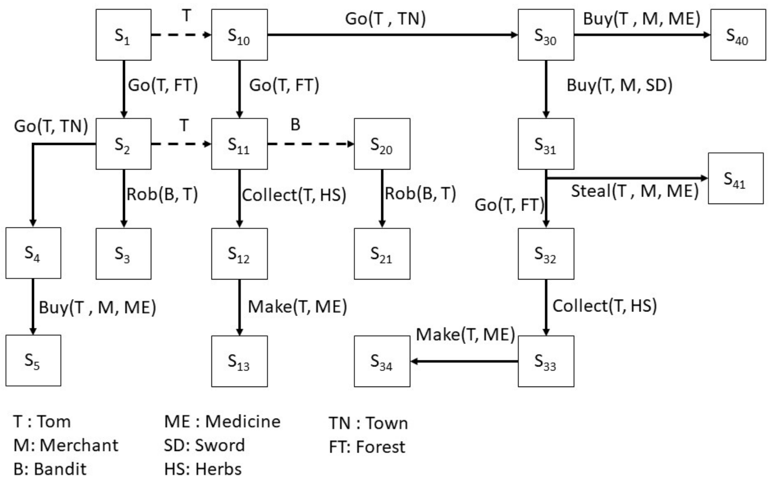


Figure 3.3: A Portion of the State Space of Tom's Tale with Epistemic Edges

et al., 2017]. An epistemic edge may point to the same state if the corresponding character's beliefs are the same as the actual world state.

In Figure 3.3, if we follow the edge for Tom (T) and then the edge for the bandit (B) (states s_2 to s_{11} to s_{20}), we can see what Tom believes the bandit believes. In doing so, we say that we are inferring about two layers of belief. This model of belief can simulate infinitely nested layers of belief.

3.1.5 Anticipation

An important advantage of this belief model is that a character can expect certain actions by other characters and thus incorporate them into their own plans [Shirvani et al., 2017]. For instance, If the bandit believes that Tom would and could go to the forest to make medicine, the bandit could incorporate $Go(Tom, Forest)$ into his own plan to rob Tom. I used the terms would and could because in order for a character to anticipate the actions of another, those actions must be possible (their precondition must hold in the preceding state) and those actions must increase that character's utility (that character would consent to taking those actions).

This also extends the definition of an explained action as follows. If character c_1 can imagine a sequence of actions for character c_2 that ends in a state that increases

c_2's utility, we say that for all actions in that sequence, c_1 believes that action is explained for c_2.

A valid character plan for character c is defined as a sequence of actions that increases c's utility, and for all actions in that sequence, c believes that action is explained for all its consenting characters[2].

3.1.6 Conflict

Considering that a state space represents the space of all possible worlds, we can reason about how characters may fail to fulfill their plans. For instance, Tom goes the forest and realizes that there are no herbs there. In this state, Tom forms another plan to go to town and buy the medicine. However, there is also another possible world in which Tom gets robbed by the bandit. This scenario where only one of the two possible worlds may occur at the same time, is referred to as a conflict.

Ware et al. mark certain actions as intended but not executed to represent a plan that characters wanted to execute but could not due to causal conflicts with other characters or the environment [Ware and Young, 2011]. For a character plan, a conflict represents two possible worlds, one in which the plan fails and another in which the plan succeeds. A conflict is <u>resolved</u> when the corresponding plan succeeds or fails.

I update the definition of a conflict using the utility functions that represent character goals. A conflict ensues when a character c_1 expects that their utility could decrease as a result of a plan of another character c_2. We say that a conflict is <u>resolved</u> when either c_1's utility decreases as a result of that plan or c_1 no longer expects that plan to happen. An example of a conflict in Tom's Tale is the bandit robbing Tom when he goes to the forest. When Tom buys the sword from the merchant, Tom no longer expects that the bandit could rob him; thus, we say that the conflict has been resolved in favor of Tom.

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[2] The formal definitions of explained actions and explained action sequences are presented in Chapter 4.

As with the above example, characters need to be able to anticipate a conflict. In my model of anticipation, characters can expect actions of other characters that could increase their utility, as well as those that could decrease it. In later chapters, I will show how this definition of conflict is used in explaining character actions, and how we can enable the experience manager to intelligently generate conflicts.

3.2 Emotion

Reasoning about the emotions of virtual agents helps in the design process and in reasoning about agent behaviors [Meyer, 2006]. Emotions offer guidance about the possible consequences of actions and, in turn, motivate other actions in order to face the resulting emotions. In this section, I will introduce the established model of emotion in psychology that my model is inspired by.

3.2.1 The OCC Model of Emotion

The OCC model of emotion [Ortony et al., 1990] is one of the most widely known and validated appraisal-based models of emotion. Different individuals evaluate (appraise) the same event in different ways and that appraisal is responsible for triggering emotions. Appraisal characterizes individual consequences of events in terms of the different appraisal variables, such as how desirable those consequences are or who caused the appraised event.

There are several reasons that the OCC model is suitable for being adapted to reason about emotional virtual agents.

- Its simple and elegant tree structure and finite set of appraisal variables facilitates its adaptation to Artificial Intelligence.
- The objects of the emotions defined by the OCC model, i.e. goals, agents, actions, and events, are congruent with commonly used notions of virtual agents.
- All emotions are either negatively or positively valenced and their valence is always the same.

- The OCC model allows agents to emotionally react to a variety of situations.

Steunebrink et al. extend OCC to include 24 different emotions that are triggered based on the following appraisal variables [Steunebrink et al., 2009].

- The type of the stimuli could be consequences of events, actions of agents, and aspects of objects.

- The consequences of an event could be desirable or undesirable for the agent itself or for other friend / non-friend agents.

- A prospective event is unconfirmed when it has not happened yet and becomes either confirmed when it occurs or disconfirmed when it does not.

- An action could be praiseworthy or blameworthy based on the standards of an agent.

- An object could be familiar or unfamiliar to the agent.

Figure 3.4 presents Steunebrink et al.'s revision of the tree structure defined by the OCC model [Steunebrink et al., 2009]. For instance, satisfaction is triggered when the consequences of a prospective event are confirmed, or remorse is triggered when an agent performs a blameworthy action with undesirable consequences.

The model distinguishes between well-being emotions and prospect-based emotions. Well-being emotions correspond to being pleased or displeased about a desirable or undesirable event. If a desirable event occurs, the characters feels Joy; but if an undesirable event occurs, they feel Distress. In terms of character goals, Joy is triggered by achieving (sub)goals and Distress is triggered by the failure of a plan or loss of an active goal.

Prospect-based emotions are centered around the prospect of an event and its confirmation or disconfirmation. A character feels Hope if they expect a desirable event to happen and Fear if the expected event is undesirable. Once again in terms

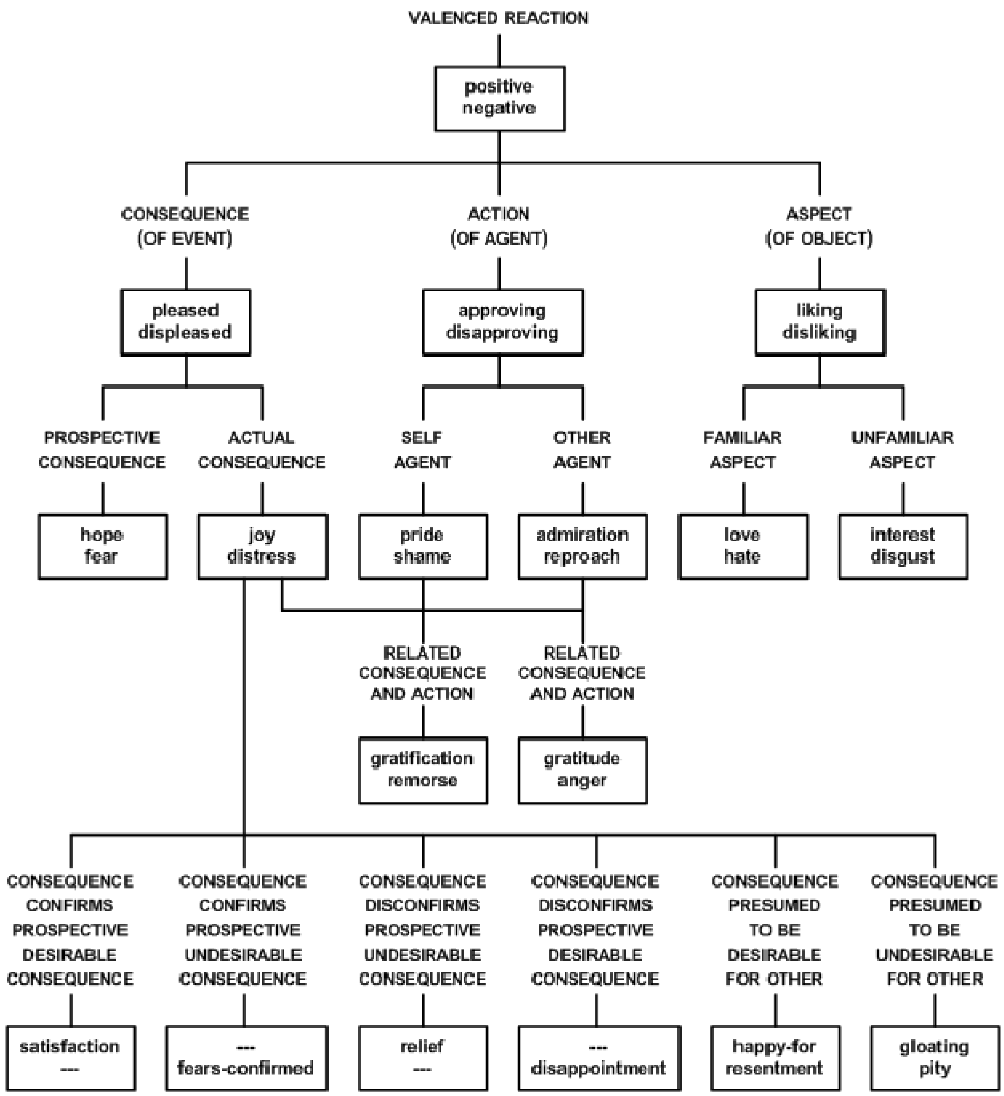

Figure 3.4: The Hierarchy of OCC Emotions

Table 3.1: Emotions and Their Corresponding Appraisal Variables

Emotion	Appraisal
Joy	The occurrence of a desirable event
Distress	The occurrence of an undesirable event
Hope	An unconfirmed desirable event
Fear	An unconfirmed undesirable event
Satisfaction	A confirmed desirable event
Fears-Confirmed	A confirmed undesirable event
Disappointment	A disconfirmed desirable event
Relief	A disconfirmed undesirable event
HappyFor	A desirable event that is desirable for a friend
Resentment	An undesirable event that is desirable for a friend
Gloating	A desirable event that is undesirable for a non-friend
Pity	An undesirable event that is undesirable for a non-friend

of character goals, Fear is triggered when there is a threat of self-preservation goals or a conflict.

Once such event occurs (becomes confirmed), Hope turns into Satisfaction and Fear turns into Fears-confirmed. However, if that event does not occur (becomes disconfirmed), Hope turns into Disappointment and Fear turns into Relief. Table 3.1 presents a summary of the well-being and prospect-based emotions and their corresponding appraisal variables.

In my research, I only consider these 12 well-being and prospect-based emotions. The reason for this choice is that the corresponding appraisal variables of these emotions are related to agent's goals, plans, and beliefs, all of which are familiar concepts of a narrative planner.

In contrast, the other appraisal variables depend on an agent's standards or an object's attractiveness and this makes them highly domain dependent. For instance, the act of slaying a person might be considered praiseworthy in a barbaric Viking-esque world. In other words, it is not possible to adapt those emotions without introducing additional author burden into the definition of their story domain, e.g. labeling every action as praiseworthy or blameworthy.

3.3 Personality

The personality of a character is reflected by the choices they make in different situations. These choices must portray a consistent pattern of behaviors to make the character more believable to the audience. My model of personality is inspired by the Big Five and the Five Factor model[3] [McCrae and Costa; Goldberg, 1987; 1992]. The five factors considered by the Big Five and the FFM are Openness to experience, Conscientiousness, Extroversion, Agreeableness, and Neuroticism. An individual could score high or low on each of the five factors.

The Big Five is a widely-studied taxonomic personality model derived from a factor analysis of a large number of self and peer reports on personality-relevant adjectives [DeYoung et al., 2007]. The underlying theory of the Big Five is that personality traits create basic tendencies [McCrae and Costa, 2003] and with environmental influences, these tendencies create a disposition for particular behavior [Bouchard Jr and McGue, 2003]. The Big Five is currently widely accepted as a valid description of human personality traits. It is bounded in biology, and the lexical approach used to determine the underlying factors carefully refines personality descriptors based on the terms that are developed over time. There is theoretical and methodological justification for the validity of this model.

Though the Big Five is rooted in psychology and personality traits in real life, it can also be used to provide descriptors for fictional characters. MacCrae et al. (2012) argue that we could apply the methods and findings of contemporary trait psychology to broad questions about genres and the interpretation of individual characters.

Flekova et al. propose a model to predict the personality of protagonists in novels based on the FFM [Flekova and Gurevych, 2015]. Johnson et al. show that the FFM can describe the personality of literary figures, at least those in Victorian novels [Johnson et al., 2008]. The authors gathered data on attributes of fictional characters,

[3] Although MacCrae et al. distinguish between the Big Five and FFM [McCrae et al., 2012], I will refer to them interchangeably throughout this document.

such as their role in the novel, their personal goals, and their romantic styles. Their analyses showed a correlation between these attributes and the five factors. For example, they reported that, as in real life, characters with high Openness to Experience were motivated by interests in creativity and discovery or those low in Agreeableness had a strong need for power [Johnson et al.; Johnson et al., 2008; 2011].

While the Big Five refers only to the highest level of a hierarchy of traits, the FFM refers to a classification of many traits in terms of the five factors. Much of the research on FFM defines a two-level hierarchy, with the five broad categories, called factors, at the top subsuming more specific traits, called facets. There is a debate on the definition of the second layer. For instance, Costa and McCrae produced 6 facets for each of the five factors [Costa and MacCrae, 1992], or the Abridged Big Five Dimensional Circumplex (AB5C) defines each facet as a blend of two of the five factors [Hofstee et al., 1992].

I draw primarily from the Big Five Aspect Scales (BFAS), which define 10 aspects (2 per factor) [DeYoung et al., 2007]. My goal is to oversimplify rather than overlook. In other words, although I simplify each factor, I consider all 10 facets defined by BFAS, and thus all five factors of the Big Five. This contrasts with other works, e.g. [Bahamón and Young, 2017], which choose to overlook rather than oversimplify.

Openness to Experience

Highly open individuals—with high scores—are abstract thinkers and motivated by intrinsic interest. Low scores are observed in conventional and conservative people. Open individuals can be described as imaginative, creative, and intellectual. The first BFAS aspect of Openness to experience is (confusingly) named openness, which focuses on imagination, creativity, and interest in art, music, and nature. The other aspect, aptly named intellect, is associated with ideas, e.g. enjoying philosophical discussions and solving complex problems.

Conscientiousness

High scores are observed in organized and persistent individuals who prioritize order and efficiency. They are motivated by being active and orderly, in contrast to people with low scores, who are messy, lazy, and care-free. While individuals with high Openness are generally better at making plans, highly conscientious ones are best at implementing those plans. The two aspects of this factor are industriousness and orderliness. Industrious individuals are self-disciplined and diligent, while orderliness indicates attention to tidiness and dutifulness.

Extroversion

Extroverts are social, active, optimistic, and motivated by enthusiasm. Introverts are reserved, shy, and quiet. High scores indicates a tendency to interact with others and make friends, while also being assertive and taking charge. The aspects of Extroversion are enthusiasm and assertiveness. Enthusiasm indicates a tendency to interact with others and make friends. Assertiveness reflects a strong personality, who takes charge and leads the way.

