Automated Planning and Player Modelling for Interactive Storytelling

Alejandro Ramirez and Vadim Bulitko

***Abstract*—Storytelling plays an important role in human life, from everyday communication to entertainment. Interactive Storytelling (IS) offers its audience an opportunity to actively participate in the story being told, particularly in video games. Managing the narrative experience of the player is a complex process that involves choices, authorial goals and constraints of the given story setting (e.g., a fairy tale). Over the last several decades, a number of experience managers using Artificial Intelligence (AI) methods such as planning and constraint satisfaction have been developed. In this paper we extend existing work and propose a new AI experience manager called Player-specific Automated Storytelling (PAST), which uses automated planning to satisfy the story setting and authorial constraints in response to the player's actions. Out of the possible stories algorithmically generated by the planner in response, the one that is expected to suit the player's style best is selected. To do so, we employ automated player modelling. We evaluate PAST within a video-game domain with user studies and discuss the effects of combining planning and player modelling on the player's perception of agency.**

***Index Terms*—Artificial intelligence, Interactive Storytelling, Evaluation, Entertainment Industry, Automated Planning**

I. INTRODUCTION

STORYTELLING is central to human cognition. From old campfire tales to modern movies and video games, we cherish relatable stories. One approach to improving these stories is to shape them dynamically based on the audience's input. Allowing the audience to become an active participant in the narrative is the foundation of Interactive Storytelling (IS), a multi-disciplinary field that has flourished over the last several decades, particularly in the context of video games.[1]

In an IS setting, the audience/player is given *agency*: the ability to affect the narrative by taking actions. Player agency is important not only because it affords freedom and customizable stories, but also because the perceived control has been previously linked to positive personal emotions [1, 2]; additionally, it is a selling point of many commercial video games. However, by exercising agency, the player may choose to deviate from the original narrative and block story progression towards an authorial goal. Traditionally, to cope with this situation multiple alternative narratives are manually authored.

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[1]Within the research community, Interactive Storytelling (IS) is also known as *interactive narrative*, *interactive fiction* or *interactive drama*.

To illustrate, consider the well-known *Little Red Riding Hood* story: the tale of a little girl who must traverse a treacherous forest to take a food basket to her sick grandmother [3]. In the original story, a mean wolf eats the grandmother (an authorial goal), posteriorly impersonating her in order to eat Red. In an interactive version, the player can assume Red's role and is able to interact with story characters. For instance, the player may choose to shoot the wolf early in the game – disabling the authorial goal. To re-enable it, the story needs to be modified: maybe a magical resurrecting fairy would appear, or perhaps another wolf. Accommodating such actions needs to happen while telling the story, since this pre-computation in a realistically-sized game can be prohibitive given the combinatorial nature of actions and story states. In a video game context, this accommodation can be performed by an AI experience manager, running along the game engine.

An agency-based AI experience manager within IS faces three primary challenges. First, it must accommodate player actions consistently with both past events and the story setting. Second, it should preserve authorial goals (e.g., Red and Granny must be eaten). Third, it should attempt to increase the player's perception of agency while reducing the number of narrative trajectories that need to be manually authored.

We present a new approach to IS in video game settings by combining and extending prior work [4, 5, 6]. We use both automated planning [7] to accommodate the player's actions while attaining authorial goals and player modelling [8, 9] to select accommodations based on the player's gaming style.

Video games are a natural test-bed for studies on player experience management within IS. Conversely, the research in IS can contribute back to the video game industry with procedural methods for story space generation and player experience management, thus improving the experience quality while simultaneously aiding in the development phase. For these reasons, previous work in IS was often situated with video games – a trend that we also follow in our work.

This paper is organized as follows: in Section II we formally define the problem, followed by a related work review in Section III. We detail our experience manager in Section IV and formally evaluate (i.e., via user studies employing a validated instrument and statistical methods) in Section V. Section VI discusses the strengths, shortfalls, and future research. We conclude in Section VII. A longer and more detailed account of this work is found in an M.Sc. thesis [6].

II. PROBLEM FORMULATION

The problem we tackle in this paper is to increase the player's perception of his/her agency within an interactive

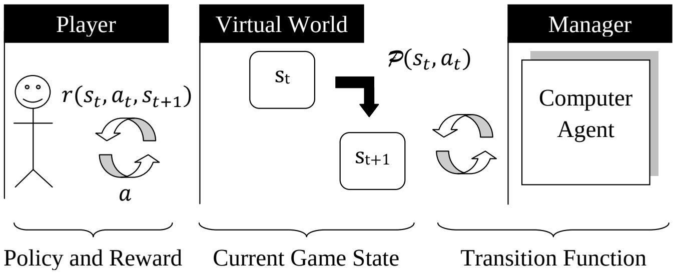


Fig. 1. The elements of a video game in an experience management framework, modelled as an MDP.

story by dynamically accommodating player's actions while keeping the story coherent and consistent with authorial goals.

To define the problem formally, we adopt the approach of Thue and Bulitko [10] and model experience management in IS as the task of changing the game's dynamics in response to player actions with the goal of increasing the perception of his/her agency. In this framework, the player is an agent in a Markov Decision Process (MDP) whereas the experience manager is an AI agent monitoring and modifying the MDP behind the scenes, unbeknownst to the player (Figure 1).

Formally, the framework can be denoted by the tuple $\langle S, A, \mathcal{P}, r \rangle$, where S is a finite set of *states*, each state being a narrative snapshot of the world. The interactive experience starts at an initial state ($s_0 \in S$) and it is required to end at one of the final goal states ($S_F \subset S$). Additionally, the author can shape the experience by designating a set of intermediate goals ($S_I \subset S$) that the player is preferred to pass through. Both intermediate/final goal states provide authorial control over the space of story trajectories that could be possibly experienced.

To illustrate: in an interactive version of the *Little Red Riding Hood* narrative by Riedl et al. [7] the starting state could be set to $s_0 =$ "Red leaves her house", the final goal state s_n = "Red gives the basket to her grandmother" ($S_F = \{s_n\}$) and the two intermediate goals s_i = "Wolf eats Red", and $s_j =$ "Wolf eats Grandmother" ($S_I = \{s_i, s_j\}$).

A is a finite set of *actions* available to the player. Taking an action leads to another state. This is captured by the *transition function* $\mathcal{P} : S \times A \to S$, which for a given state ($s \in S$) and an action ($a \in A$) provides the next state ($s' \in S$).[2] Transition functions that can lead to state re-visits under any sequence of player actions are disallowed under this model. Note that states capture narrative information only, and thus other details (e.g., player's position on a map) are not included in them.

A function $r : S \times A \times S \to \mathbb{R}$ provides a *reward* $r(s, a, s')$ to the player for transitioning from the state s to the state s' via the action a. The reward expresses the instant quality of the player's experience (in our case, player's perception of his/her agency at the current time). The overall experience quality is formalized as the *return*, denoted by $\mathcal{R}$: the sum of all rewards collected by the player in the game from start to finish. The AI experience manager does not observe the reward stream the player is experiencing and therefore must estimate it from observable variables (e.g., player's actions). We denote the manager's estimates of r and $\mathcal{R}$ by $\tilde{r}$ and $\tilde{\mathcal{R}}$.