Agreeableness

Individuals with high scores are altruistic, cooperative, and empathetic. Low scores are observed in competitive, distrustful, and uncompromising people. The two aspects of Agreeableness are compassion and politeness. Compassionate individuals show sympathy and tend to take interest in others' feelings. Individuals lacking politeness are disrespectful and pursue their own goals at the expense of others. While Extroversion rewards social affiliation, Agreeableness reflects affiliation driven by empathy.

Neuroticism

Neurotic individuals are motivated by their desire to decrease stress and anxiety. High scores indicates strong emotional reactions to external stimuli and sensitivity to threat and punishment. Low scores represent fewer observable emotional reactions. DeYoung et al. distinguish between two aspects of Neuroticism, withdrawal and volatility [DeYoung et al., 2007]. Withdrawal refers to the inward expression of negative emotions like depression and anxiety; while volatility is the outward expressions of negative emotions in forms of anger and panic. Withdrawal can be compared to the behavioral inhibition system, and volatility to the fight or flight instinct.

3.4 Intelligent Generation of Conflicts

The combination of emotion, personality, and strong story enables me to improve upon the detection and generation of conflict in narrative planning. Before I describe the mechanics of this process, I need to describe what a conflict and, more generally, a player choice is and how we can distinguish between different choices.

Mawhorter et al. define a choice structure as follows [Wardrip and Jhala, 2014]. A choice structure consists of the framing, options, and outcomes associated with a choice. Framing is the content preceding the presentation of a choice that influences how a player interprets it. Options, along with the framing of a choice, allow expectations about the consequences of choosing an option. Finally, the outcome of a choice refers to the content that is presented when each option is chosen. As an example, assume that as the player enters the forest, they are faced with the bandit who draws their sword. This frames a choice for the player with three options: the player could either do nothing, flee, or, in the context of this example, try to talk their way out of being robbed. The actual outcomes of this choice may match the player's expectations or not, e.g. the player may succeed or fail to talk his way out of being robbed.

In order to reason about a choice, we need to make assumptions about player goals, player expectations, and perceived outcomes [Mateas et al., 2015]. An author can predict some basic player goals, e.g. they want to keep their character healthy and alive, and use methods for encouraging the pursuit of various goals. If the player indeed values their character's health, a choice that would put the player character's health at risk can cause tension. On the other hand, for the players who don't value those goals, the choice will lack the tension that the author intended, but it does not mean that the author's strategy for creating a tense moment was invalid. Indeed, strong story allows us to explore all possible stories, but if the domain defined by the author does not allow any stories that achieve what the author wants, that is a problem with the domain, not the experience manager

Consider the choice and its options mentioned in the last paragraph. While generating this choice, the system determines a player expectation for each option based on the player goals and the perceived outcomes, i.e. how the player would expect the outcomes of an option affect their goals. The perceived outcome of an option could be one of the following cases:

- Irrelevant: this outcome does not affect a goal.
- Hinder or fail: this outcome hinders progress towards achieving a goal or directly fails a goal.
- Advances or achieves: this outcome contributes to achieving a goal or directly achieves a goal.

In this example, the option of doing nothing hinders the player's goal. Being robbed by the bandit hinders the player's goal because they lose their coins. On the other hand, the option to flee is irrelevant to their goal, because they need to collect the herbs in the forest to advance their plan (of making the medicine). It is only through the third option, to talk out of being robbed, that the player expects to advance their goal.

We can consider conflicts as choices with perceived outcomes that hinder or fail a goal. Presenting the player with a conflict is one way that authors can encourage the pursuit of certain goals. For instance, in the example above, by presenting the option to talk their way out of a dangerous situation, the author can encourage the player to use their wit and social skills.

On the other hand, imagine that the player is presented with the same choice, but instead of the option to talk to the bandit, they had the option to draw their own sword and attack the bandit. The presentation of this choice implicitly encourages violence to resolve conflicts. We can distinguish between different choices (conflicts) based on their options.

I must distinguish between implicit and explicit encouragement. In implicit encouragement of a behavior type, the system makes sure to always provide the player with the option to resolve conflicts using that behavior type. This reasoning takes place before the player is presented with a conflict. If the system is unable to implicitly encourage the intended behavior, it does not present the conflict to the player.

In explicit encouragement of a behavior type, the system expresses affirmation through symbolic representations after the player has demonstrated that type of behavior. More specifically, if the player chooses to exhibit the intended behavior, they see more positive results, and otherwise, more negative results. For instance, the author specifies that if the player attacks any of the NPCs, they receive a lower overall score on their performance. While the proposed system enables implicit encouragement, the author can always devise the story domain to also enable explicit encouragement. Authors will most likely intend to explicitly, as well as implicitly, encourage behaviors in training simulations. However, implicit encouragement suffices in most entertainment applications, as the author may not want to directly punish or reward the player for making choices.

I use this notion in conjunction with planning, emotion, and personality. While exploring the story space, the system recognizes a conflict for the player when the player fears a negative outcome. In other words, the player expects an outcome and fears that it will hinder or fail at least one of their goals. The system then searches for options that advance the player goal and make them feel relieved instead. This is where the strong-story nature of the system shines, as it can explore all possible worlds that could ensue by different courses of action. This also allows them to reason about the player's expectations based on their goals and beliefs. After reasoning about these considerations, a strong-story system can then puppeteer all virtual characters to guide the player experience on the intended trajectory.

Considering a personality model, a choice option reflects one or more personality traits. For instance, the option to talk to the bandit reflects being social and extroverted, and the option to attack the bandit conveys a disagreeable trait. By distinguishing between options based on the traits they represent, the system intelligently chooses to create a conflict for the player or not. As a result, it enables the author to encourage certain types of behaviors in the player. For instance, assume the author wants to encourage Agreeableness. The systems foresees the choice described above, the bandit facing the player with his sword drawn, and searches for options that convey Agreeableness. If it fails to find such option, the bandit would never show up to face the player in the first place.

Similar to assuming player goals in the above paragraphs, the system does its best to tell a good story to the extent that the author-provided story domain allows it, and the absence of a conflict does not mean the system's strategy was invalid.

There are some considerations in the application of this model. First, I emphasize that this model <u>encourages</u> the player to adopt specific personality traits at specific times to deal with specific types of situations. It does not mean that the system attempts to <u>change</u> the player's personality as a result of assuming the role of that character.

Second, as mentioned, strong story works best in serious games and training simulations where the author often aims to encourage certain types of behaviors. However, it does not mean that strong-story systems would not work for entertainment applications. In an entertainment context, we can use conflicts to elicit player values or improve enjoyment and immersion by ensuring that player choices are always compatible with their personality and rarely, if ever, push them out of their comfort zone.

CHAPTER 4. PROPOSED MODELS OF PERSONALITY AND EMOTION

4.1 Narrative Planning

4.1.1 State-Space Planning

I build on what Helmert calls a Multi-Valued Planning Task [Helmert, 2006]. A virtual world is represented by some number of variables, each of which is assigned a value. For example, Tom's location is a variable that could be assigned the value $Town$, $Forest$, etc [1]. An assignment of a value u to a variable v is written $v = u$.

Definition 1. A proposition follows the grammar $p \rightarrow True|False|v = u|p \wedge p$. In other words, I permit four kinds of propositions: the constants $True$ and $False$, the assignment of a value to a variable, and a conjunction of such propositions.

Definition 2. A state is a function which, for any proposition, returns True or False. For instance, the initial state of Tom's Tale return True for $at(Bandit) = Forest$ and False for $at(Herbs) = Forest$.

Definition 3. An action a describes an event which can occur in the world using the following specifications:

- $Pre(a)$: A proposition—the precondition of a—that must hold immediately before the action occurs.
- $Eff(a)$: A proposition—the effect of a—that becomes True immediately after a. The action effect is required to be deterministic.
- $Par(a)$: A set of constants that are involved in a.

[1] Here $at(Tom)$ and $at(Herbs)$ are two different variables (not functions). In my examples, I use notations, such as at, to make these variables more readable. but the planner considers each variable as a unique symbol.

Preconditions and effects cannot be contradictory. For instance, $Pre(a)$ or $Eff(a)$ of action a cannot be

$$at(Bandit) = Forest \wedge at(Bandit) = Town$$

Definition 4. A state space is a graph whose nodes are states and whose directed edges represent actions. An edge $s \xrightarrow{a} s'$ exists if action a's precondition is satisfied in state s and applying a's effects would change the state to s'. Figure 3.2 presents an example of a state space.

Definition 5. A plan is a sequence of actions, or a path through the state space.

4.1.2 Narrative Planning Problem

Narrative planners ([Porteous et al.; Young et al., 2010; 2013], and many others) extend this formalism to tell believable stories. They reason about the author's goal, as well as the beliefs and goals of each character. Rather than expressing goals as propositions, I use utility functions.

Definition 6. A narrative planning problem is defined as $\langle s_0, U, A, C, U_C \rangle$ where s_0 is the initial state, U is the author utility function, A is a set of actions, C is a set of characters, and U_C is a set of character utility functions.

Definition 7. The initial state is a conjunction which contains an assignment for every domain variable. It represents the state of the world before any planning takes place. The initial state of Tom's Tale is as follows.

$$at(Tom) = Home \wedge at(Merchant) = Town \wedge at(Bandit) = Forest \wedge$$
$$at(Medicine) = Merchant \wedge at(Sword) = Merchant \wedge$$
$$at(Coin1) = Tom \wedge at(Coin2) = Tom$$

Definition 8. A utility function is a function that receives a state as input and returns a real number. Although my models make no particular commitment to how a utility function is defined, I use the following definition to describe the utility functions in the presented examples. I represent a utility function as a sequence of conditional expressions, in form $p \rightarrow n$ (if proposition p holds then real number n),

$$\langle p_1 \rightarrow n_1, p_2 \rightarrow n_2, ..., p_m \rightarrow n_m \rangle$$

This sequence is evaluated in order and if no condition holds in a given state, the function returns 0.

A utility function is defined by the author for the overall story, denoted by $U(s)$, and every character, denoted by $U(c, s) \in U_C$. For instance, the author's utility function in Tom's Tale is as follows.

$$U(s) = \left\langle \begin{array}{c} at(Medicine) = Tom \rightarrow 1, \\ at(Coin1) = Bandit \rightarrow 1, \end{array} \right\rangle$$

Definition 9. A <u>character</u> $c \in C$ is defined as a special constant that represents an agent with intentions and beliefs. The intentions of a character are defined in terms of a utility function ($U(c, s)$). Each character intends to increase the value of their utility function. For instance, Tom's utility function is as follows.

$$U(Tom, s) = \left\langle \begin{array}{c} at(Medicine) = Tom \rightarrow 4 \\ at(Coin1) = Tom \wedge at(Coin2) = Tom \rightarrow 2, \\ at(Coin1) = Tom \rightarrow 1, \\ at(Coin2) = Tom \rightarrow 1, \end{array} \right\rangle$$

Definition 10. In narrative planning, an <u>action</u> $a \in A$ has the following additions to Definition 3:

- $Con(a)$: A set of characters $\in C$ where $Con(a) \subseteq Par(a)$, that shows which characters are responsible for taking the action. This set includes the characters who must have a reason to take the action and not necessarily all characters affected by that action. For instance, in action *Rob*, the robber is a consenting character, but the victim is not.

- $Obs(a, s)$: A set of characters $\in C$ that shows the characters who observe the action when it occurs. $Obs(a, s)$ is a function of the current state and the parameters of the action[2].

For example in Figure 3.1, The parameters of action *Go* are character c and place *to*, and that character is the consenting character. The precondition of *Go* is True, which means that the action is possible in any given state, and its effect is that the character is now at *to*. The set of observing characters of *Go* is defined as all the characters at *to*, as well as the consenting character.

4.1.3 Narrative Planners with Beliefs

Actions also change the beliefs of characters. The beliefs of a character are represented by modal propositions $believes(c, p)$ (or $b(c, p)$ for short), meaning character c believes proposition p. The grammar for propositions is extended to:

$$p \rightarrow True|False|v = u|p \wedge p|b(c, p)$$

and the following applies to beliefs about conjunctions:

$$b(c, p \wedge q) \leftrightarrow b(c, p) \wedge b(c, q)$$

Belief propositions can be nested, e.g. $b(c_1, b(c_2, p))$ means character c_1 believes that character c_2 believes proposition p. For example, the following propositions hold

[2] Although methods for automatically determining action observers have been suggested by others [Christian and Young; Ten Brinke et al.; Teutenberg and Porteous, 2004; 2014; 2015], this model makes no particular commitment to how $Obs(a, s)$ is chosen.

in state s_1:

$$b(Tom, Location(Herbs) = Forest),$$

$$b(Tom, Location(Bandit) = Forest),$$

$$b(Tom, b(Bandit, Location(Herbs) = Forest)$$

The closed world assumption is also extended to account for character beliefs.

- When a belief for a proposition is not explicitly stated for a character, that character is assumed to believe the true value of that proposition, i.e. $b(c, p) \leftrightarrow p$ unless stated otherwise.

- Unless explicitly stated otherwise, characters are assumed to believe that other characters believe the same things they do, i.e. $\forall c_i, c_j \in C : b(c_i, b(c_j, p)) \leftrightarrow b(c_i, p)$ unless stated otherwise.

Definition 11. For some sequence of actions π in a state s, let $\alpha(\pi, s)$ denote the state after taking the actions in π. In Figure 3.3, $\alpha(\langle Go(Tom, Forest)\rangle, s_1) = s_2$. α is only defined when, for every action $a \in \pi$, the precondition of a is satisfied in the state immediately before taking a, i.e. $s \models Pre(a)$.

Definition 12. For some character c in a state s, let $\beta(c, s)$ denote what c believes the state to be when it is actually s. In Figure 3.3, $\beta(Tom, s_1) = s_{10}$. In s_1, there are no herbs in the forest, but in s_{10} there are, so Tom wrongly believes there are herbs in the forest. The belief notation also shows that this model limits each character to have exactly one belief about every proposition in the domain. In other words, we cannot show that a character is uncertain about a proposition.

After taking action a, the beliefs of every character may be updated as follows[3]:

- $\forall c \in C : c \in Obs(a, s) \Rightarrow \beta(c, \alpha(a, s)) = \alpha(a, \beta(c, s))$

[3]The details of updating character beliefs for an action whose effect models $b(c, p)$, e.g. to model deception, are not directly relevant to my models of emotion or personality. For full details, please refer to Shirvani et al. (2017).

- $\forall c \in C : c \notin Obs(a, s) \Rightarrow \beta(c, \alpha(a, s)) = \beta(c, s)$.

It is possible that character c believes the precondition of action a is False and yet observes a. In that case, c's beliefs are first updated to believe the preconditions of a (to believe that action was possible contrary to their wrong beliefs) and then believe its effects. In other words, if $c \in Obs(a, s)$ and $\neg b(c, Pre(a))$, after observing a, $b(c, Eff(a) \wedge \forall p : Pre(a) \models p \wedge Eff(a) \not\models p \Rightarrow p)$ where p is an assignment to a variable or a belief proposition. I refer to this as a surprise action. Since the character is surprised by an action that they believed was not possible.

For instance, if Tom did not believe that the bandit is in the forest, after Tom observes action *Rob*, he first believes the precondition of *Rob*, i.e. the bandit is in the forest, and then its effect, i.e. bandit has his coins now.

4.1.4 Narrative Planning Solution

Various narrative planning frameworks differ in how they define explained actions. I use the following definition for explained actions.

Definition 13. In state s, an action a is explained for character $c \in Con(a)$ when there exists a sequence of actions π such that:

1. a is the first action in π
2. $U(c, \alpha(\pi, \beta(c, s))) > U(c, s)$
3. Every action after a in π is explained.
4. π does not contain a strict subsequence that also meets these four requirements.