We assume that the player seeks to maximize his/her return; unbeknownst to him/her, the AI experience manager is helping. With no direct control over the player's actions (a) or his/her perception of the experience quality (r), the experience manager is limited to manipulating the transition function $\mathcal{P}$, in an attempt to lead the player through a trajectory $T = (s_0, s_1, ..., s_n)$ with the highest return. This trajectory is subject to authorial constraints: it should pass through all intermediate goals ($S_I \subset T$) and end in a final state ($s_n \in S_F$). Henceforth, we define a *narrative* as the set of trajectories available to the player at a given time during the game.

The performance of an AI experience manager is evaluated on the basis the increase of the player's agency cumulative perception during the game. In this paper we conduct the evaluation empirically by comparing our manager to a baseline manager as detailed later in the paper (Section V). The cumulative perception of agency is measured with a validated psychological instrument – a post-experience questionnaire administered to the player.

III. Related Work

In this section, we review some related IS prior work from three different viewpoints: *drama management*, *player agency*, *procedural generation* and *evaluation.*

Based on dramatic theory, Laurel [11] proposed the theoretical foundation for *interactive fantasy systems*, primarily focusing on drama, fantasy roles, and interactivity. *Drama managers* followed, initially proposed by Bates [12], working with cognitive/emotional agents, presentation, and drama. *Façade* [13] was a notable drama manager that involved a five-year multi-disciplinary project that created a "(...) a novel architecture that integrates emotional, interactive character behaviour, drama-managed plot and shallow natural language processing." This system maintained an Aristotelian tension arc (i.e., the exposition, rising action, climax, falling action, and resolution) while promising the player a great amount of agency by means of exploring the virtual story and using natural language processing [13]. Nevertheless, *Façade* was neither formally evaluated for player agency nor designed around procedural narrative generation.

Experience managers generalized drama management to non-dramatic situations, educational and serious games, and interactive tutors. For instance, a system presented by Cheong and Young [14] was aimed at increasing the player's suspense. While this experience manager may have also increased the perception of agency, it was not formally evaluated for it.

Player agency has been specifically targeted by some IS systems: "The core research challenge is how to balance the need for a coherent story progression with player agency, which are often at odds." [15]. The Automated Story Director (ASD) [7, 16] allowed the player to deviate from the original narrative and used automated planning to rebuild the rest of the story while ensuring that it was still narratively coherent and consistent with authorial goals. Despite its agency-centric approach, the ASD was not formally evaluated for agency.

Player-Specific Stories via Automatically Generated Events (PaSSAGE) [8, 17, 18, 19, 9] also attempted to increase the

[2]For simplicity, we only consider the deterministic case in this paper; however, our approach can also be extended to the stochastic case.

player's sense of his/her agency by selecting pre-authored story fragments on the basis of a dynamically learnt player model. PaSSAGE was formally evaluated with promising results. On the other hand, it did not use procedural generation to rebuild the story in response to player actions and relied instead on manually pre-authored narrative. Another player modelling system is the *Prefix-based Collaborative Filtering (PBCF)* [20, 21] which used explicit player modelling (i.e., interrupted the interactive experience to request a rating of experience). These responses were used to create a player model that was subsequently used to select better suited stories for the player, albeit manually pre-authored.

IN-TALE was one of the first systems to procedurally generate narrative by producing stories in plain English based on user-provided attributes and information [22]. Later research focused on automated planning and case-based reasoning [23]. Examples of the former include the *Merchant of Venice* [24] and *Mimesis* [25]; neither used player modelling. With regards to case-based reasoning, Ontanon and Zhu [26] proposed *Story Analogies through Mapping (SAM)* system which employed an analogy-based story generation approach: it would take a source story, find analogies in a target story, and generate a new text story using elements from both.

Many experience managers have not been formally evaluated; furthermore, no validated instrument was widely used until the recent introduction of the *IRIS Evaluation Toolkit*, which provides several sub-scales for "(...) systematic, comparative research on IS prototypes and systems" [27]. One version of PaSSAGE was evaluated using this instrument in multiple large-scale user studies and obtained favorable results [9].

Other evaluated systems, such as *Anchorhead*, treated experience management as a search problem to improve the player's experience by using "(...) a set of plot points, a set of actions the drama manager can take, and an evaluation of story quality": the evaluation was done with a randomly simulated user [28]. *Haunt 2*, a system based on the Interactive Drama Architecture (IDA), attempted to drive the player away from possible action that would conflict with the plot, and had shown to effectively intervene by anticipating such player actions [29]. In both *Anchorhead* and *Haunt 2* the effects of said approaches on agency are unclear (e.g., persuading players away from actions could be detrimental to perceived agency) as the systems were not evaluated specifically for it.

In summary, no prior experience manager appears to have targeted increasing the player's perception of his/her agency, accommodated the player's actions in an automated way and been formally evaluated with a validated instrument – the three objectives of our work.

IV. Proposed Approach

In this section, we present our approach, PAST, to experience management within IS. Algorithm 1 depicts the system from a high level. In the following subsections we detail the individual steps and illustrate with concrete examples.

A. An Intuitive Account of PAST

PAST aims to solve the problem of increasing the player's perception of agency within IS by dynamically accommodating player's actions consistently with pre-defined authorial goals. We integrate and extend existing approaches: the ASD and PaSSAGE (discussed in the previous section) as follows.

Algorithm 1 PAST

$t \leftarrow 0$
$\bar{p}_t \leftarrow (0.5, 0.5, 0.5, 0.5, 0.5)$
while $s_t \notin S_F$ **do**
  present state s_t to the player
  input player's action a_t
  if a_t is a rupture **then**
    N $\leftarrow$ *computeAccommodations*(s_t, a_t, S_I, S_F)
    $n \leftarrow$ *selectAccommodation*$(N, \bar{p}_t)$
    $\mathcal{P}_{t+1} \leftarrow$ *updateTransitionFunction*$(n, \mathcal{P}_t)$
  else
    $\mathcal{P}_{t+1} \leftarrow \mathcal{P}_t$
  end if
  $s_{t+1} = \mathcal{P}_{t+1}(s_t, a_t)$
  $\bar{p}_{t+1} =$ *updatePlayerModel*$(\bar{p}_t, a_t, s_t)$
  $t \leftarrow t + 1$
end while

First, whenever the player takes an action that invalidates one of the authorial goals (e.g., the player "kills Wolf" thus invalidating the goal "Wolf eats Red"), we use the automated planner of the ASD to generate an alternative narrative, called an *accommodation*, to re-enable authorial goals consistently with previous player actions. We refer to actions that invalidate authorial goals as *ruptures*. As an example, PAST could react to Wolf's death by either introducing another wolf (Grendel) or by bringing in a resurrecting fairy [7].

Second, we use player modelling adopted from PaSSAGE to select the most suitable accommodation on the basis of the player's observed play-style. For instance, a player inclined to fighting would get Grendel, a bigger wolf to fight, whereas a method-acting player may get the fairy.

Third, once the accommodation is selected, our manager modifies the MDP transition function to implement it. Suppose that the magical fairy is introduced after Wolf's death; then, the transition function is modified so that Red encounters the magic fairy on her way to the grandmother. This process is illustrated in Figure 2, where s' and s'' are the two possible next states. The algorithmic details follow.

B. The MDP in PAST

In PAST, *states* and *actions* are supplied by the author: S, A, S_F, S_I with $(S_F \cup S_I) \subset S$, and the initial state ($s_0 \in S$), all encoded in a Lisp-like notation.[3] The author also provides an initial set of story trajectories: the *exemplar narrative* [7].

Each state is a set of several world facts in the form of `(attribute character)`, `(action subject direct-object)`, or `(action subject direct-object indirect-object)`. For instance, in the Little Red story the state of Red meeting Wolf

[3]PAST is built on top of an existing ASD/Longbow implementation, which had been done entirely using Allegro Common Lisp. We preserved most of the Common-Lisp code and substituted proprietary libraries with Steel Bank Common Lisp (SBCL) open-source equivalents or created our own.

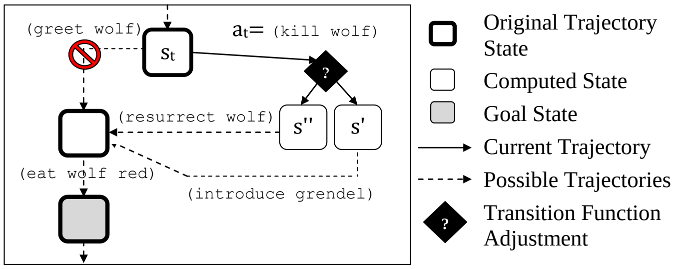


Fig. 2. The virtual story setting after the player kills Wolf. Two accommodation states are computed: s' and s''.

Action template: `eat`

```
(define (action eat)
:parameters (?eater ?eatee)
:constraints ((wolf ?eater) (person ?eatee))
:precond ((know ?eater ?eatee) (hungry ?eater)
    (alive ?eater) (alive ?eatee)
    (:not (eaten ?eatee))
    (:not (asleep ?eater)) (:neq ?eater ?eatee))
:postconditions ((eaten ?eatee) (in ?eatee ?eater)
:annotation #(1 0 0.8 0.6 0))
```

Fig. 3. Sample action template.

State s_t	*Action*	*State* s_{t+1}

`(person red)`
`(alive red)`
`(wolf wolf)`
`(alive wolf)`
`(hungry wolf)`
`(know wolf red)`
`(know red wolf)`
	`(eat wolf red)`	`(person red)`
		`(alive red)`
		`(wolf wolf)`
		`(alive wolf)`
		`(know wolf red)`
		`(know red wolf)`
		`(in wolf red)`
		`(eaten red)`

Fig. 4. Sample transition from state s_t to s_{t+1} caused by the action `eat`.

is represented as `(person red) (alive red) (wolf wolf) (alive wolf) (hungry wolf) (know wolf red) (know red wolf)`. The states containing `(eaten red) (in red wolf)` and `(eaten granny) (in granny wolf)` are intermediate goals and `(has granny basket)` defines the final goal state.

An action connects two states and is an instance of an *action template*. An example is shown in Figure 3 for the action `eat`. Action templates are a mechanism to generalize attributes of similar actions. For instance, the action template `(kill x)` can be annotated with a fighter inclination update for the player model generalizing the information over a large class of kill actions. Thus, any instance of the `kill` template (e.g., the action `(kill wolf)` or the action `(kill grendel)`) will indicate the player's fighter inclination. Briefly speaking, the model is a vector of five numbers, each representing the players inclination for a certain play-style. We detail the player model in Section IV-E.

A template includes participating characters and elements as its variables, pre-conditions that enable the action, post-conditions and time-invariant constrains. The variables are denoted by a question mark and are bound at run-time. For instance, `(eat ?eater ?eatee)` can be bound to `(eat wolf red)` but only if all the pre-conditions and constraints are met in the current state (e.g., `(person red)`, `(hungry wolf)`, `(know wolf red)`). Post-conditions are applied to the state s_t and result in the new state s_{t+1} (Figure 4).

Each template is annotated with an update vector for the player model: the *annotation*, shown in the last line in Figure 3. The annotations represent different player inclinations, and are used to create and maintain the model.

For both states and actions, actual game content (e.g., graphics, voice-overs) needs to be authored. In our PAST implementation, we limited the content to text which is shown to the player when actions are available and when states are reached (detailed in Section IV-F).

C. Procedural Narrative Generation in PAST

The narrative in PAST is a set of trajectories available in the MDP under a transition function $\mathcal{P}$. To preserve the authorial intent, PAST plans to include all intermediate and one final goal state in all trajectories. PAST's procedural narrative generation is performed by a combination of the automated planner *Longbow* [30] and the ASD experience manager; together these systems accommodate ruptures [5]; note that when the player takes actions down the exemplar narrative, this mechanism is not activated.

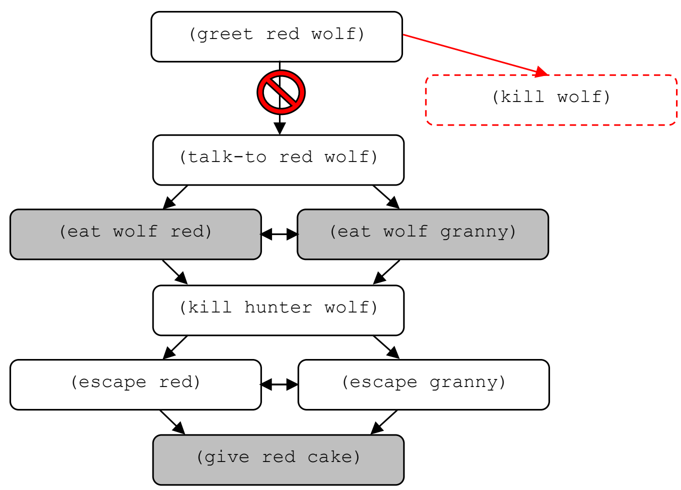


Fig. 5. The exemplar *Little Red* narrative and the rupture `(kill wolf)` taken by the player. For simplicity, states show only the enabling action.

Figure 5 shows Little Red's exemplar narrative taken from Riedl et al. [7]. The exemplar narrative contains several possible narrative trajectories all of which pass through the intermediate goals `(eat wolf red)`, `(eat wolf granny)` and end in the final goal `(give red cake)`.

Note that if the player were to follow the exemplar narrative, Red must greet Wolf followed by a conversation. As the narrative is interactive, the player is able to `(kill wolf)` thereby rupturing the exemplar narrative and getting into the state `(dead wolf)` which invalidates both intermediate goals. In response, PAST engages *Longbow* to replace the new state with another state which will start an alternative narrative accommodating Wolf's death and yet satisfying the intermediate and final authorial goals.