In other words, an action makes sense for a character when that character can imagine a plan that (1) starts with that action, (2) they believe will lead to a higher utility, (3) the plan makes sense for the other consenting characters, and (4) it doesn't contain unnecessary or redundant actions.

Definition 14. In state s, an action a is explained when, for all consenting characters $c \in Con(a)$, a is explained for c in s. In other words, an action is explained when it is explained for all the characters that need a reason to take it. Characters can have different reasons for taking an action. Tom can buy the medicine because he wants it, and the merchant will sell it because she wants coins. The merchant has no reason to give away the medicine, so Tom cannot expect her to.

Definition 15. A sequence of actions π is explained when, for all actions $a \in \pi$, a is explained in the state before a occurs. In other words, a sequence is explained when all its actions are explained.

Definition 16. A solution to a narrative planning problem is an explained sequence of actions that increases the author's utility and does not contain a strict subsequence that also meets these requirements.

Note that one character can expect another character to act; I call this anticipation [Shirvani et al., 2017]. A character should not only anticipate actions that help them increase their utility, e.g. expecting the merchant to consent to *Buy*, but also those that could decrease their utility, e.g. expecting *Rob*.

Definition 17. A sequence of actions π is expected for character c in state s when every action in π is explained and c's utility is changed as a result of π, i.e.

$$U(c, \alpha(\pi, \beta(c, s))) > U(c, s) \vee U(c, \alpha(\pi, \beta(c, s))) < U(c, s)$$

This criterion highlights the difference between this definition and the definition of an explained sequence of actions (Definition 15). An expected sequence of actions for c does not necessarily lead to a higher utility for c. For instance, we cannot say that *Rob* is explained for Tom because Tom is not a consenting character. However, we say that *Rob* is expected for Tom because it could decrease his utility and (Tom believes that) it is explained for the action's consenting character, the bandit.

Indeed, characters can expect actions (often the actions of others) to decrease their utility. In keeping with the ideals of a strong-story system, characters can expect many sequences, not just one. Characters do not commit to a single expectation (what a BDI system might call an intention), but can expect any sequence that meets these requirements. This enables the planner to choose from a wide variety of believable stories when trying to meet the author's requirements.

In the next section, I will expand these definitions to incorporate emotions and personality. I will show how emotions are triggered as a consequence of actions and how characters distinguish between different plans based on their personality.

4.2 Emotion

The OCC model of emotion [Ortony et al., 1990] defines 22 different emotions. Out of 22, 12 emotions are triggered based on the significance of events to goals, whereas the rest also consider the standards and attitudes of a character towards events and objects. Only the former set of emotions can be readily adapted into narrative planning without introducing a degree of domain-dependence. In this document, I will focus on the 12 emotions presented in Table 4.1.

Table 4.1 presents how each emotion is triggered based on the the consequences of events for the character itself or other characters [Ortony et al., 1990].

An event is desirable for a character if it achieves their goal (increases their utility) or undesirable if it causes their goal to fail (decreases their utility). On the other hand, a prospective event is unconfirmed when it has not occurred yet (the character expects that it could happen), confirmed when it actually occurs (the character observes it), and disconfirmed when it does not eventually happen (the character no longer expects it to happen). The model defines prospective emotions as expecting an event to occur at a certain time. Since there is no planning structure that keeps track of time, I change the definition of a disconfirmed event to "when the event is no longer expected to happen."

Table 4.1: Emotions, Their Appraisal, and Planning Triggers

Emotion	**Prospects**	**Consequences (Self)**	**Trigger**
Joy	Irrelevant	Desirable	Utility increases
Distress		Undesirable	Utility decreases
Hope	Unconfirmed	Desirable	Expects a higher utility
Fear		Undesirable	Expects a lower utility
Satisfaction	Confirmed	Desirable	Achieves the expected higher utility
FearsConfirmed		Undesirable	Achieves the expected lower utility
Disappointment	Disconfirmed	Desirable	No longer expects the higher utility
Relief		Undesirable	No longer expects the lower utility
Emotion	**Consequences (Other)**	**Consequences (Self)**	**Trigger**
HappyFor	Desirable	Desirable	Own utility does not decrease Other's utility increases
Resentment		Undesirable	Own utility decreases Other's utility increases
Gloating	Undesirable	Desirable	Own utility does not decrease Other's utility decreases
Pity		Undesirable	Own utility decreases Other's utility decreases

Column 4 adapts these trigger conditions to narrative planning based on a character's utility function. Since the model of belief allows characters to form expectations about events, the emotions triggered based on prospective events can be adapted to with no additional cost to domain independence.

4.2.1 Positive Emotions

In this section, I provide a formal definition of how each positive emotion is triggered and how the intensity of an emotion is calculated.

1. **Joy**

   Definition: Joy is triggered for character c at state s after taking/observing action a if $U(c, s) > U(c, s')$, such that $\alpha(a, s') = s$.

Intensity: How much c's utility increases after a or $U(c, s) - U(c, s')$.

Example: Joy is triggered for Tom in state s_5 because his utility increases to 3.

2. **Hope**

   Definition: Character c feels Hope to achieve utility u as long as there is at least one expected plan π starting from state s, such that $hu = U(c, \alpha(\pi, \beta(c, s)))$ and $hu > U(c, s)$. I refer to hu as <u>hoped utility.</u>

   Intensity: How much c's utility increases when it reaches hu or $U(c, s) - hu$.

   Example: In state s_1, Tom hopes for utility values 4 (by making the medicine himself) or 3 (by buying the medicine).

3. **Satisfaction**

   Definition: Satisfaction is triggered for character c at state s if $U(c, s) = hu$, such as hu is the corresponding hoped utility. if a character is surprised by an action that increases their utility, they feel Joy but not Satisfaction.

   Intensity: The intensity of the corresponding Hope.

   Example: Satisfaction triggers for Tom in s_5 for achieving his hoped utility of 3.

4. **Relief**

   Definition: Relief is triggered for character c at state s if c no longer fears utility fu—Fear is defined later—and $U(c, s) > fu$.

   Intensity: The reciprocal of the intensity of the corresponding Fear.

   Example: Relief is triggered for Tom at state s_{31} because Tom buys a sword and no longer expects to be robbed.

5. **HappyFor**

   Definition: Character c feels happy for character c' at state s after action a if for c, $c \in Con(a)$ or $U(c, s) > U(c, s')$, and for c', $U(c', s) > U(c', s')$, such that $\alpha(a, s') = s$.

Intensity: How much c''s utility increases or $U(c', s) - U(c', s')$.

Example: HappyFor is triggered for Tom at state s_5 because after buying the medicine, the merchant's utility is increased by 1.

6. **Gloating**

   Definition: Character c feels gloating towards character c' at state s after action a if for c, $c \in Con(a)$ or $U(c, s) > U(c, s')$, and for c', $U(c', s) < U(c', s')$, such that $\alpha(a, s') = s$.

   Intensity: How much c''s utility decreases or $U(c', s') - U(c', s)$.

   Example: Gloating is triggered for the bandit at state s_3 because the bandit's utility increases to 2 and Tom's utility decreases to 0.

4.2.2 Negative Emotions

The set of negative emotions are as follows.

1. **Distress**

   Definition: Distress is triggered for character c at state s after taking/observing action a if $U(c, s) < U(c, s')$, such that $\alpha(a, s') = s$.

   Intensity: How much c's utility decreases after a or $U(c, s) - U(c, s')$.

   Example, Distress is triggered for Tom in state s_3 because his utility reduces to 0.

2. **Fear**

   Definition: Character c fears that their utility could decrease to u as long as there is at least one expected plan π starting from state s, such that $fu = U(c, \alpha(\pi, \beta(c, s)))$ and $fu < U(c, s)$. I refer to fu as feared utility.

   Intensity: How much c's utility decreases when it reaches fu or $fu - U(c, s)$.

Example: Tom fears his utility to decrease to 0 because he expects that the bandit could and would steal his coins.

3. **FearsConfirmed**

   Definition: FearsConfirmed is triggered for character c at state s if $U(c, s) = fu$, such as fu is the corresponding feared utility. If a character is surprised by an action that decreases their utility, they feel Distress but not FearsConfirmed.

   Intensity: The intensity of the corresponding Fear.

   Example: FearsConfirmed is triggered at s_3 when Tom is robbed as he feared he would be.

4. **Disappointment**:

   Definition: Disappointment is triggered for character c at state s if c no longer hopes for utility hu and $U(c, s) < hu$.

   Intensity: The reciprocal of that of the corresponding Hope.

   Example: Disappointment is triggered for Tom in state s_2 because he realizes there are no herbs in the forest.

5. **Resentment**

   Definition: Character c feels resentment for character c' at state s after action a if for c, $U(c, s) < U(c, s')$ and for c', $c' \in Con(a)$ or $U(c', s) > U(c', s')$, such that $\alpha(a, s') = s$.

   Intensity: How much c's utility decreases or $U(c, s) - U(c, s')$.

   Example: Resentment is triggered for Tom at state s_3 because the bandit's utility increases to 2 and Tom's utility decreases to 0.

6. **Pity**

   Definition: Character c feels pity for character c' at state s after action a if $U(c, s) < U(c, s')$ and $U(c', s) < U(c', s')$, such that $\alpha(a, s') = s$.

   Intensity: How much c''s utility decreases or $U(c', s) - U(c', s')$.

4.2.3 Defining a Conflict using Emotions

A conflict occurs when a character's plan could decrease another character's utility, and a conflict is resolved when either that character's utility has decreased as a result of that plan or that plan is no longer expected to occur. Using the emotion definitions above, a conflict is defined as follows:

Definition 18. A conflict occurs for character c in state s when in state s, c fears that their utility could decrease to a lower number. A conflict is resolved when the corresponding fear is transformed either into Relief or FearsConfirmed.

For instance, Tom fears the bandit could rob him (the anticipation of conflict). This conflict could be resolved in two ways. If Tom goes to the forest and gets robbed by the bandit, Tom will feel FearsConfirmed. On the other hand, if Tom goes to town and buys a sword, he will resolve the conflict and feel Relief.

By defining a conflict in terms of Fear, I am considering many similar plans that trigger the same Fear emotion as the same conflict. For instance, let's assume Tom is in the forest and he fears that the bandit could rob him. Tom fears this plan:

$$\langle Rob(Bandit, Tom) \rangle$$

If Tom goes to town, this plan is no longer possible. However, Tom would not feel Relief because he can still expect a plan in which the bandit could rob him. For instance

$$\langle Go(Tom, Forest), Rob(Bandit, Tom) \rangle$$

or

$$\langle Go(Bandit, Town), Rob(Bandit, Tom) \rangle$$

Indeed, Tom fears all plans that end up in the bandit robbing him (feared utility of 0). It is only after he buys a sword that his Fear turns to Relief and the conflict is resolved. This improves upon many previous models of conflict, e.g. [Ware and Young, 2011], that consider these two situations as two different conflicts. According to those models, to resolve the conflict of Tom getting robbed by the bandit, Tom can just leave the forest. But that is simply not true. Even though the state has changed, the character still expects the feared utility (that they could be robbed).

Moreover, using previous planners, e.g. [Riedl and Young; Ware and Young; Shirvani et al., 2010; 2014; 2017], this conflict could not be resolved in favor of Tom. This is because "buying a sword" does not increase Tom's utility and thus, is not a valid character plan (see Definition 13). Therefore, I need to update the definition of an explained action to enable this type of story.

4.2.4 Emotional Planning

Based on the expected emotions, I redefine explained actions as follows.

Definition. In state s, an action a is explained for character $c \in Con(a)$ when there exists a sequence of actions π such that:

1. a is the first action in π
2. A positive emotion is triggered for c in $\alpha(\pi, \beta(c, s))$.
3. Every action after a in π is explained.
4. π does not contain a strict subsequence that also meets these four requirements.

According to the previous definition (Definition 13), criteria 2 states that an action is explained for character c if it increases c's utility, thus making them feel Joy or Satisfaction. My definition of explained actions generalizes criteria 2 to include all other positive emotions. For instance, characters can now consent to actions in pursuit of friendship or rivalry to feel HappyFor or Gloating. Characters can also act in response to their fears (expected sequences of actions that could decrease their utility) to feel Relief. A simple example is when Tom decides to buy a sword. This is an explained action because, with the sword, he is relieved that the bandit can no longer rob him. His utility not only does not increase, but also decreases for using one of his coins. In short, the proposed model allows characters to act emotionally rather than just rationally.

4.3 Personality

Depending on the story domain, a narrative planner can find multiple valid plans for every character. Existing planning systems return the first valid plan, which is potentially the shortest, unless explicitly asked otherwise.

However, I believe that this choice must depend on the character's personality rather than being non-deterministic. We have already answered why characters choose to act—to feel positive emotions—and now we should address how they act—based on their personality. There are different ways to achieve the same goal, e.g. how we affect other characters in the story. In order to distinguish between different plans, we can select a set of features to describe those plans to then use those features to rank them based on different personalities. Those features should represent plans independent of their domain-specific details in order to be reusable in different story domains.

In the next section, I will describe what behavior patterns each factor represents and how they are adapted to narrative planning. Before I discuss adapting the FFM to narrative planning, I must clarify the limitations of my model. First, I strive to achieve high domain independence to make it easy to apply the model to many story domains. In doing so, I intentionally limit myself to structures already provided by narrative planners. For instance, since narrative planning does not readily allow defining social conventions, modeling the markers of Openness or Conscientiousness that address those concepts comes at the cost of impairing domain independence.

Moreover, I focus on expressing character personality through external actions,

Table 4.2: Personality Markers to Author Story Domains

F	0		1
O	Unimaginative	⟷	Creative
	Simple	⟷	Intelligent
C	Disorganized	⟷	Efficient
	Dependent	⟷	Self-Efficient
E	Shy	⟷	Sociable
	Unassertive	⟷	Assertive
A	Selfish	⟷	Altruistic
	Antagonistic	⟷	Compassionate
N	Collected	⟷	Anxious
	Decisive	⟷	Indecisive

particularly via the choice between different actions, since domain actions are the building blocks of narrative planning. This additionally restricts modeling certain aspects of the FFM that correspond to internal thoughts that are addressed more frequently in other contexts such as theater or novels.

4.3.1 Character Personality Vector

A character's personality is represented by a personality vector $\langle p_1, \ldots, p_5 \rangle$ for each of the five factors where p_i is a real number in $[0, 1]$. Factor values 0 and 1 respectively represent the lowest and highest scores of the corresponding factor. The author is responsible for specifying a character's personality and if not specified, a character will have 0.5 for all their factor values.

However, to avoid having authors to first learn about the five factors before creating their characters. I give the author the option to describe their characters using a set of markers that are automatically mapped into a personality vector.

Table 4.2 presents the markers and their corresponding factor. The author can use one of the adjectives in each row to describe their characters (representing either 0 or 1 for that row). If the author omits using an adjective from a row, the value of that row is considered 0.5. Each factor's score is set to the average of its two values.

Table 4.3: Proposed Personality Plan Features

F	Feature	Facet	Description (High scores)
O	CPF	Intellect	The intensity of Satisfaction
	SPF	Openness	Average intensity of the Fear (R)
C	SEF	Orderliness	# of actions with self as the consenting character
	EPF	Industriousness	# of actions in a plan (R)
E	SPF	Enthusiasm	# of actions with other consenting characters
	ASPF	Assertiveness	# of actions with other non-consenting characters
A	COOPF	Compassion	Average intensity of HappyFor
	PPF	Politeness	Average intensity of Gloating (R)
N	SRF	Withdrawal	The intensity of Relief
	NBF	Volatility	# of times the character changes their mind

4.3.2 Plan Features

Given multiple plans that could achieve their goal, an agent should choose the one which best fits its personality. In order to do so, a plan is described by a set of features, presented in Table 4.3, that can be automatically calculated across different story domains.