Longbow computes only a single plan using a heuristic function during its search. When Longbow was used within ASD, its heuristic preferred plans that are closer to the exemplar narrative but was player-agnostic. PAST added the player model to the planning heuristic. Thus, the single plan that Longbow within PAST produces is tailored to the specific player as detailed in the following section. Furthermore, since different players may require different accommodations and the number of possible different players is high, pre-computing all accommodations off-line (as ASD did) is likely to be intractable. Thus, unlike ASD, PAST plans accommodations on-line, upon a player-induced rupture.

D. Selecting the Most Suitable Accommodation

There may be several ways of accommodating a player-induced rupture, some more suitable for a particular player than others. As explained in the previous section, PAST engages an automated planner Longbow to compute a single accommodation most suitable for the given player. The planning heuristic that can be conceptually thought as a ranking over possible accommodations. The ranking function is based on the product of the estimated return for the player (i.e., his/her perceived agency) and the proximity of the accommodation to the exemplar narrative. The former is a new contribution whereas the latter comes from the ASD [7].

In line with PaSSAGE, we base our estimation of the return/reward on the *control heuristic* [31], assuming that the player perceives more agency when his/her actions lead to more desirable states. To illustrate, if the player exhibits a fighting inclination, he/she is assumed to find fighting events more desirable and, consequently, perceive more agency from his/her action that led to such an event.

Formally, we compute state desirability (i.e., immediate perception of agency) as the dot product of the player's model and the next state annotation: $\tilde{r}(s_t, a_t, s_{t+1}) = \bar{m}(s_{t+1}) \cdot \bar{p}_t^T$, where $\bar{m}(s_{t+1})$ is the annotation of the state s_{t+1} and $\bar{p}_t$ is the player model at time t. The annotation of the state is taken from the first action of the accommodation (e.g., `(greet grendel)` in s', Figure 6). The estimated return $\tilde{\mathcal{R}}$, or the total agency perceived by the player from time step t until the end of the game) is set myopically as the estimated immediate reward: $\tilde{\mathcal{R}}_t = \tilde{r}(s_t, a_t, s_{t+1})$. This is appropriate since PAST does not model the player's policy and therefore is unable to predict the player's future actions.

In summary, upon a rupture a_t, PAST engages the planner to compute a set of accommodations consistent with the previous player's actions and satisfying the intermediate goals and a final goal. It ranks the accommodations and selects the new transition function for the top ranked accommodation.

This process is illustrated in the selection frame of Figure 6: $\bar{p}_2 = (0.5, 0, 0, 0, 0.5)$ represents the player model at time step $t = 2$, when $a_2 =$ `(kill wolf)` ruptures the exemplar narrative thereby disabling the authorial goal `(eat wolf red)`. There are two possible accommodations: one starts by introducing Grendel, who will then be greeted by Red `(greet grendel)`, whereas the other starts with a fairy resurrecting Wolf `(resurrect wolf)`. To perform the former, the MDP transition function needs to be modified by

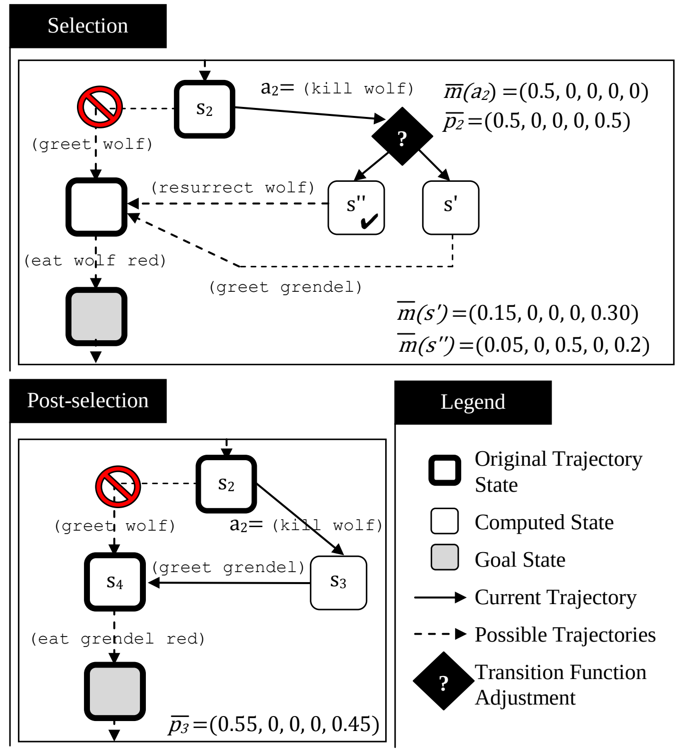


Fig. 6. **Top:** the player creates a rupture by taking the action a_2. PAST selects between two candidate accommodations. **Bottom:** the resulting new state and updated player model.

PAST so that the player's action $a_2 =$ `(kill wolf)` leads to the state s': $\mathcal{P}'(s_2, a_2) = s'$. Analogously, another transition function needs to produce the state $s'' = \mathcal{P}''(s_2, a_2)$ for the latter. Hence, PAST needs to select between transition functions $\mathcal{P}'$ and $\mathcal{P}''$. The player's return under the first is estimated to be $\tilde{\mathcal{R}}' = \tilde{r}(s_2, a_2, s') = (0.15, 0, 0, 0, 0.30) \cdot (0.5, 0, 0, 0, 0.5)^T \approx 0.23$. Likewise, the player's return under the second is $\tilde{\mathcal{R}}'' = \tilde{r}(s_2, a_2, s'') = (0.05, 0, 0.5, 0, 0.2) \cdot (0.5, 0, 0, 0, 0.5)^T \approx 0.13$. Assuming for simplicity that both accommodations have an equal proximity to the exemplar narrative, the accommodation with the highest estimated return will be selected by PAST. Consequently, the transition function is set to $\mathcal{P}'$ and the next state becomes $s_3 = \mathcal{P}'(s_2, a_2) = s'$ (as shown in Figure 6).

As mentioned above, the process of computing and ranking possible accommodations is combined within the planner via a heuristic function. Thus, *Longbow* within PAST actually fully plans out only the top-ranked accommodation.