I must note that features marked as (R) are negatively correlated with their corresponding aspect. For instance, EPF in Table 4.3 is "# of actions in a plan (R)." This means highly conscientious agents try to minimize the number of actions in their plans, but low conscientious agents maximize and choose the longest plan. On the contrary, feature SEF is positively correlated to conscientiousness, so highly conscientious agents maximize the number of actions with themselves as consenting characters (and vice versa).

Creative Plan Feature

According to Boden (2004)'s model of creativity [Boden et al., 2004], creativity refers to the exploration and transformation of a conceptual space by creative agents.

More specifically, a conceptual space is a set of concepts and creativity is the act of identifying new concepts within that space. Here, I focus on <u>exploratory</u> creativity, which is the process of searching an area of the conceptual space governed by certain rules. These rules not only determine the membership of concepts to the conceptual space but also their <u>value</u>.

In this context, a concept is a plan and the conceptual space is the space of all possible plans. Based on this definition, a creative character is capable of exploring this space to find the most valuable concept (the plan that maximizes their utility—feeling Satisfaction with the highest intensity). By saying that creative individuals tend to maximize their satisfaction, I do not mean that unimaginative individuals do not value Satisfaction; they simply are not creative enough to be able to think of plans that maximizes their satisfaction.

The Creative Plan Feature (CRPF) of plan π for character c is equal to the intensity of the Satisfaction that c expects to be triggered at the end of π.

In Tom's Tale, with high Intellect, Tom makes the medicine himself because it maximizes his utility by not losing a coin.

Successful Plan Feature

Highly open individuals are intellectual; they want to solve complex problems and their plans rarely fail. The Successful Plan Feature (SPF) shows how a character choose plans that are more likely to succeed. Here, the likelihood of success refers to the number of expected plans that could cause that character's plan to fail or could decrease their utility. For instance, the likelihood of success of going to the forest is lower than that of going to the town because it is possible for Tom to get robbed in the forest.

Considering plan π for character c starting from state s, there is a set of expected plans P such that all expected plans p_i in P have the following criteria:

- c fears expected plan p_i.

- Expected plan p_i starts with a sequence of actions *seq* with minimum length 1, such that c is a consenting character of all actions in *seq*, and $seq \subset \pi$.

The successful plan feature (SPF) of plan π is calculated as the average intensity of Fear triggered by $\underline{\pi}$.

$$SPF(c, \pi, P) = \frac{\sum_{p_i \in P} \mathbb{I}(I(Fear(c, p_i)) > 0)}{\sum_{p_i \in P} I(Fear(c, p_i))}$$

Where, I returns the intensity of the corresponding emotion and function $\mathbb{I}$ is an indicator function[4] and returns 1 if the *condition* holds and 0 otherwise. In short, the character takes actions that they do not expect could fail. In Tom's Tale, with high Openness, Tom buys the medicine because this plan is the least likely to fail.

Self-Efficacy Feature

This feature is meant to represent the self-confidence and self-efficacy of conscientious individuals. The plans are preferred that express independence and self-reliance. The Self-Efficacy Feature (SEF) of character c for plan π is calculated the number of actions that c is taking themselves.

$$SEF(c, \pi) = \sum_{a_i \in \pi} \mathbb{I}(c \in Con(a_i))$$

Where, a_i represents an action in plan π. For instance, if Tom's Orderliness was low, he would wait for the merchant to come to him to sell the medicine rather than going to town himself.

Efficient Plan Feature

Conscientious individuals are industrious and focused, and thus get things done quickly and efficiently. The Efficient Plan Feature (EPF) of plan π reflects minimizing the length (number of actions) of π.

[4]An indicator function receives a condition that can be true or false, e.g. $a < b, a > b, a \in b$, etc.

$$EPF(c, \pi) = \frac{1}{|\pi|}$$

Where, $|\pi|$ represents the length of π. In Tom's Tale, if Tom is highly Industrious, he prefers to buy the medicine because that plan only has two steps.

Social Plan Feature

Since extroverts prefer to include others into their everyday lives, they tend to prefer actions that involve as many other characters as possible. The Social Plan Feature (SPF) of plan π for character c is calculated as the number of other consenting characters in π.

$$SPF(c, \pi, C) = \sum_{\substack{a_i \in \pi \\ c_j \in C - \{c\}}} \mathbb{I}(c_j \in Con(a_i))$$

Where, C is the set of characters in the domain. In Tom's Tale, with high Enthusiasm, Tom buys the medicine because it involves the merchant.

Assertive Plan Feature

I represent the assertiveness of extroverts in how they include other characters in their plans whether they want it or not. The Assertive Plan Feature (ASPF) of plan π for character c is calculated as the number of other non-consenting characters in a plan.

$$ASPF(c, \pi, C) = \sum_{\substack{a_i \in \pi \\ c_j \in C - \{c\}}} \mathbb{I}(c_j \in Par(a_i) \times (1 - \mathbb{I}(c_j \in Con(a_i)))$$

A character c is considered to be a non-consenting character in an action a, if $c \in Par(a)$ but $c \notin Con(a)$. An action may affect a non-consenting character in a positive or negative way. One may choose to give an item to or attack another character where, in both cases, that character's consent is not needed by those actions. In Tom's Tale, an assertive Tom would choose to buy the sword and rob the merchant.

I must note that this action is also affected by Agreeableness. Tom may not choose this plan if his Agreeableness is high.

Compassion Plan Feature

Highly agreeable individuals prefer actions that assist other characters along the way. The Cooperative Plan Feature (COPF) of plan π for character c is calculated as the average intensity of the HappyFor that c expects to be triggered by π.

$$COPF(c, \pi, C) = \frac{\sum_{\substack{c_j \in C - \{c\} \\ a_i \in \pi}} I(HappyFor(c, c_j, a_i))}{\sum_{\substack{c_j \in C - \{c\} \\ a_i \in \pi}} \mathbb{I}(I(Happyfor(c, c_j, a_i)) > 0)}$$

Where, I returns the intensity of the corresponding emotion. In Tom's Tale, with high Compassion, Tom buys the sword and medicine from the Merchant.

Politeness Plan Feature

Agreeable individuals show their compassion for other people by avoiding to harm them in the process. In terms of emotions, a character with high Compassion prefers plans that minimizes their Gloating.

The Politeness Plan Feature (PPF) of character c for plan π is calculated as the average intensity of Gloating that c expects to be triggered by π.

$$PPF(c, \pi, C) = \frac{\sum_{\substack{c_j \in C - \{c\} \\ a_i \in \pi}} \mathbb{I}(I(Gloating(c, c_j, a_i)) > 0)}{\sum_{\substack{c_j \in C - \{c\} \\ a_i \in \pi}} I(Gloating(c, c_j, a_i))}$$

Where, I returns the intensity of the corresponding emotion. In Tom's Tale, a very polite Tom would not rob the merchant.

Stress Relief Feature

Neurotic individuals are prone to anxiety and try to take actions that help to remove their stressors and feel Relief. The Stress Relief Feature (SRF) of plan π for character c is calculated as the intensity of Relief that c expects to be triggered at the end of π. In Tom's Tale, with high Withdrawal, Tom prefers to buy a sword because it eliminates the threat of being robbed by the bandit.

Neurotic Behavior Feature

Highly neurotic individuals can be described as indecisive, self-doubting, or impulsive. One way to express such characteristics is through showing how often a character changes their mind and abandons their current plan.

In order to calculate this feature for a slightly to highly neurotic character—scores of higher than 0.5, I relax the criterion of a valid plan which constrains it to have no strict subsequences that follow the same criteria. The Neurotic Behavior Feature (NBF) of plan π for character c is calculated as follows:

$$NBF(c,\pi) = \begin{cases} 0 & p_{neuroticism}(c) < 0.5 \\ \Omega(\pi) & p_{neuroticism}(c) > 0.5 \end{cases}$$

Where $\Omega(\pi)$ is the number of strict subsequences of π that are valid plans. For instance, $\Omega(\pi) = 2$ for the following plan

$$\begin{gathered} \langle Go(Tom, Town), \\ Go(Tom, Forest) \\ Go(Tom, Town) \\ Buy(Tom, Merchant, Medicine) \rangle \end{gathered}$$

because it has two strict subsequences that are valid plans:

$$\langle Go(Tom, Forest)$$
$$Go(Tom, Town)$$
$$Buy(Tom, Merchant, Medicine)\rangle$$

and

$$\langle Go(Tom, Town)$$
$$Buy(Tom, Merchant, Medicine)\rangle$$

4.3.3 Preference Modeling

Now that I have defined and described my 12 features, I will show how a character chooses between a set of valid plans at any given state. Algorithm 1 returns the best plan for a character at a state based on their personality. Line 1 shows the inputs of the algorithm, all valid plans for character c at state s, as well as c's personality vector. The personality of the character is specified by five number in [0, 1] for each of the five factors (0.5 showing neutrality).

For each plan, we calculate the value of the 12 features in Table 4.3 (line 3). We then calculate the preference vector with five values for each of the big five. Each value is a function of a personality factor and the features corresponding to that factor. The character's preference for a plan is represented by the plan's utility (U_i) which is calculated as the Euclidean norm of the preference vector (line 4).

4.4 Intelligent Conflict Generation

"Conflict structures narrative" [Abbott, 2020]. "Drama is conflict" [Field, 2006]. "Story means conflict" [Brooks and Warren, 1979]. There is an agreement among many that conflict is an essential part of a story [Meehan; Szilas; Barber and Kudenko; Ware and Young, 1977; 1999; 2007; 2011]. In interactive narratives, conflicts make the player face difficult choices that may need them to divert from their current plans and take action to achieve a desired resolution. I use conflict to enable experience

Algorithm 1 $Preference(\Pi, P_c, c, s)$

Let Π be the set of valid plans for character c at state s, and P_c be personality of character c with five values $p_\alpha, \alpha \in \{O, C, E, A, N\}$.
for each plan $\pi_i \in \Pi$ **do**
    Calculate the set of feature values $\{f_{iO_1}, f_{iO_2}, f_{iC_1}, f_{iC_2}, ..., f_{iN_1}, f_{iN_2}\}$, representing two features for each factor as in Table 4.3 for plan π_i.
    Let
    $F_\alpha = p_\alpha \times \frac{f_{i\alpha_1} + f_{i\alpha_2}}{2}, \alpha \in \{O, C, E, A, N\}$
    $U_i = \sqrt{\sum_{\alpha \in \{O,C,E,A,C\}} F_\alpha^2}$
    return $argmax_{\pi_i \in \Pi} U_i$

managers to guide the story toward specific important choices.

Previous planners have taken measures to ensure a resolution exists when a conflict has irreversible consequences. For instance, experience managers may ensure a resolution exists when the conflict brings the narrative to a dead end, e.g. if an NPC plans to kill the player, the story does not always end with the player dying. However, they often make no attempt to create conflicts in an intelligent way.

As an example, The Best Laid Plans, an interactive narrative adventure game, automatically generates conflicts in real time [Ware and Young, 2015]. However, the system only tries to find a conflict if one exists and makes no effort to choose conflicts intelligently to tell the best possible story. We can leverage the ability of strong-story systems to a much higher extent by distinguishing between different conflicts based on how they can be resolved. We can not only answer what a conflict is, but how a conflict is resolved, and how its resolution affects different characters.

I propose to use conflicts in an intelligent and meaningful way by considering a player model (for player goals and expectations) and player choices that resolve those conflicts. The experience manager can implicitly encourage author-intended behavior by creating opportunities for the player to resolve conflicts via that behavior.

Algorithm 2 presents how the experience manager decides about NPC actions for intelligent conflict generation. The inputs of the function are a plan π, that is nondeterministically chosen for the NPC, the current state, and the player character

Algorithm 2 $CheckNPCAction(\pi, s, p)$

1: Let π be a plan for an NPC, s is the current state, and p is the player character.
2: **if** $Fear(p, \pi)$ **then**
3:     **if** $\exists \pi' \rightarrow Relief(p, \alpha(\pi', s)) \wedge \Omega(p, \pi')$ **then**
4:         **return** True
5: **return** False

(Line 1). It is possible that the player fears that π could decrease their utility (Line 2), represented by $Fear(p, \pi)$—player p fears plan π. If so, the experience manager finds a plan π' such that it (1) starts from state s, triggers Relief, represented by $Relief(p, \alpha(\pi', s))$—plan π ending in player p feeling Relief, and (2) is line with the behavior intended by the author, represented by function $\Omega(p, \pi')$ (Line 3). For instance, if the author wants to encourage Agreeableness, $\Omega(p, \pi')$ return False if π' includes actions that reduces another character's utility, or if the author wants to encourage Extroversion, $\Omega(p, \pi')$ return True if π' includes actions that involve other characters (see Table 4.3). If no such plan exists, then function returns False.

In short, the experience manager ensures that there is always at least one plan that uses the intended behavior to resolve a conflict. Otherwise, the experience manager will not allow NPC actions that make the player expect such conflict in the first place.

CHAPTER 5. EVALUATION

5.1 Overview

In my previous work, I evaluated the model of belief using multiple human subject studies. Since the belief model is not the focus of this document, I do not discuss their design and results. For more information about those experiments, please refer to Shirvani et al. (2017) and Shirvani et al. (2018).

In this section, I will evaluate the proposed models of personality and emotion for strong-story narrative planners. I will first investigate the effect of personality, emotion, and both on the perceived believability of generated (interactive) narratives. I will show that the modeled personality traits can be perceived and recognized by human readers and the use of personality improves the perceived consistency of character behaviors. I will also demonstrate that the proposed model of emotion accurately simulates what characters should feel at certain parts of a short story and the use of the model enhances player empathy towards story characters, as well as character believability through the expression of characters' internal thoughts. Finally, I will show the readers' preference over stories that use both personality and emotion to generate character behavior.

For these (four) experiments, I recruited participants from Amazon's Mechanical Turk (AMT). I did not target any specific populations and all AMT workers had an equal opportunity to view and accept the activity. Participants received a small monetary compensation for accepting the activity, e.g. 10 cents, and a larger amount for finishing the story and answering the questionnaires, e.g. 1 dollar.

Furthermore, I will present a showcase of the application of personality and emotion in strong-story planning through intelligent conflict generation. I generated all possible stories (with a set maximum length) within two interactive narratives. Results support that using intelligent conflict generation, players will experience a smaller number of conflicts in total, but a larger percentage of conflicts that can be resolved through specified personality traits.

5.2 Emotion

To evaluate the model of emotion, I claim that:

1. The set of stories generated by my model is a superset of stories generated by narrative planners that do not reason about emotions.

2. The emotions specified by my model are similar to the emotions that human readers expect characters to experience.

3. Human readers find the character behavior generated by my model more believable than those created by narrative planners that do not reason about emotions.

I support my first claim as follows. For all the stories generated by narrative planners that do not reason about emotions, characters only take actions that contribute to making them feel Joy, i.e. by increase their utility (see Definition 13). Therefore, my model can generate all stories that are generated by narrative planners without emotions. In addition to those stories, there exists a set of stories in which characters take actions that could make them feel Relief, HappyFor, and Gloating. Since such actions do not necessarily increase the character's utility, this set of stories can be generated by my model but not narrative planners without emotions.

An example story is one where Tom goes to town, buys a sword, goes to the forest (realizes there are no herbs in the forest), goes back to town, and buys the medicine. This story can only be generated by my model since "buying a sword" makes Tom feel Relief. However, narrative planners without emotions do not generate this story since not only does "buying a sword" not increase Tom's utility, but actually decreases it.

I empirically evaluate my second and third claims using Experiment 1 and Experiment 2 in the following sections.

5.2.1 Experiment 1: Character Emotion Validation

In this section, I evaluate how accurately my model operationalizes six basic OCC emotions, Joy, Distress (Sadness), Hope, Fear, Disappointment, and Relief. I only considered these six emotions to avoid overwhelming the participant with a large number of options for each question. I did not include Satisfaction and FearsConfirmed since, in this example story, they were always triggered respectively when Joy and Distress were triggered.

In this experiment, I used the Tom's Tale story. I first provided a description of the story domain as follows.