E. Player Model

The player model was adopted from PaSSAGE given the good performance achieved in previous user studies [8, 9]. It is a vector of five numbers each indicating the magnitude of the player's inclination to one of the five RPG types (Table I). Each component is a real number in $[0, 1]$ with 1 indicating the maximum inclination and 0 indicating the maximum counter inclination. To illustrate: a player model $\bar{p} = (1, 0, 0.5, 0, 0.4)$ describes, from left to right component, a play-style with a high inclination to fighting, strong counter inclination to power-gaming, a neutral inclination to storytelling and strong

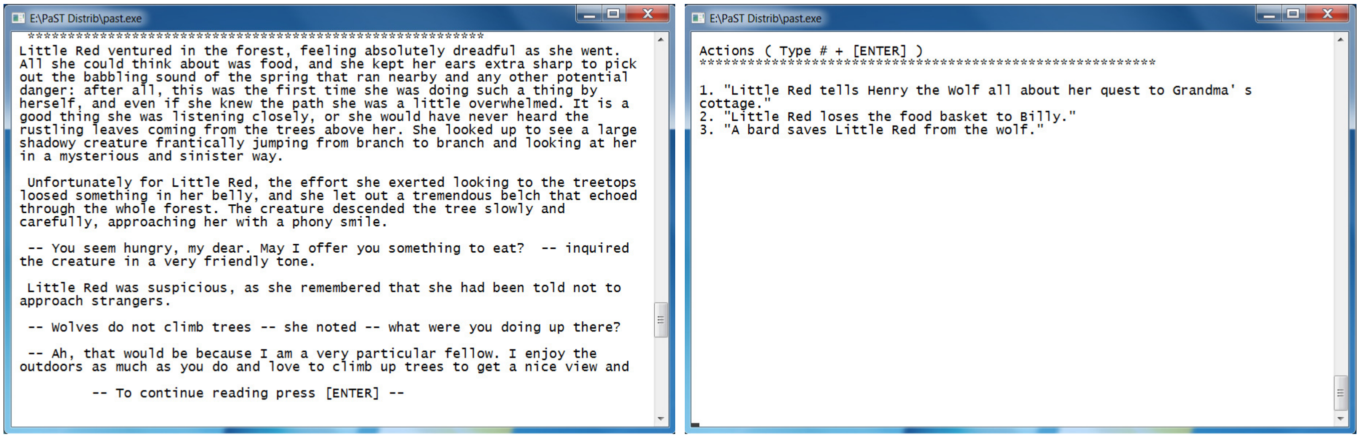


Fig. 7. Screenshots from the PAST text-based implementation. **Left:** text description for a state. **Right:** available player actions in text.

counter inclinations to method acting and mild counter inclination to tactics.

Type	*Description*
Fighter	Prefers brute force to achieve goals.
Power Gamer	Increases statistics: more money, more power and items.
Storyteller	Prefers complex plots, stories and rich characters.
Method Actor	Prefers in-depth personality of the main character.
Tactician	Ponders choices carefully, well-thought decisions.

TABLE I

THE RPG PLAYER TYPES AND DESCRIPTION USED BY PASSAGE AND PAST, BASED ON TYPES PROPOSED BY LAWS [32].

The initial model, $\bar{p}_0 = (0.5, 0.5, 0.5, 0.5, 0.5)$, is set to neutral. Every time the player takes an action, the annotation on the corresponding action template is used to update the player model as follows:

$$\bar{p}_{t+1} = \begin{cases} \bar{p}_t + \alpha \cdot \bar{\delta}, & \text{if } \exists a \in A_t \text{ s.t. } \beta(a_t, a) > \xi \\ \bar{p}_t, & \text{otherwise} \end{cases} \tag{1}$$

where A_t is the set of all actions available to the player at time t; $a_t \in A_t$ is the player's action; $\bar{m}(a_t)$ is the annotation from the action template, $\bar{p}_t$ is the player model, $\bar{\delta} = \bar{m}(a_t) - \bar{p}_t$ is the model update and α is the learning step size.

For model updates, PAST considers all actions taken, including ruptures; note that the player's action tells something about the player only if the player had an actual choice. Thus, the update to the player model in the formula above is conditional on the presence of diverse choices. Formally:

$$\beta(a_t, a) = \frac{1}{\sqrt{5}} \left\| \frac{\bar{m}(a_t)}{\|\bar{m}(a_t)\|} - \frac{\bar{m}(a)}{\|\bar{m}(a)\|} \right\| \tag{2}$$

This formula measures divergence between the annotation of the action the player actually took (a_t) and the annotation of an alternative available action a. The model is updated only when an action different enough (as determined by $\xi \in [0, 1]$) was indeed available to the player. The operator $\|\|$ is the Euclidean distance in the five-dimensional vector space.

To elucidate, suppose that the player model at time 3 is $\bar{p}_3 = (0.5, 0, 0, 0, 0.5)$ and the player takes the action a_3 = `(kill wolf)` whose template has the annotation $\bar{m}(a_3) = (0.5, 0, 0, 0, 0)$. Suppose also that the action `(greet wolf)` was available to the player as well and $\bar{m}($`(greet wolf)`$) = (0, 0, 0, 0.8, 1)$. The annotations are sufficiently different as $\beta($`(kill wolf)`, `(greet wolf)`$) \approx 0.34$ exceeds $\xi = 0.1$. Thus PAST performs a model update: $\bar{p}_4 = (0.5, 0, 0, 0, 0.45)$ (Figure 6, $\alpha = 0.1$). We empirically found that in our stories $\alpha = 0.1, \xi = 0.1$ performed well.

F. Interface

In our implementation of PAST, the world is presented to the player via text and the player selects his/her actions via a text menu. For instance, in the left frame of Figure 7, the textual description of `(red greets wolf)` is shown to the player. The player then selects among possible actions such as `(tell-about red wolf granny)`, `(:not (has red cake))`, `(persuade wolf)` textually displayed in the right frame of Figure 7.

V. EVALUATION

A. Methodology

In line with the previous work [7], we situated PAST within a choose-your-adventure [33] interactive story. The states and actions were fleshed out into text narrative (penned by the authors in collaboration with Wayne DeFehr and Shane Riczu). In doing so we substantially extended the interactive version of the *Little Red Riding Hood* story [3] used with the ASD [7].

Participants were randomly drawn from the Department of Psychology at the University of Alberta research pool and received a partial course credit for participating. Each participant was randomly assigned to a condition, determined by the experience manager used to manage their interactive narrative experience. New participants were assigned to each user study. The experiment lasted up to one hour after which the participants filled out a survey on their perception of fun and agency. The survey was built atop a validated instrument designed for such studies [27] and previously used to evaluate PaSSAGE [9]. We evaluated both *effectance* (i.e., agency) and *enjoyment* (i.e., fun); the latter was of interest given a potential correlation between agency and fun. The instrument provides