"Tom needs to buy some **medicine**. The **merchant** sells medicine in **town** in exchange for **a coin**. Tom has two coins, but he thinks he can make the medicine himself if he finds some **herbs** in the **forest**. At each moment, Tom may feel one of the following emotions: Relief, Hope, Fear, Joy, Sadness, and Disappointment."

I then presented the story one action at a time (Table 5.1). Each action was a translation of the corresponding domain action using simple natural language templates. After specific sets of actions, I asked what the participant thinks Tom may feel at that moment (each set of actions is numbered in Table 5.1), and participants could choose from one of the six emotions. Figure 5.1 presents an example of the experiment web-page. The emotion determined by the proposed model at each step is presented in the first column of Table 5.1.

Experiment 1 Results

For Experiment 1, among 70 total participants, only 2 participants chose not to answer all questions and their responses were removed. There were a total of 7 questions that presented 6 emotions to the participant to choose from. Using Krippendorff's α [Krippendorff, 2012], the inter-rater reliability was $\simeq 0.4$[1]. I then used the binomial

[1]There are some Amazon's Mechanical Turk workers, who may be choosing options randomly as quick as possible to earn a larger sum of compensation in a shorter amount of time. One reason that the inter-rater reliability is low is that, in this experiment, I did not use any techniques to filter out those participants.

Table 5.1: The Steps and Corresponding Emotions in Experiment 1

Hope	1. Tom forms a plan to go to the forest, collect herbs, and make the medicine without spending any of his coins.
Fear	2. Tom thinks it's possible that the bandit will find him. in the forest and rob him of his coins.
Sadness	3. Tom goes to the town. Tom buys a sword from the merchant. Now, Tom only has one coin.
Relief	4. With the sword, Tom thinks the bandit won't try to steal his coins anymore.
Disappointment	5. Tom goes to the forest. Tom looks for herbs but he doesn't find any. Tom realizes he can't make the medicine himself.
Sadness	6. Tom goes to the town. Tom buys the medicine from the merchant. Now, Tom doesn't have any coins anymore.
Joy	7. Nonetheless, Tom needed medicine and now he has it.

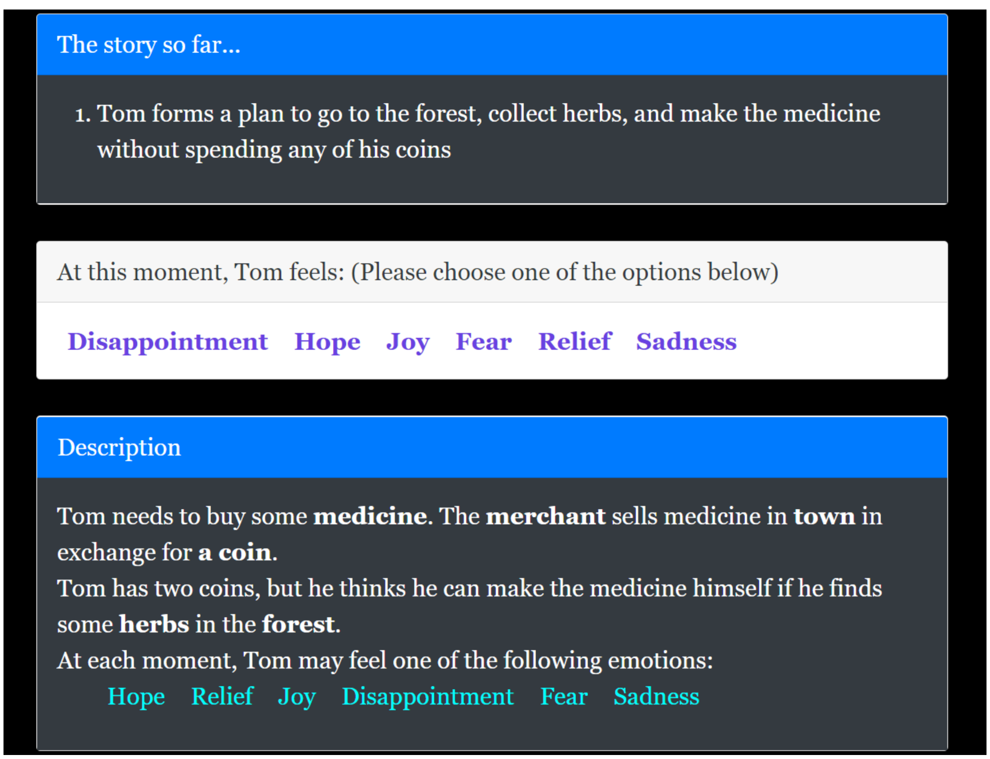

Figure 5.1: An Example of the Experiment 1 Web Page

exact test [Howell, 2012] to determine the correct answer to each question. If for a question, the binomial exact test's p-value (p) is smaller than 0.05, I say that the participants significantly agree on an answer and consider that as the correct answer. For 5 questions, the participants agreed on exactly one option ($p < 0.05$), and for 2 questions, the participants agreed on two options ($p < 0.05$—for both options). For those two questions, participants agreed that Tom feels Relief and Sadness when he spends a coin to buy a sword (sad for losing a coin and relieved for having a sword), and Tom feels Joy and Relief when he makes it home with the medicine.

To calculate the accuracy of my model, the correct answer to each question was then compared to how my model answers that question (as presented in Table 5.1. The accuracy of my model was 100% for the 6 considered emotion and the considered short story.

5.2.2 Experiment 2: Believability and Empathy in an Interactive Story

To show that the characters generated by my model are more believable, I generated a short interactive story in which the participant played the role of the main character. The rules of the story are similar to Tom's Tale and the player's goal is to have medicine. The description presented to each participant at the beginning of the experiment is as follows.

- You need to buy some **medicine**. The **merchant** sells medicine in town in exchange for **a coin** and some **herbs**.
- Fortunately, you have **two coins** and there are some herbs in the **forest**. However, there is a **bandit** in the forest that **may** steal your coins if he finds you!
- If the bandit notices someone who has a **sword**, he will not show himself or try to rob them.
- The merchant has a sword to sell for one coin and he also will buy it back for one coin.

- There are two more villagers in town, **Tom** and **William**, and they both want to buy some bread from the merchant.
- The story is finished when you have **medicine** and go back to **the cottage**.
- **If** you choose to help either Tom or William, remember that you **cannot help them both**.

The differences between this interactive story and Tom's Tale are as follows.

- There are herbs in the forest and the player has to collect them first, give them to the merchant to make the medicine, and then buy the medicine for one coin.
- The player has the option to buy the sword for one coin and subsequently, sell it for one coin. It is possible for the player to buy the sword, go to the forest, come back to town, buy the medicine, sell the sword, and have one coin that they could give to an NPC.
- I mention the forest bandit to the player, and the player has the option to first go to town and buy a sword. However, the bandit will never rob the player regardless of the sword.

The story also included two NPCs (John and William) with only one expressing emotions through text and facial expression. The participant can view both characters' portraits and thoughts, which may change after certain player actions. At first, the NPCs state that they want bread, they have an axe, they plan to collect and sell lumber to buy bread, and that the bandit may rob them in the forest. If the player chooses to give them a coin (Choice 1), they will now say that they have a coin and that they can buy bread (the emotional character expresses their joy and satisfaction). If the player chooses to buy a sword and give them the sword (Choice 2), they state that the bandit cannot rob them anymore (the emotional character expresses relief). After the player comes back from the forest, if the player had not given them anything, both NPCs state that the bandit stole their axe and they can no longer collect lumber and buy bread. The player will again have the choice of giving them a coin at this point (Choice 3).

Figure 5.2 presents an example of these two characters. At different steps, the emotional character can express Happy, Sad, or Scared facial expressions (Figure 5.3), and express their thoughts using emotion keywords, e.g. hope, fear, and so on. For different participants, the emotional character is randomly chosen to be John or William, or to be shown on the left or the right. The player has several opportunities to help either character or neither of them, e.g. they could give them a sword or a coin. I hypothesized that the expressions of the emotional character would cause the player to feel empathy and thus, help that character.

The player's goal is to buy the medicine and go back to the cottage. After satisfying this goal, I asked them a series of questions about the NPCs, for instance, whether they found each character to be not at all believable, somewhat believable, or very believable.

Experiment 2 Results

For Experiment 2, among 70 participants, 15 did not finish the experiment and their incomplete data was discarded. Using the binomial exact test and Bonferroni correction for testing multiple hypotheses [Holm, 1979], the following results were obtained for the rest of the participants.

- The players chose to buy a sword before going to the forest (34 out of 55—$p < 0.03$). This supports my hypothesis that characters may take actions that make them feel Relief even at the cost of their utility.

- The players chose to help the emotional character[2] (27 out of 55 —$p < 0.01$) by giving them one of their coins. This supports my model that characters may

[2]They had the option to help either character or help neither. Success is defined as choosing to help the emotional character out of the 3 total options they had.

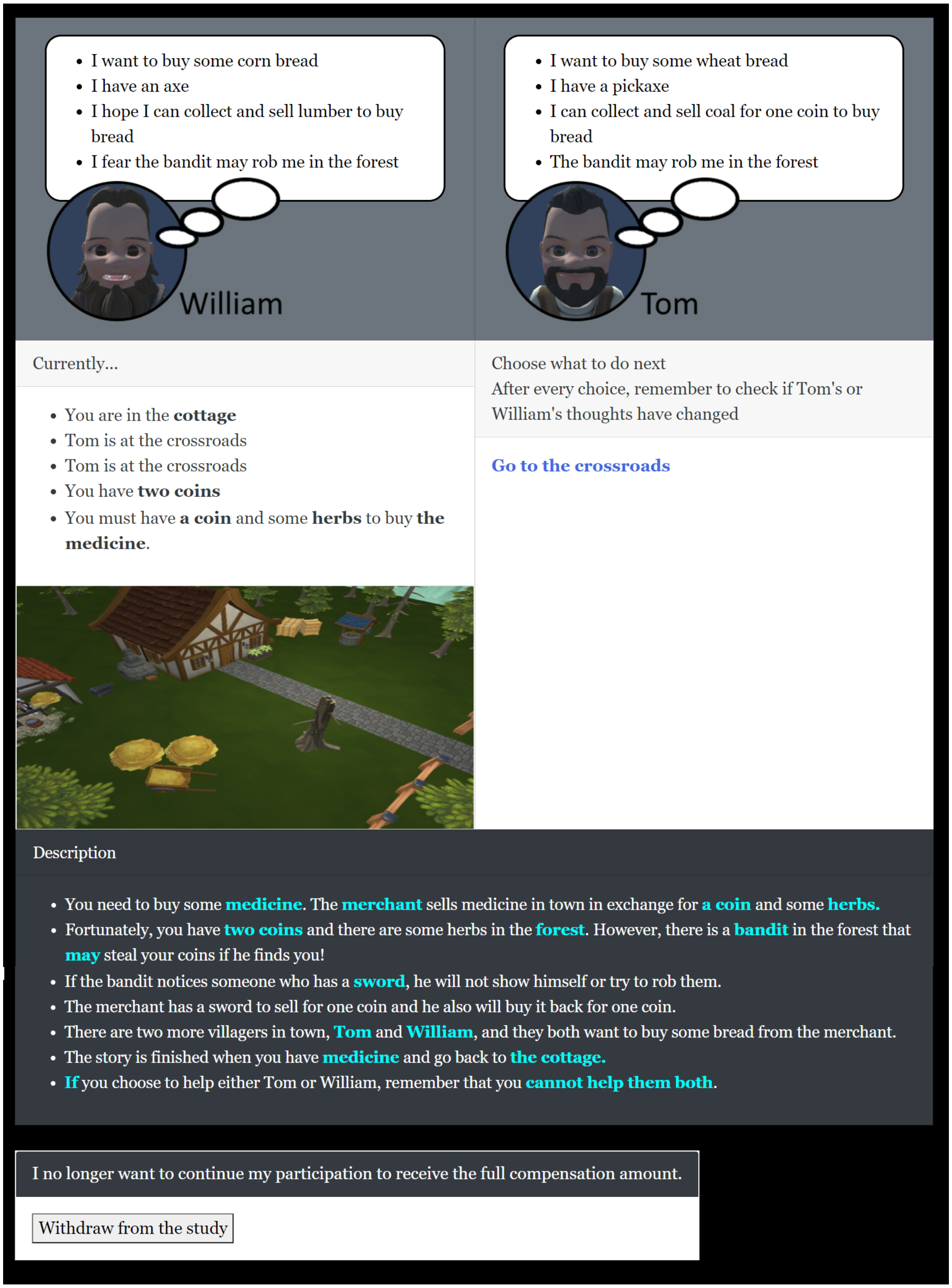

Figure 5.2: An Example of the Interface in Experiment 2

Figure 5.3: Character Expressions in Experiment 2

take actions that make them feel HappyFor even at the cost of their utility. The players also stated that they would have helped both characters if they could (45 out of 55—$p < 0.01$). This shows that characters generated by my model make players feel empathy towards them and significantly more so than the character without emotions. Moreover, these results also supports that characters may take actions that make them feel HappyFor even at the cost of their utility.

- The players agreed that the emotions and reactions of the emotional character were somewhat to very believable (51 out of 55—$p < 0.01$) and more so than the character that expressed no emotions (35 out of 55—$p < 0.03$) [3]. These results support my hypothesis that my model of emotion can improve character believability compared to narrative planners that do not reason about emotions.

5.3 Personality

For the stories generated by my model of personality, I claim that:

- Human readers can perceive that a character's behavior in a story is demonstrating certain personality traits, and

[3]The latter refers to when players chose very believable for the emotional character and somewhat believable or not at all believable for the other character, or chose somewhat believable for the emotional character and not at all believable for the other.

> In a land far away, Tom is very sick with the flu. The nearby town has an alchemist, who has a recipe for healing potions. She makes a bottle from a batch of medicinal herbs and sells them for a silver coin. But she is all out of healing potions and medicinal herbs! Luckily, all Tom has is only a silver coin and there is also only a single batch of herbs in the cottage. The alchemist is sound asleep, feeling safe because of the town guard patrolling the streets, arresting anyone who dares to steal.

Figure 5.4: The Description of the Story in Experiment 3

- They can also recognize other stories in which the character is exhibiting the same personality traits.

I will test my above hypotheses in Experiment 3.

5.3.1 Experiment 3: Character Personality Perception and Recognition

I conducted Experiment 3 to evaluate my model of personality. In the first stage, for each participant, Tom's personality was chosen randomly to reflect high or low scores of a specific factor. More specifically, it was selected from the 10 possible options: one where Tom has high Openness, one where he has low Openness, one where he is highly Conscientious, etc. For each option, Tom has either a high score (1) or low score (0) for one factor and average values (0.5) for the other four.

Subjects first read a brief description of the domain (Figure 5.4). I then prompted the participants that Tom is considering four different plans to achieve his goals, and showed four different stories that could unfold based on those plans. The plans were different from the stories that unfolded as a result of executing those plans. For instance, Tom could get arrested at the end of a story, but he wouldn't plan for that to happen. After reading these four possible stories, I narrated which one actually happened, which demonstrates Tom's personality through his choice.

Subjects then responded to statements about Tom's personality using a 5 point Likert scale. The following presents the statements and which FFM inventory they were adapted from. I only asked the statements that corresponded to the selected factor out of the 10 possible options.

1. Openness
    - Finds creative solutions to problems [DeYoung et al., 2007].
    - Tends to analyze possible outcomes of his plans [Hofstee et al., 1992].
    - His ideas are ordinary and hardly unique [Hofstee et al., 1992].
    - Has difficulty coming up with excellent plans (that rarely fail) [Goldberg, 1992].
2. Conscientiousness
    - Gets things done quickly [DeYoung et al., 2007].
    - Wastes his time [DeYoung et al., 2007].
    - Makes plans and sticks to them [DeYoung et al., 2007].
    - Does just enough work to get by and rather relies on others [Costa and MacCrae, 1992].
    - He wants everything to be just right so he prefers to do things himself [DeYoung et al., 2007].
3. Extroversion
    - Keeps others at a distance [DeYoung et al., 2007].
    - Finds it difficult to approach others [DeYoung et al., 2007].
    - Feels comfortable around people [Costa and MacCrae, 1992].
    - Takes charge [DeYoung et al., 2007]
    - Has an assertive personality [DeYoung et al., 2007].
4. Agreeableness
    - Takes advantage of others [DeYoung et al., 2007].

- Avoids conflict [DeYoung et al., 2007].
- Is out for his own personal gain [DeYoung et al., 2007].
- Likes to do things for others [DeYoung et al., 2007].
- Can't be bothered with other's needs [DeYoung et al., 2007].

5. Neuroticism
    - Is filled with doubts about things [DeYoung et al., 2007].
    - Is NOT easily discouraged [DeYoung et al., 2007].
    - Rarely changes his mood [DeYoung et al., 2007].
    - Does not know why he does some of the things he does [Hofstee et al., 1992].
    - Does things that he later regrets [Hofstee et al., 1992].

Since I only use existing planning features to simulate a simplified version of the Big Five, I selected the markers that best captured my simulated traits. For instance, I excluded markers such as "Feel comfortable with myself", "Rarely feel depressed", "Keep things tidy", "Laugh a lot", "Avoid philosophical discussions", or "Get deeply immersed in music". Such markers could not be conveyed through external actions or their inclusion came at the cost of increasing author burden.

In the second stage, subjects were shown four new stories and asked which one they thought would happen for Tom. These four stories were all different from the previous four. They included one that reflected a plan with high preference value for Tom, one with low preference value, the first story generated by the Glaive narrative planner (which does not reason about personality) [Ware and Young, 2014], and a randomly chosen story that was not a duplicate. Appendix 2 presents a complete run of Experiment 3.

5.3.2 Experiment 3 Results

I generated 26 stories and collected results for 228 subjects. At least 40 subjects evaluated each factor (at least 20 for the high Openness, at at least 20 for low Openness, etc.). All stories were the same for the participants viewing the same condition except for the random story in the second stage.

I claim that human readers can perceive that a character's behavior in a story is demonstrating certain personality traits. To support this claim, in the first stage of the experiment, I defined success as subjects reporting agree or strongly agree if the statement is positively correlated (or disagree or strongly disagree if it was negatively correlated) with Tom's score for the corresponding factor. I used a binomial exact test to detect if I observed more successes than I should expect to see by chance. The p-value and effect size (expressed as relative risk) for each factor are given in Table 5.2. I rejected the null hypothesis at the $p < 0.05$ level for 3 factors, and at the $p < 0.1$ level for the other two.

I also claim that human readers can recognize other stories in which the character is exhibiting the same personality traits. To support this claim, I show that in the second stage of the experiment, subjects chose a story for Tom that best expressed his personality according to my model. I defined success as a participant choosing the best matching story out of the four presented. The p-value and effect size for a binomial exact test for each factor are given in Table 5.2. I rejected the null hypothesis at the $p < 0.05$ level for all factors.

Though many tests were significant, effect sizes were relatively low. Again, I attribute some of this to the high noise collected from Mechanical Turk data.

5.4 Emotion and Personality Combined

I claim that incorporating my models of personality and emotions into narrative planning results in generating more believable behaviors. I conducted Experiment 4 to support this claim. I used the Tom's Tale domain in Experiment 4. However,

Table 5.2: Experiment 3 Results

	Hypothesis 1		Hypothesis 2	
	p-value	Effect Size	p-value	Effect Size
O	0.072	1.160	0.026	1.60
C	**0.016**	1.160	0.001	1.73
E	**0.024**	1.167	0.014	1.61
A	**0.048**	1.167	$\prec$0.001	2.80
N	0.063	1.128	0.002	2.04

to evaluate personality, I needed to create two different situations (here referred to as acts), so that Tom's decisions in those two acts could be used to portray his personality. I extended the story to require Tom to go home after acquiring the medicine. He could go through the forest, which is the shorter but the riskier path. He also could pay the town guard a coin as a toll so that he would lower the bridge for Tom to go home.

5.4.1 Experiment 4: Evaluating the Space of All Stories

Based on the inclusion of personality or emotion in narrative planning, the space of all possible stories divides into four different sets. Figure 5.5 presents a Venn diagram for these four sets. In Experiment 4, I generated all the stories of the Tom's Tale domain for all four sets of stories:

1. PN: Stories that only model personality. For a story to model personality, Tom's actions must be consistent over the two acts (first acquiring the medicine, and then going home) based on my personality model. More specifically, if there is at least one factor where Tom's actions reflect a high score for that factor in one act and a low score in the other that story is considered to lack a model of personality.

2. NE: Stories that only model emotion. For this set of stories, I added emotion keywords in the natural language templates that described the story. For instance, instead of "Tom plans to buy the medicine", I say "Tom hopes to buy

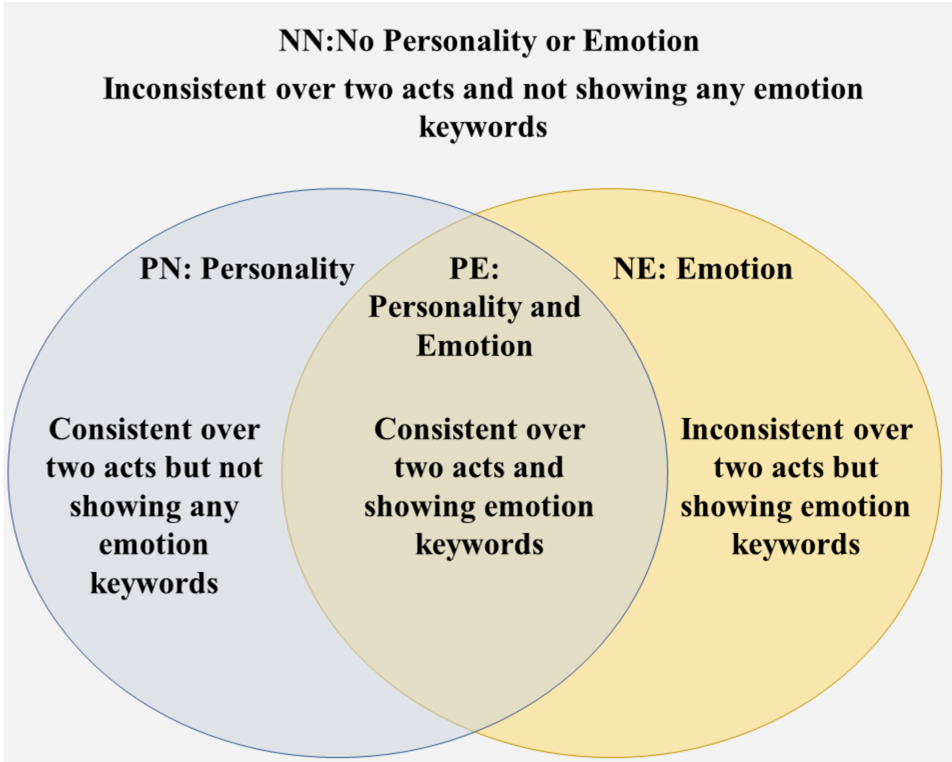

Figure 5.5: Four Different Sets of Possible Stories with Emotion or Personality

the medicine". I also added extra sentences wherever necessary, e.g. to convey that Tom feels disappointment.

3. PE: Stories that model both emotion and personality. In these stories, I both use emotional descriptions and ensure Tom's actions are consistent over the two acts.

4. NN: Stories that model neither personality nor emotion.

There is a noticeable difference between stories with emotions and stories with personality. Although emotions affect character behaviors, e.g. taking actions to feel relief, they can also be used as external expressions, for instance, in the context of my experiment, as emotion keywords. This explicitly prompts the participant about the difference between stories with and without emotions. However, I only express personality externally through behavior, actions in narrative planning, and

Table 5.3: Experiment 4 Questionnaire Presented After Each Story

	Questions
1	Tom feels like a realistic lifelike character.
2	Tom has a unique personality based on his actions.
3	The story provides good descriptions of Tom's internal thoughts.
4	Tom's actions in act 1 were inconsistent to his actions in act 2.

Table 5.4: Experiment 4 Questionnaire Presented After Both Stories

	Questions
1	Choose the story that Tom's actions were consistent in both acts.
2	Choose the story that makes Tom feel more human like.
3	Choose the story that you found more realistic.
4	Choose the story that you personally prefer to read.

not visually or in the text. Participants would only implicitly perceive a difference between the stories with and without personality, and they would need to do so over the two acts.

Experiment Design

After showing a description of the domain (similar to Section 3.1.1), I randomly chose two stories from two different story sets. Participants first viewed the first act of each story followed by its second act and then a series of questions about that story (Table 5.3). After participants read both stories, I then asked another set of questions that asked them to choose between the two stories (Table 5.4).

Table 5.3 presents the 5-point Likert[4] questions that were presented to the player after reading each story. Table 5.4 presents the comparison questions (choosing between story 1 and story 2) that were presented to the player after reading both stories.

Experiment 4 Results

The first question for analysis was whether participants responded as predicted to the dependent variables, existence of personality or existence of emotion. To test this, participants responded to prompts related to these variables with a 5-point

[4]Possible answers are Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree.

Likert questions from strongly disagree to strongly agree.

Likert-type ratings are of ordinal but not interval measurement—that is, the difference between disagree and neutral is not necessarily the same as the difference between agree and strongly agree. To better assess the ordinal differences between questions, I used a cumulative link model (CLM). Sometimes known as ordinal regression, CLMs are a special case of logistic regression which assume that values are ordinal, with the added benefit of testing for interactions between multiple variables. The interaction between variables indicates whether their effect is additive or not. We generally hope to see no interaction between independent variables.

For each question, I additionally conducted pairwise Wilcoxon sum-rank tests to compare responses to each combination of conditions, using the Benjamini-Hochberg method of false discovery rate correction [Benjamini and Hochberg, 1995].

- Participants who read stories with emotion gave higher Likert ratings to the prompt "The story provides good descriptions of Tom's internal thoughts" ($z = 5.370$, $p < 0.001$). This was not true of stories with personality ($z = .447$, $p = 0.655$), and there was no interaction effect ($z = -1.359$, $p = .174$). Pairwise Wilcoxon tests indicated that all conditions with emotion had significantly higher ratings than conditions without emotion ($p < 0.001$), with no significant differences with or without personality.

- Similarly, participants who read stories with personality gave lower ratings to the prompt "Tom's actions in act 1 were inconsistent to his actions in act 2." ($z = 5.834$, $p < 0.001$), with no effect of emotion ($z = 1.239$, $p = 0.215$) or interaction ($z = -1.188$, $p = .235$). Pairwise Wilcoxon tests indicated that all conditions with personality had significantly higher ratings than conditions without personality ($p < 0.001$), with no significant differences with or without emotion.

- Two additional prompts ("Tom feels like a realistic lifelike character" and "Tom has a unique personality based on his actions") had no significant differences by condition (all conditions and interactions $|z| < 1.185$, $p > 0.234$).

Table 5.5 compares the effect of dependent variables, personality, emotion, and both against having neither features. The effects for having both personality and emotion were not significant. This means that there is no effect where having both is significantly different than expected from the added effect of either independently.

Table 5.6 further supports the significance of difference between different of pairs of conditions (each value corresponds to the significance of difference between the condition in the corresponding row and the corresponding column). Since these tests compare all conditions, the results also show the significance of difference between having both personality and emotion over having either independently.

- For "The story provides good descriptions of Tom's internal thoughts", having emotion and personality is significantly preferred over having only personality or having neither.

- For "Tom's actions in act 1 were inconsistent to his actions in act 2", having emotion and personality is significantly preferred over having only emotion or having neither.

In sum, these results confirm that the personality and emotion conditions successfully influenced participant's interpretation of the character's consistency of behavior and emotional states, respectively. Since there were no interactions, personality and emotion contribute to preference additively and (seemingly) independently.

The second question for analysis was whether users prefer stories that have either personality, emotion, or both, versus stories without those features. To conduct this analysis, participants were simply asked which story they preferred on a variety of dimensions. As participants saw only two stories of the four potential conditions, and

Table 5.5: CLM Results (p-values) in Experiment 4

Question	Emotion	Personality	Both
Tom feels like a realistic lifelike character	0.252	0.422	0.532
Tom has a unique personality based on his actions	0.590	0.468	0.236
The story provides good descriptions of Tom's internal thoughts	0.655	**<0.001**	0.174
Tom's actions in act 1 were inconsistent to his actions in act 2	**<0.001**	0.215	0.235

Table 5.6: Wilcoxon Sum-Rank Tests (p-values) in Experiment 4

(a) Tom feels like a realistic lifelike character

	NE	NN	PE
NN	0.85	-	-
PE	0.85	0.85	-
PN	0.85	0.85	0.96

(b) Tom has a unique personality based on his actions

	NE	NN	PE
NN	0.50	-	-
PE	0.11	0.39	-
PN	0.39	0.63	0.50

(c) The story provides good descriptions of Tom's internal thoughts

	NE	NN	PE
NN	**<0.001**	-	-
PE	0.221	**<0.001**	-
PN	**<0.001**	0.766	**<0.001**

(d) Tom's actions in act 1 were inconsistent to his actions in act 2

	NE	NN	PE
NN	0.38	-	-
PE	**<0.001**	**<0.001**	-
PN	**<0.001**	**<0.001**	0.83

those stories were in different orders, I used a logistic regression to predict preference or dislike of a story based on condition (Table 5.7).

For each question, I calculated odds ratios of each condition relative to the no-personality, no-emotion condition (NN) (Table 5.8). Odds ratio can be thought of as the odds that an outcome will occur more in the comparison group than in the reference group. For instance, comparing NN to PE with an odds ratio of 1.50 means that the preferred story is 1.5 times more likely to be the PE story than the NN story.

- Participants significantly preferred stories with personality features in response to the prompt "Choose the story that Tom's actions were consistent in both acts" ($p < 0.001$), with the highest Odd ratio for personality and no effect of emotion ($p = 0.229$).

- Both personality and emotion contributed to preference in response to the prompt "Choose the story that makes Tom feel more human like" ($p < 0.001$)—with a higher Odds ratio for emotion—and "Choose the story that you found more realistic." ($p = 0.0117$).

Tables 5.7 and 5.8 summarize the results. In sum, these results confirm that participants preferred stories with personality and emotion and found Tom more realistic and human like in those stories. Although, having both was not significantly different than the added effect of either independently, results show the highest Odds ratio for having both personality and emotion.

5.5 Conflict Generation

In this section, I will investigate the model's ability to intelligently generate conflicts. In order to do so, I implemented two experiences manager in entertainment and training contexts. The first experience manager was implemented in conjunction with my open-source game engine, Camelot [Samuel et al.; Shirvani and Ware, 2018; 2020], and the second was developed to work with a police-use-of-force virtual reality

Table 5.7: Linear Regression Results (p-value) in Experiment 4

	Personality	Emotion	Both
Question	p	p	p
Choose the story that Tom's actions were consistent in both acts.	**<0.001**	0.229	0.447
Choose the story that makes Tom feel more human like.	**0.0117**	**<0.001**	0.0942
Choose the story that you found more realistic.	**0.0253**	**0.0252**	0.861
Choose the story that you personally prefer to read.	0.288	**0.005**	0.957

Table 5.8: Linear Regression Results (Odd's Ratio) in Experiment 4

	Personality		Emotion		Both	
Question	/174	OR	/191	Odds Ratio	/200	OR
Choose the story that Tom's actions were consistent in both acts.	111	3.716	73	1.304777	129	3.8320
Choose the story that makes Tom feel more human like.	78	1.760	114	3.207792	122	3.388
Choose the story that you found more realistic.	87	1.630	95	1.613782	121	2.497
Choose the story that you personally prefer to read.	78	1.261	103	1.816825	120	2.328

training simulation.