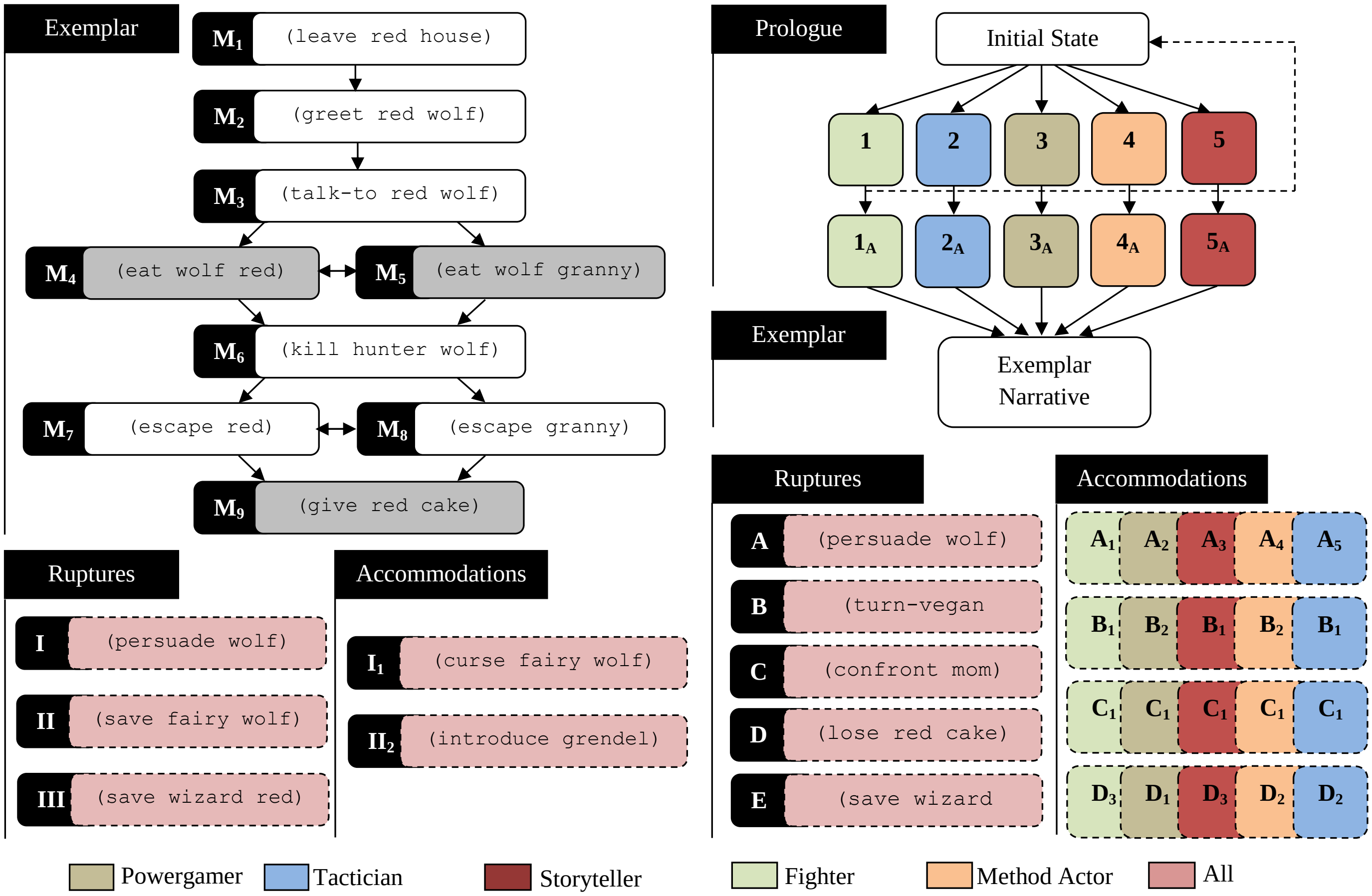


Fig. 8. **Left:** trajectories for the narrative space #1 (user study 1). **Right:** trajectories for narrative space #2 (user studies 2 and 3). **Legend:** rounded rectangles represent states and their enabling actions; the exemplar narrative has 9 states, two intermediate goals (M_4 and M_5) and a final goal (M_9). When ruptures were enabled, the narrative can be broken before M_6.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	394.91	1	394.906	5.46	0.0221
GS	321.05	1	321.052	4.44	0.0384
EM $\times$ GS	0.46	1	0.455	0.01	0.9370
Error	5495.78	76	72.313		
Total	6276.99	79			

TABLE II
ANOVA RESULTS FOR FUN IN USER STUDY 1.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	719.48	1	719.48	20.46	0.0001
GS	64.53	1	64.53	1.84	0.1795
EM $\times$ GS	7.43	1	7.428	0.21	0.6471
Error	2707.92	77	35.168		
Total	3563.28	80			

TABLE III
ANOVA RESULTS FOR AGENCY IN USER STUDY 1.

5-point Likert-scale questions to measure the respondent's perception of agency (7 questions) and fun (13 questions). To obtain the dependent variable for agency, we added up each participant's responses to the 7 Likert-scale questions (the result ranged from $7 \times 1 = 7$ to $7 \times 5 = 35$). Analogously, the dependant variable for fun ranged from 13 to 65. This allowed us to run ANOVA — a parametric test — on the two dependant variables for hypothesis testing [34]. Data of weekly gaming hours and weekly reading hours were also collected [6].

We used Analysis of Variance (ANOVA) with two factors: type of *experience manager* (EM) and prior *gaming skills* (GS). Gaming skills were included as a factor in the analysis as we felt that gamers may be conditioned by existing commercial games to expect different effects of their actions on the narrative. The inclusion of gaming skills as an analysis factor has been done in the literature [9].

Two levels of GS were assessed, *non-gamers* (gaming hours < 1) and *gamers* (gaming hours ≥ 1). *Tukey's Honestly Significant Difference post hoc* test was used when multiple test correction was needed. For all analyses, we set $\alpha = 0.05$ and verified all ANOVA's assumptions (independence of observations, homogeneity of variances, and normally distributed errors using Levine, Welch and Kolmogorov-Smirnov tests).

The participant data that was suspected to come from participants not reading carefully enough the interactive narrative were removed on the basis of the average reading speed (i.e., people reading too fast for thorough comprehension) [35, 36]. Additionally, *Tukey's Outlier Test* was used to remove any

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	27.7	2	13.848	0.22	0.8059
GS	3.01	1	3.014	0.05	0.8289
EM × GS	605.67	2	302.837	4.73	0.012
Error	4222.67	66	63.98		
Total	5053.94	71			

TABLE IV
ANOVA RESULTS FOR FUN IN USER STUDY 2 PART A.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	60.47	2	30.2335	1.13	0.3289
GS	2.3	1	2.3002	0.09	0.7702
EM × GS	102.98	2	51.4878	1.93	0.1538
Error	1791.59	67	26.7401		
Total	1949.92	72			

TABLE V
ANOVA RESULTS FOR AGENCY IN USER STUDY 2 PART A.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	101.26	2	50.6299	0.76	0.4722
GS	29.88	1	29.88	0.44	0.5057
EM × GS	19.46	2	9.7318	0.15	0.8645
Error	4335.85	65	66.7054		
Total	4557.49	70			

TABLE VI
ANOVA RESULTS FOR FUN IN USER STUDY 2 PART B.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	180.48	2	90.239	2.8	0.068
GS	0.13	1	0.1327	0	0.9490
EM × GS	62.02	2	31.0094	0.96	0.3875
Error	2193.28	68	32.2542		
Total	2385.09	73			

TABLE VII
ANOVA RESULTS FOR AGENCY IN USER STUDY 2 PART B.

outliers outside the interquartile range with a factor of 1.5.