5.5.1 Experiment 5

As an entertainment application, I generated the interactive narrative using the following domain:

Tom is sick and he needs medicine. He also has two coins. In order to acquire the medicine, he needs to go to the forest and collect medicinal herbs. The herbs can be brewed in the alchemist's shop. The merchant brews the medicine and sells it for two coins. Tom can also brew the medicine himself in the shop but the merchant would not give permission to do so. There is also a bandit living in the cottage near the forest. The bandit sometimes enters the forest and robs anyone in his path. The merchant also sells a sword for one coin, and the bandit would not try to rob one who is armed.

Experiment Design

The experience manager also receives the following input functions in addition to the story domain:

- The author's utility function: a single complete story ends in increasing this utility function. The author's utility function in Experiment 5 increases if the player acquires the medicine or dies. The author can specify different values for different outcomes of the story and then use those values for explicit encouragement. For instance, if the author's utility reaches 2, the author may choose to express affirmation through "good job!" or "well done!" messages to the player.

$$U(s) = \left\langle \begin{array}{c} \neg alive(Player) \rightarrow 1 \\ at(Medicine) = Player \rightarrow 2 \end{array} \right\rangle$$

- The player utility function: this utility function assumes what the player's goals are in the narrative. The player utility function in Experiment 5 is as follows.

$$
U(Player, s) = \left\langle \begin{array}{c} \neg alive(Player) \rightarrow -1 \\ at(Coin1) = Player \wedge at(Medicine) = Player \rightarrow 5 \\ at(Medicine) = Player \rightarrow 4 \\ at(Coin1) = Player \wedge at(Coin2) = Player) \rightarrow 2 \\ at(Coin1) = Player \rightarrow 1 \\ at(Coin2) = Player \rightarrow 1 \end{array} \right\rangle
$$

- The author's intended behavior function: this function checks whether a plan exhibits the behavior that is intended by the author. In Experiment 5, I assume that the author intends to encourage the player to demonstrate certain personality traits. The author's intended behavior function is determined based on the preference value calculated in 4.3.3.

A player agent was simulated to play the role of the player. Two different player agents were simulated in different iterations of the experiment with the following criteria: (1) an agent with the same utility function as the player utility function and (2) an agent that acted randomly. To record the number of conflicts, the random agent also has the same utility function as the player utility function, but when acting, chooses randomly between all possible actions (even those not explained).

I also used two different author intended behavior functions where the author aimed to encourage the player to be (1) conscientious, and (2) agreeable.

Conflicts

Some examples of conflicts in this story domain are as follows.

First possible conflict:

$$
\begin{array}{c} \langle Go(Player, City, Camp), \\ Go(Bandit, Cottage, Camp)\rangle \end{array}
$$

By observing the bandit, the player anticipates a conflict. The conflict can be resolved as follows:

$$\langle Collect(Player, Herbs),$$
$$Rob(Bandit, Player)\rangle$$

or

$$\langle Go(Player, Camp, City),$$
$$Go(Player, City, Shop),$$
$$Buy(Player, Merchant, Sword)\rangle$$

The player expects to feel Relief after executing the latter plan. The experience manager considers this plan before executing $Go(Bandit, Cottage, Camp)$. This plan meets the constraints for Agreeableness and Conscientiousness, and thus, the experience manager allows the bandit to enter the camp.

Second possible conflict:

$$\langle Fire\_Up(Player, Cauldron),$$
$$Draw(Merchant, Sword)\rangle$$

To brew the medicine, one must first fire up the cauldron. If the player attempts to do so, the merchant becomes angry and draws her sword. By observing this action, the player anticipates a conflict. This conflict can be resolved as follows:

$$\langle Brew(Player, Medicine),$$
$$Attack(Merchant, Player)\rangle$$

or (the second plan:)

$$\langle Give(Player, Merchant, Herbs),$$
$$Brew(Merchant, Medicine),$$
$$Buy(Player, Merchant, Medicine)\rangle$$

or (the third plan:)

$$\langle Attack(Player, Merchant)\rangle$$

The player expects to feel Relief by executing the second or third plans. The second plan is not possible if the player does not have enough coins to buy the medicine. The third plan is not possible if the player does not have a sword (the merchant refuses to sell him a sword when she is angry).

Before executing $Draw(Merchant, Sword)$, the experience manager considers the second and third plans above based on the intended behavior function:

- Only the third plan meets the Conscientiousness constraints (the second plan has two actions that rely on other characters). The merchant would not draw her sword if the player does not have a sword.

- Only the second plan meets the Agreeableness constraints (the third plan reduces the merchant's utility). The merchant would not draw her sword if the player does not have enough coins to buy the medicine.

5.5.2 Experiment 5 Results

I generated all stories with maximum length of 12 steps for the story domain described earlier in the section. There were a total of 43,291 stories generated. I then categorized this set of stories based on the following criteria:

- Whether the player agent acted randomly or based on the player utility function (Random vs. Utility). For Utility, the player agent only chose actions that either made them feel Joy or Relief. For Random, the player agent could choose actions with no limitations, i.e. even actions that were not explained.

- Whether the author's intended behavior was Agreeableness or Conscientiousness (IBA vs. IBC). For IBA, the author encourages any behavior that did not harm NPCs (though the Attack action). For IBC, the author encourages plans that are efficient and self-reliant, e.g. the following plan to resolve a conflict with the merchant does not meet the constraints for Conscientiousness:

$$\langle Give(Player, Merchant, Herbs),$$
$$Brew(Merchant, Medicine),$$
$$Buy(Player, Merchant, Medicine)\rangle$$

- I defined three categories of stories based on whether they accounted for conflicts that can or cannot be resolved using the intended behavior:
  1. Intelligent: The set of stories in which all stories did not present a conflict to the player if they could not resolve it using the intended behavior.
  2. Opposite: The set of stories in which all stories did present a conflict to the player that they could not resolve using the intended behavior[5].
  3. Total: The total set of stories for that type of agent (Random or Utility), i.e. $Intelligent \cup Opposite$.

For each categories of stories, I measured the following information:

- The number of stories (Stories): the number of stories that match the criteria of that category.

- The number of times the player agent anticipated a conflict based on the player utility function (Conflicts): There were two instances that the story presented a conflict to the player. The bandit enters the forest when the player is in the forest, and the merchant draws their sword and approaches the player. Each story may include 0, 1, or 2 conflicts.

- The number of times the conflict could not be resolved using the author's intended behavior (NRes): If any of the above conflicts were presented and the player did not have the option to resolve them using the intended behavior. The goal is to reduce this number as much as possible.

[5] I must note that I do not intentionally generate this type of story. The Opposite set refers to the stories among the set of all generated stories that match the stated criterion.

- The number of times the agent felt FearsConfirmed after the resolution of a conflict (FearsConfirmed): If the bandit robs the player agent or the merchant kills them.

- The number of times the agent felt Relief after the resolution of a conflict (Relief): If the player observes the bandit in the forest, they could go and buy a sword, and if they observe the merchant is threatening them, they could either attack them with the sword or give them the herbs to let them make the medicine. These two options are not always available to the player at the same time.

- The percentage of conflicts, on average, that the player could not resolve using the intended behavior (AVGRes): Among all instances of the conflicts presented to the player, what percentage of those conflicts could not have been resolved by agreeable or conscientious behavior? Similar to NRes, we aim to reduce this number as much as possible.

- The percentage of conflicts, on average, that the player resolved using the intended behavior (Intended Resolutions): If the player was presented with a conflict, on average, what percentage of times they resolved that conflict using agreeable or conscientious behavior? I hypothesized to see a higher value for Intended Resolutions as a result of implicit encouragement.

Tables 5.9 and 5.10 present the results. Among 43,291 stories, there were 100 stories in which all player agent actions were explained. When using intelligent conflict generation, a smaller number of conflicts are presented to the player. This is due to the fact that for all conflicts, the player cannot always resolve them using intended behavior.

In the context of this experiment, I define success as a smaller NRes, a smaller AVGRes, or a larger Intended Resolutions. Other measures, i.e. Conflicts, FearsCon-

Table 5.9: Experiment 5 Results

Categories			Stories	Conflicts	NRes	FearsConfirmed	Relief
IBA	Random	Intelligent	32,790	0.410	0	0.036	0295
		Opposite	10,400	1.435	1	0.401	0.423
	Utility	Intelligent	48	1.229	0	0.250	0.500
		Opposite	52	1.884	1	0.557	0.961
IBC	Random	Intelligent	37,064	0.523	0	0.524	0.352
		Opposite	6,126	1.464	1	0.557	0.169
	Utility	Intelligent	72	1.458	0	0.291	0.916
		Opposite	28	1.857	1	0.714	0.285

firmed, and Relief, provide some ground to make more meaningful comparisons, but do not directly indicate an improvement.

Without intelligent conflict generation, there are more conflicts that cannot be resolved using the intended behavior. When the intended behavior function was Agreeableness, the player could not resolve a conflict using the intended behavior in 10,452 stories (34.87% of the time). When the intended behavior function was Conscientiousness, the player could not resolve a conflict using the intended behavior in 6,154 stories (19.7% of the time).

For all conflicts in the stories, the player could either (1) ignore the conflict, (2) resolve the conflict using the intended behavior, or (3) resolve the conflict using any other type of behavior. Column AVGRes in Table 5.10 presents the percentage of the conflicts that were resolved by the player using the intended behavior. As shown, when using intelligent conflict generation, on average, the player agent was more likely to resolve a conflict using the intended behavior.

5.5.3 Experiment 6

In this experiment, I used the following domain to generate an interactive story for a police-use-of-force training simulation, named Traffic Stop. The Traffic Stop virtual reality training simulation is an ongoing project funded by National Science Foundation in partnership with the University of Kentucky Police Department. The following scenario is based on an actual de-escalation training role-play exercise used

Table 5.10: Experiment 5 Results (Continued)

Categories			AVGRes(%)	Intended Resolution(%)
IBA	Random	Intelligent	0	71.95
		Total	36.63	45.93
	Utility	Intelligent	0	40.67
		Total	33.12	38.21
IBC	Random	Intelligent	0	65.84
		Total	21.57	47.11
	Utility	Intelligent	0	62.85
		Total	17.83	42.03

by UKPD, which is designed based on real events.

A police officer stops a speeding car. The police officer contacts dispatch to check the plates. They realize that the owner of the plates has filed a restraining order that may or may not be against the passenger. The police officer can then ask the passenger for their driver's license. After checking the driver's license, if the passenger is indeed the person stated in the restraining order, the police officer asks the passenger to leave the car and proceeds to handcuff them. Otherwise, the police officer writes a citation and lets the driver go.

The passenger has a gun that the police officer is not aware of. If the passenger draws their gun, the police officer realizes that they or the driver are in immediate danger and that they have no other option but to shoot the passenger. It is also possible that the passenger expresses their anger and frustration when the officer asks them to do something, i.e. hand over their driver's license or leave the car. If the officer senses the passenger's frustration, they may choose to explain the situation in order to calm them down and avoid potentially endangering the passenger.

Experiment Design

The experience manager also receives the following input functions:

- The author's utility function: a single complete story ends in increasing this utility function. The author's utility function in Experiment 6 increases if the player dies, the passenger dies, the passenger is arrested or the driver is given a citation.

$$U(s) = \left\langle \begin{array}{c} \neg alive(Player) \rightarrow 1 \\ \neg alive(Passenger) \rightarrow 2 \\ arrested(Passenger) \rightarrow 3 \\ cited(Driver) \rightarrow 3 \end{array} \right\rangle$$

- The player utility function: this utility function assumes what the player's goals are in the narrative. The player utility function in Experiment 6 is as follows. The player want to keep themselves and the driver alive, arrest the passenger if they are named in the restraining order, or otherwise, write a citation for the driver.

$$U(Player, s) = \left\langle \begin{array}{c} \neg alive(Player) \rightarrow -2 \\ \neg alive(Driver) \rightarrow -1 \\ restraining(Passenger) \wedge arrested(Passenger) \rightarrow 1 \\ \neg restraining(Passenger) \wedge cited(Driver) \rightarrow 1 \end{array} \right\rangle$$

- The author's intended behavior function: this function checks whether a plan exhibits the behavior that is intended by the author. In Experiment 6, I assume that the author intends to encourage the player to demonstrate certain personality traits. The author's intended behavior function is determined based on the preference value calculated in 4.3.3. In Experiment 6, the author intends to encourage Agreeableness.

Similar to Experiment 5, two different player agents were simulated in different iterations of the experiment with the following criteria: (1) an agent with the same utility function as the player utility function and (2) an agent that acted randomly. To record the number of conflicts, the random agent also has the same utility function as the player utility function, but when acting, chooses randomly between all possible actions (even those not explained).

Conflicts

Some examples of conflicts in this story domain are as follows:

First possible conflict:

$$\langle Draw(Passenger, Gun)\rangle$$

When the passenger draws their gun, the player anticipates a conflict. The conflict can be resolved as follows:

$$\langle Shoot(Passenger, Driver)\rangle$$

or

$$\langle Shoot(Passenger, Player)\rangle$$

or

$$\langle Draw(Player, Gun),$$
$$Shoot(Player, Passenger)\rangle$$

The player expects to feel Relief after executing the last plan. The experience manager considers this plan before executing $Draw(Passenger, Gun)$. As this plan does not meet the constraints for Agreeableness, the experience manager would not allow the passenger to draw their gun.

Second possible conflict:

$$\langle AskFor(Player, Passenger, Drivers\_License),$$
$$Angry(Passenger)\rangle$$

Third possible conflict:

$$\langle AskFor(Player, Passenger, Leave\_Car),$$
$$Angry(Passenger)\rangle$$

If the player asks the passenger to do something, e.g. hand over their driver's license, they may express their anger and frustration, e.g. because they were not driving at the time. If the passenger becomes angry, it is possible that they would harm the driver. By observing this action, the player anticipates a conflict. This conflict can be resolved as follows:

(the first plan:)

$$\langle Harm(Passenger, Driver)\rangle$$

or (the second plan:)

$$\langle Explain(Player, Passenger)\rangle$$

or (the third plan:)

$$\langle Draw(Player, Gun),$$
$$Shoot(Player, Passenger)\rangle$$

The player expects to feel Relief by executing the second or third plans. The experience manager considers the second and third plans above before executing $Draw(Merchant, Sword)$. Only the second plan meets the requirements for Agreeableness.

5.5.4 Experiment 6 Results

I generated all stories with maximum length of 10 steps for the story domain described earlier in the section. There were a total of 400,535 stories generated. I then categorized this set of stories based on the following criteria. These criteria are the same as described in the previous section.

- Whether the player agent acted randomly or based on the player utility function (Random vs. Utility).

- Whether the story presents conflicts that the player can resolve using the intended behavior (Intelligent), or the player cannot resolve using the intended behavior (Opposite), or the player may or may not be able to resolve using the intended behavior (Total).

For each categories of stories, I measured the following information. These measures are the same as described in the previous section.

- The number of stories (Stories)
- The number of times the player agent anticipated a conflict based on the player utility function (Conflict): There were two instances that the story presented a conflict to the player: (1) the passenger expresses their anger, and (2) the passenger draws their gun. Each story may include 0, 1, or 2 conflicts.
- The number of times the conflict could not be resolved using the author's intended behavior (NRes): If the passenger draws their gun.
- The number of times the agent felt FearsConfirmed after the resolution of a conflict (FearsConfirmed): If the passenger harms the driver, shoots the driver, or shoots the player[6].
- The number of times the agent felt Relief after the resolution of a conflict (Relief): If the player shoots the passenger or explains the situation to them depending on the corresponding conflict.
- The percentage of conflicts, on average, that the player could not resolve a conflict using the intended behavior (AVGRes).
- The percentage of conflicts, on average, that the player resolved a conflict using the intended behavior (Intended Resolution).

[6]For the purposes of this experiment, I distinguish between harming and shooting the driver, since the player does not originally believe that the passenger has a gun.

Table 5.11: Experiment 6 Results

		Stories	Conflicts	NRes	FearsConfirmed	Relief
Random	Intelligent	178,711	0.923	0	0.251	0.785
	Opposite	209,046	1.821	1	0.573	0.907
Utility	Intelligent	2,876	0.976	0	0.714	0.945
	Opposite	9,901	1.913	1	0.981	0.965

Table 5.12: Experiment 6 Results (Continued)

		Stories	AVGRes(%)	Intended Resolution(%)
Random	Intelligent	178,711	0	71.51
	Total	387,757	38.30	38.71
Utility	Intelligent	2,876	0	63.19
	Total	12,777	45.51	31.58

Tables 5.11 and 5.12 present the results. Among 400,534 stories, there were 12,777 stories in which all player agent actions were explained. When using intelligent conflict generation, a smaller number of conflicts are presented to the player. This is due to the fact that for all conflicts, the player cannot always resolve them using intended behavior.

Without intelligent conflict generation, there is a higher number of conflicts that cannot be resolved using the intended behavior. There were 218,948 stories (Opposite) in which the player could not resolve a conflict using agreeable behavior. In fact, on average, 45.51% of the conflicts in all stories (Total) could not be resolved using agreeable behavior.

Column AVGRes in Table 5.12 presents the percentage of the conflicts that were resolved by the player using the intended behavior. As shown, when using intelligent conflict generation, on average, the player agent was more likely to resolve a conflict using the intended behavior.

5.5.5 Discussion

I considered all possible stories (with a length restriction) for two story domains. These stories included ones where the system chose to present or not present a conflict to the player. With intelligent conflict generation (Intelligent), the system chooses conflicts intelligently based on the author's intended experience for the player. The Intelligent experience manager avoids "bad" conflicts that cannot be resolved in the intended way, hence, reducing NRes to 0, and, overall, presenting a smaller number of conflicts.

These stories also includes ones where after the conflict was presented, the player chose to take action and feel Relief or continue with their previous plan. If the player chose to continue with their previous plan, the system non-deterministically chose to do nothing or resolve the conflict, making the player feel FearsConfirmed. For instance, in some stories, the bandit faces the player but does not rob them afterwards. It is possible to have the system always resolve the conflict, but in doing so, it would force the player to choose one of their options to resolve the conflict themselves.

Among the stories where the player felt Relief, their actions were either in line with or against the intended behavior. Using the Intelligent experience manager, all conflicts could always be resolved using the intended behavior. Therefore, on average, the player was more likely to demonstrate the intended behavior when resolving a conflict.

These results apply whether the player follows the utility function assumed by the author or chooses to act randomly. Both kinds of players have experiences that are more in line with the author's intentions—they were more likely to resolve conflicts using the intended behavior. In short, both kinds of players have more opportunities and are more likely to demonstrate the intended behavior thanks to choosing conflicts intelligently.

CHAPTER 6. CONCLUSIONS AND FUTURE WORK

Interactive narratives are prevalent in a wide variety of applications that involve human-computer interaction. These application range from educational and training simulations that intend to guide the player experience in pursuit of certain goals to entertainment contexts that may only need to be engaging and immersive for their users. Believable characters are an essential requirement for effective interactive narratives. They allow users to more willingly suspend their disbelief and have a more impactful experience.

Previous narrative systems, whether in strong story or strong autonomy, proposed and developed various models to improve character believability. Those models include intentionality, belief, emotion, and personality. In my research, I focused on strong-story narrative planning to study and improve believable behavior generation. I built upon previous narrative planners that enabled their agents to have goals and beliefs, and extended them with models of personality and emotion.

My models of personality and emotion are respectively inspired by the Big Five and OCC, which are two widely validated models in psychology. I drew from the concepts shared between those models and narrative planning, and adapted those concepts into their computational counterparts. I investigated my proposed models in human subject studies that asked subjects to read or play a(n) (interactive) story and answer a few questions about them. My findings showed that using my proposed models, the generated behavior was perceived to be more believable by human readers. In some cases, the virtual characters even caused the player to feel empathy towards them.

There are some limitations to my models of personality and emotion. I intentionally limited myself to structures that were already present in narrative planning to ensure a high degree of reusability and add the smallest amount of author burden.

For personality, I focused on traits that were communicated through external actions and disregarded traits that were domain-specific. In short, I chose to oversimplify rather than overlook. Further modifications to narrative planning structures can enable adapting more personality traits and provide a deeper computational model of personality.

For emotion, I only adapted 12 out of 22 emotion types. Although it is possible to extend my model to include the rest, it is necessary to define a model of social context that reasons about character standards. Those emotions specifically address how an action might be praiseworthy or blameworthy in the eyes of different characters.

To demonstrate the power of strong story in generating interactive stories, I used my models of emotion and personality to intelligently generate conflicts. More specifically, I enabled the author to define a set of behavior patterns that they wanted to encourage in their users. The system then implicitly encouraged those behaviors by planning stories in which the player could resolve the presented conflicts using those behaviors. Using simulated experiments, I showed that through intelligent conflict generation, we can properly distinguish between different conflicts and by providing more opportunities for the player, they are more encouraged to demonstrate author-intended behaviors.

There are a few way that I could improve intelligent conflict generation. First, I defined conflicts as situations where a character fears that another character could reduce their utility. It is possible to extend this model to account for situations where a character expects that another character could make them feel disappointment. For instance, if the bandit steals the medicine from the merchant, it does not decrease the player's utility; however, it makes the player feel disappointment because they can no longer obtain the medicine. This consideration allows for filtering out more situations which the player cannot address using the intended behavior.

Second, in its current state, my model can only implicitly encourage the intended behavior. It means that the system only provides more opportunities for the player to exhibit the intended behavior. To explicitly encourage player behavior, the system must also respond differently when the player resolves a conflict using the intended behavior or not. For instance, if the player can resolve a conflict by talking to or shooting a suspect, the system must find two different scenarios to occur based on the player's choice. Perhaps, if the player shoots the suspect, the suspect also shoots back at them, but if they try to talk to the suspect, the suspect surrenders their gun. It is necessary for the author to provide the system with explicit ways of encouragement; but the system should also be capable of searching for and planning those actions.

My proposed models of emotion and personality are designed to be extensible. I plan to continue my research and expand or exchange certain components of models. I also hope that for other researchers of the community, these models provide foundations to build upon or insights to apply to their own work.

APPENDICES

APPENDIX 1. CAMELOT

Camelot is a modular and customizable interactive narrative environment that provides a sandbox to act as a presentation layer for any narrative generation system. Camelot is a real-time 3D third-person virtual environment that takes place in a Medieval fantasy setting and includes customizable characters, places, and items. By using this environment, researchers can build and test prototypes faster and easier.

By providing a fully separate presentation layer, Camelot is independent of the programming language or technology used by the narrative generation system. This separation of concerns lets Camelot provide a standard of presentation that can be shared among the interactive narrative community. Through this standard, various AI approaches can be meaningfully compared to one another and evaluated in the same context and with the same subjects. Moreover, this standard can facilitate researchers to reproduce and build upon the works of others.

License and Availability

Camelot is published under the Non-Profit Open Source License 3.0. This license allows Camelot to be used for personal, professional, and academic projects at no cost. It is only necessary to acknowledge the original project and creators in any derivative works. You can view a comprehensive interactive documentation website for Camelot at:

http://cs.uky.edu/~sgware/projects/camelot/

The documentation provides details on how to use Camelot and its actions, as well as showcasing its characters, places, items, action icons, visual effects, and sound effects. You can also download Camelot for Windows or MacOs from the documentation website.

Modular and Customizable

Camelot comes with a set of characters and places that can be customized as intended. To create various characters, an experience manager can choose from different body-types, hair styles, hair colors, eye colors, skin tones, and outfits. Figure 1 presents some examples of these characters.

As I mentioned, places are the small, contained, pre-built locations that can be instantiated to create the story world. Figure 2 presents some examples of these places. Each place comes with a set of interactive furniture, such as shelves, chairs, tables, or cauldrons, that can be hidden or shown depending on the context of the story. Camelot does not impose any restrictions on where the doors of each place lead to. This enables Camelot's world creation to be modular and allows any configuration of the space.

Interoperability

To generate an interactive narrative, Camelot communicates with an experience manager (EM). A Camelot EM can be written in any programming language that has standard input and output capabilities. In fact, all communications between Camelot and the EM are transmitted via the standard I/O, e.g. `System.out.Println` in Java,

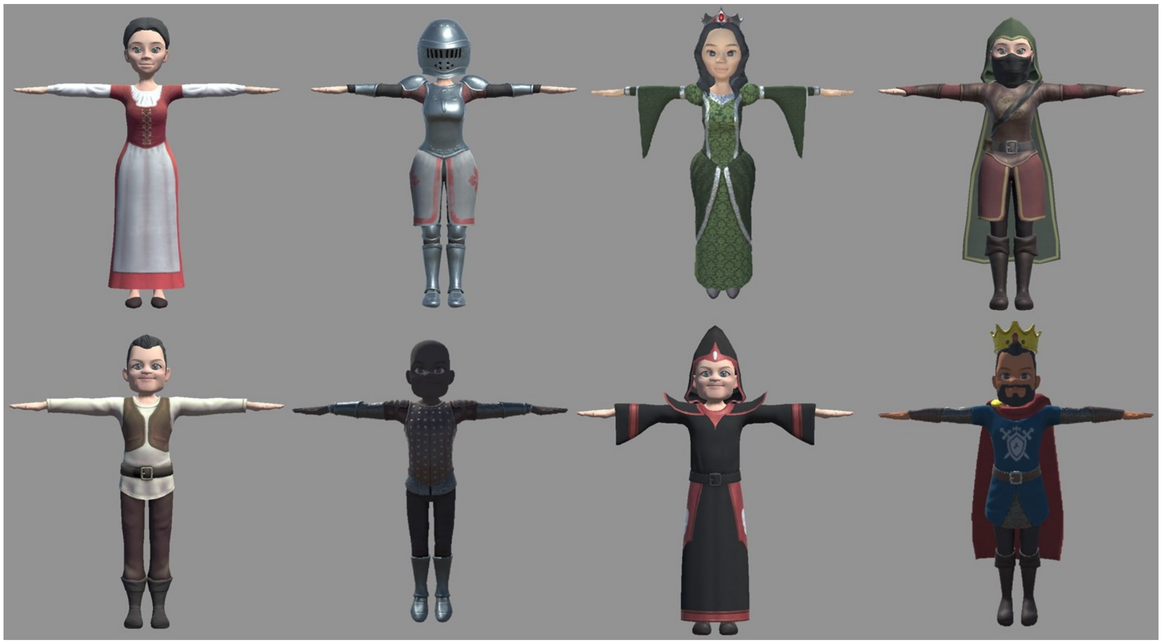

Figure 1: Some Examples of Camelot Characters

Figure 2: Some Examples of Camelot Places

`print` in Python, or `Console.WriteLine` in C#. Camelot has a large list of available commands that can be used to control its UI, characters, environments, etc. These commands are referred to as actions and have the following format:

$$ActionName(Argument1, Argument2, ...)$$
$$e.g. Attack(Hero, Villain)$$
$$Sit(Tom, Room.Chair)$$
$$PlaySound(LivelyMusic)$$

APPENDIX 2: COMPLETE RUN OF EXPERIMENT 3

In the following example, Tom has low Neuroticism. The following description includes the texts shown to the participant, as well as some details, noted by an underline, for clarification.

There are various ways Tom could get his hands on a healing potion. Some may work. Some may not! These are some of the possible stories that could happen.

Story 1

Tom goes to the town.
Tom knocks on the door and the alchemist lets him into the shop.
Tom tells the alchemist about the herbs in the cottage.
The alchemist leaves the shop to collect the herbs.
Tom steals the recipe WITHOUT anyone noticing.
The alchemist collects the herbs.
The alchemist comes back to the shop.
Tom steals the herbs from the alchemist.
Tom makes the medicine using the herbs.
The alchemist calls for the guard.
The guard arrests Tom.

Story 2

Tom collects poisonous herbs from the cottage and makes poison.
Tom collects the medicinal herbs from the cottage.
Tom goes to the town.
Tom breaks into the alchemists shop WITHOUT waking her up to steal the recipe.
Tom changes his mind. Tom poisons the alchemists drink WITHOUT her noticing.
Tom goes to the town. Tom changes his mind.
Tom breaks into the alchemists shop WITHOUT waking her up to steal the recipe.
Tom steals the recipe WITHOUT anyone noticing.
Tom makes the medicine using the herbs.

Story 3

Tom collects the medicinal herbs from the cottage.
Tom goes to the town.
Tom knocks on the door and the alchemist lets him into the shop.
Tom tells the alchemist about the herbs in the cottage.
The alchemist leaves the shop to collect the herbs.
Tom steals the recipe WITHOUT anyone noticing.

Story 4

Tom collects the medicinal herbs from the cottage.

Tom goes to the town.

Tom knocks on the door and the alchemist lets him into the shop.

Tom gives the herbs to the alchemist to make medicine.

Tom changes his mind.

Tom steals the herbs from the alchemist.

Tom steals the recipe from the alchemist.

Tom makes the medicine using the herbs.

The alchemist calls for the guard.

The guard arrests Tom.

Among all the possible ways to get the medicine, this is what Tom does.

First Story

The first story above is what actually happened. In other words, Tom did not think of the other ways to get the medicine mentioned above or if he did, he preferred to do it this way.

Tom's choice of actions reflects the kind of person he is. To what extent do you agree the following statements can be used to describe Tom? To answer, compare the first story (what Tom actually did) with the other stories that could have happened but did not.

<u>The participants answer the following 5-point Likert questions.</u>

Does not know why he does some of the things he does.

Does things that he later regrets.

Is filled with doubts about things.

Is NOT easily discouraged.

Rarely changes his mood.

Now, consider these other possible events. Based on Tom's choice and your answers to last questions, you can imagine what type of person he is. Which of these stories is most likely to happen given Tom's personality?

Story 5 (<u>Low Neuroticism</u>)

Tom goes to the town.

Tom knocks on the door and the alchemist lets him into the shop.

Tom tells the alchemist about the herbs in the cottage.

The alchemist leaves the shop to collect the herbs.

The alchemist collects the herbs.

The alchemist comes back to the shop.

The alchemist makes the medicine using the herbs.

Tom steals the medicine from the alchemist.

The alchemist calls for the guard.

The guard arrests Tom.

Story 6 (High Neuroticism)
Tom collects the medicinal herbs from the cottage.
Tom goes to the town.
Tom knocks on the door and the alchemist lets him into the shop.
Tom tells the alchemist about the herbs in the cottage.
The alchemist leaves the shop to collect the herbs.
Tom changes his mind.
Tom goes to the town.
Tom changes his mind.
Tom breaks into the alchemists shop WITHOUT waking her up.
Tom steals the recipe WITHOUT anyone noticing.
Tom makes the medicine using the herbs.

Story 7 (Genereated by Glaive)
Tom collects the medicinal herbs from the cottage.
Tom goes to the town.
Tom knocks on the door and the alchemist lets him into the shop.
Tom steals the recipe from the alchemist.
Tom makes the medicine using the herbs.
The alchemist calls for the guard.
The guard arrests Tom.

Story 8 (A Random Story)
Tom collects poisonous herbs from the cottage and makes poison.
Tom goes to the town.
Tom knocks on the door and the alchemist lets him into the shop.
Tom tells the alchemist about the herbs in the cottage.
The alchemist leaves the shop to collect the herbs.
Tom poisons the alchemists drink WITHOUT her noticing.
The alchemist collects the herbs.
The alchemist comes back to the shop.
Unknowingly, the alchemist drinks the poison and faints.
Tom steals the recipe from the unconscious alchemist.
Tom steals the herbs from the unconscious alchemist.
Tom makes the medicine using the herbs.

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