B. User Study 1: Planning Only

Objective. In user study 1, we evaluated planning-based experience management [7] for increased perceived fun and agency. No player modelling was used, instead selecting among accommodations using ASD's *ad hoc* selector, which guides the planner to a suitable accommodation close to the exemplar narrative. We used narrative space #1 (Figure 8), with 4 possible trajectories. We feel the scale of the narrative space is sufficient given the purpose of the study (evaluating ASD) and the fact that the ASD's narrative selector is deterministic and would always select the same accommodation.

Setup. There were $n = 81$ participants (98 before outlier removal). 42 (21 gamers, 21 non-gamers) of them were assigned to the experimental condition (i.e., ruptures allowed) and 39 (23 gamers, 16 non-gamers) were in the control condition (i.e., no ruptures allowed). The results for this experiment showed higher scores for both agency ($F(1, 77) = 20.46, p = 0.0001$) and fun ($F(1, 76) = 5.46, p = 0.02$) compared to the control condition ($p < 0.05$) (Tables II and III). No interaction was found between EM and GS.

These results suggest that planning-based experience management proposed in the ASD [7] can increase the players' perception of fun and agency even in the absence of player modelling (Figures 9a and 9b respectively).

C. User Study 2-A: Planning + Player Modelling

Objective. In user study 2, we evaluated the effects of adding player modelling to planning-based experience management (i.e., our approach PAST). We used the expanded narrative space #2 (right pane in Figure 8), which now included a prologue. The purpose of the prologue was to learn the player model prior to the player entering into the main story. The prologue was built from five narrative blocks, each designed specifically to appeal to one of the five player types used in our model. The player could select an action to guide Red into an appealing block (states $1-5$ in the figure) and posteriorly confirm via another state (states $1.A, 2.A, 3.A, 4.A, 5.A$). This gave a broad set of ruptures and possible accommodations to evaluate the effects of player modeling.

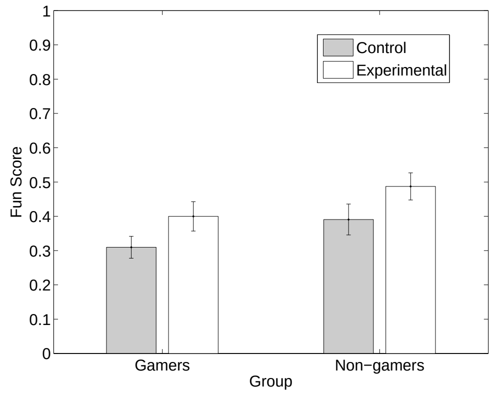
Setup. Data from $n = 72$ participants ($n = 98$ before outlier removal) were used. We had three conditions based on the experience management as follows. The experience manager in the *experimental* condition used planning and player modelling as proposed in this paper. The condition had data from 23 participants (8 gamers, 15 non-gamers). The *control* condition used the same manager but the model was taken from a participant drawn randomly without replacement from the experimental condition. This approach is known as *yoking* and was previously employed in PaSSAGE's evaluation [9]. It was meant to isolate and reveal the contribution of the player model to PAST. The control condition had 22 participants (6 gamers, 16 non-gamers). The final condition was called *exemplar* and consisted of participants who never ruptured the exemplar narrative and thus did not invoke the experience manager with its planner and player model. There were 27 participants in that condition (8 gamers, 19 non-gamers). In all conditions, the participants had the option to take ruptures.

Results. No statistically significant results were observed; however, an interaction was found for fun with ($F(2, 66) = 4.73, p = 0.012$). Tukey's HSD *post hoc* test indicated that non-gamers in the control condition perceived more fun than non-gamers in the experimental condition ($p < 0.05$). Analogously, agency showed a similar pattern but did not reach significance ($F(2, 67) = 1.93, p = 0.1538$). The findings are summarized in Tables IV, V and Figure 9.

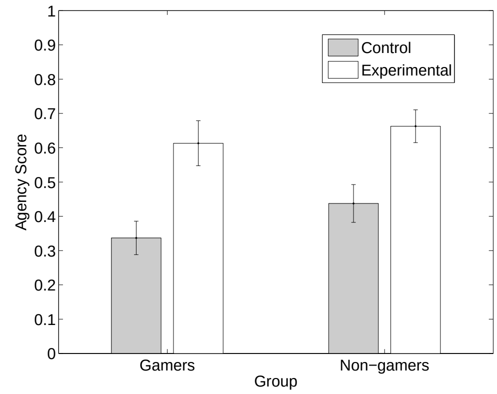
D. User Study 2-B: Planning + Player Modelling

Objective. Given the lack of statistical significance in user study 2, we decided to repeat the user study using the same setup and the same story setting.

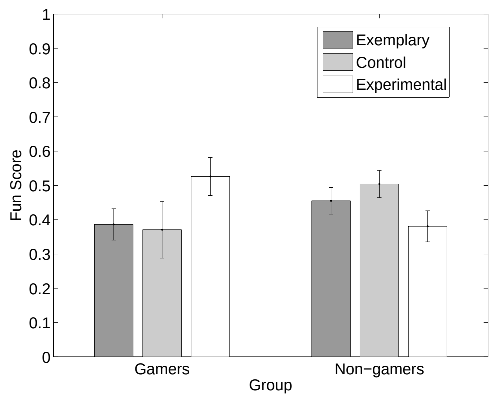
Setup. Data from $n = 63$ participants ($n = 83$ before outlier removal) was used, with this distribution: 19 participants in



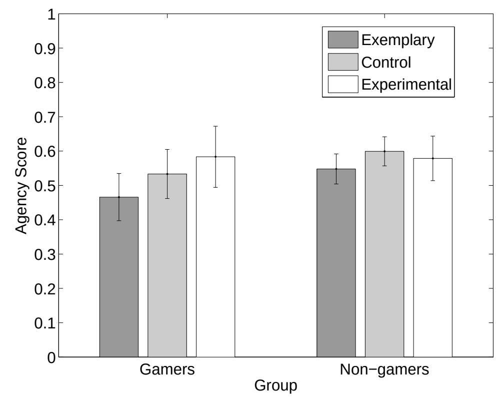
(a) User Study 1: Fun



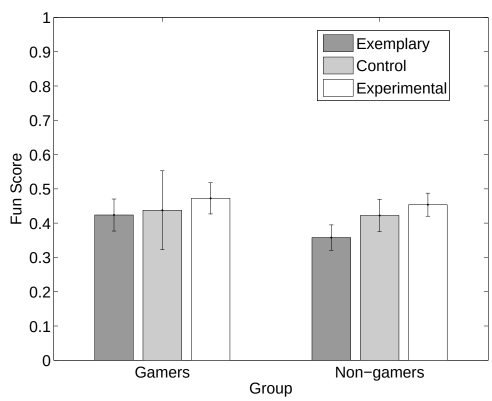
(b) User Study 1: Agency



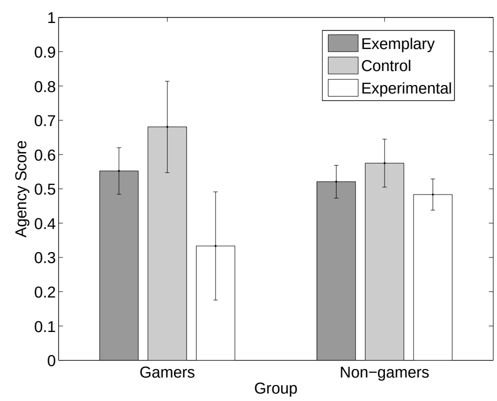
(c) User Study 2-A: Fun



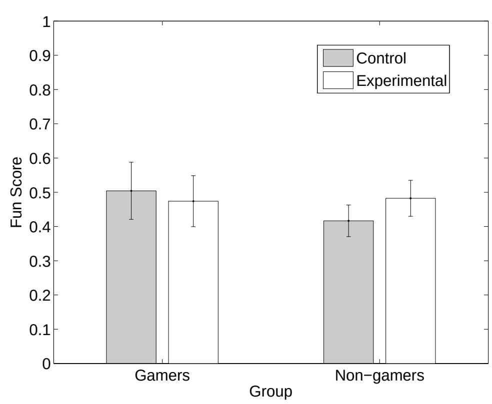
(d) User Study 2-A: Agency



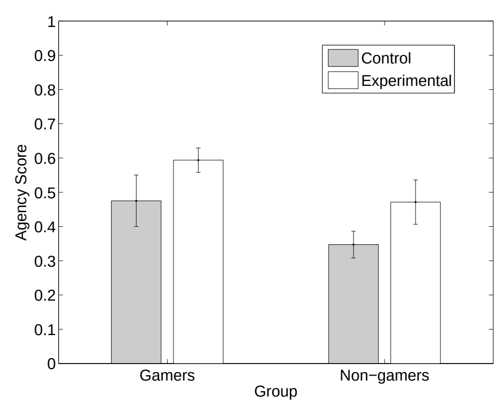
(e) User Study 2-B: Fun



(f) User Study 2-B: Agency



(g) User Study 3: Fun



(h) User Study 3: Agency

Fig. 9. Mean normalized scores and error bars in user study 3.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	4.76	1	4.75726	0.07	0.7967
GS	23.61	1	23.6143	0.34	0.5669
EM × GS	34.73	1	34.73	0.49	0.4880
Error	2113.24	30	70.4414		
Total	2204.26	33			

TABLE VIII
ANOVA RESULTS FOR FUN IN USER STUDY 3.

Factor	*Sum Squares*	*d.F.*	*Mean Square*	*F*	*p-value*
EM	55.588	1	55.5884	5.46	0.0968
GS	59.168	1	59.1682	1.84	0.0871
EM × GS	0.025	1	0.0253	0.21	0.9710
Error	567.386	30	18.9129		
Total	692.029	33			

TABLE IX
ANOVA RESULTS FOR AGENCY IN USER STUDY 3.

the experimental condition (2 gamers, 17 non-gamers), 19 in the control condition (5 gamers, 14 non-gamers), and 25 (10 gamers, 15 non-gamers) in the exemplar condition.

Results. The patterns observed in user study 2 part A were not replicated; no statistically significant results were observed, including interactions (Tables VI and VII). In addition, the means and error bars (Figure 9) show no clear trends.

A likely reason for this outcome is a severely unbalanced distribution of the story content between the experimental and the conditions. In Figure 10, the frequencies with which the participants experienced each of the 31 possible stories are shown. Despite our employment of the yoking technique, the story distribution is still unbalanced. The story experienced by the players is a factor in their reports of the perceived fun and agency since specific narrative events present in select stories may have been particularly good/bad for perceived fun/agency.

E. User Study 3: Planning + Player Modelling in a Scaled-down Narrative Space

Objective. We decided to explore the unbalanced story distribution hypothesis formulated above by repeating the studies 2-A and 2-B in a scaled down narrative space.

Setup. We scaled down the narrative space from the user studies 2-A and 2-B by allowing only a single rupture (denoted by A in Figure 8) and forced all participants to go through it. As a result, every participant ruptured the exemplar narrative, eliminating the exemplar condition of the user studies 2-A and 2-B. More importantly, the narrative space allowed for a total of 5 different narratives (versus 31 in the previous studies). We hoped that the reduction will lead to more similar distributions of the stories across the experimental and control conditions.

The number of participants was $n = 34$ ($n = 41$ before outlier removal), with 17 participants in the control condition (5 gamers, 12 non-gamers) and 17 participants in the experimental condition (4 gamers and 13 non-gamers).

Results. No significant results were observed for fun ($p < 0.05$), but a marginally significant result ($p < 0.1$) was found for agency ($F(1, 67) = 5.46, p = 0.097$). No interactions were observed (Tables VIII and IX). The content distribution in both conditions was indeed more uniform in this user study (Figure 11). Overall, positive trends were obtained as shown in Figure 9, with the means in the expected directions.

VI. DISCUSSION

In user study 1, we found evidence that planning-based experience management as proposed by Riedl et al. [7] can increase perceived fun and agency. In doing so we conducted the first formal empirical evaluation of the ASD with a user study and a validated instrument.

User study 2-A found no strong evidence of effects of player modelling and planning. However, a significant interaction was found between gaming skills and experience management for the values of fun. The gamers perception was as originally hypothesized, while the non-gamers group, a considerably larger portion of the sample, perceived more fun in the exemplar and control conditions than in the experimental condition.

In user study 2-B no clear trends were found; furthermore, the results from 2-A were not replicated. We believe this can be due to three factors. First, significantly different distributions of stories experienced in different conditions could severely affect the reported values of fun and agency. Second, this study was run during the last week of the academic term which is traditionally (albeit anecdotally) associated with less motivation in participants. Finally, given the three conditions, the sample sizes per condition were small which can jeopardize the statistical significance of the findings.

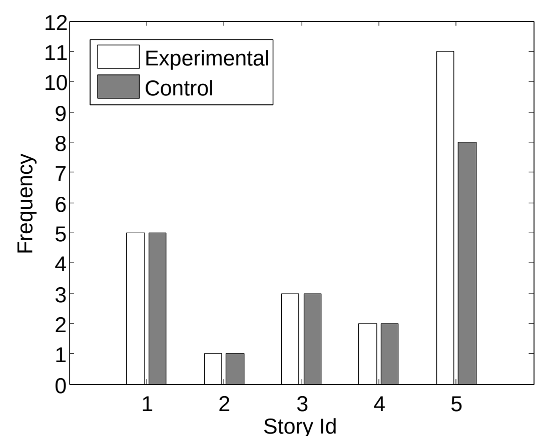


Fig. 11. Story distribution for user study 3.

User study 3 appears to confirm these factors. It had a smaller narrative space (5 instead of 31 possible unique stories) and fewer conditions (2 instead of 3). As a result, the story distributions across the conditions were better matched. The analysis found that agency was improved ($p = 0.097$) by using player modelling to select among alternative narrative accommodations computed by the planner. In other words, our approach, PAST, may improve player's sense of agency but further experimentation is needed.

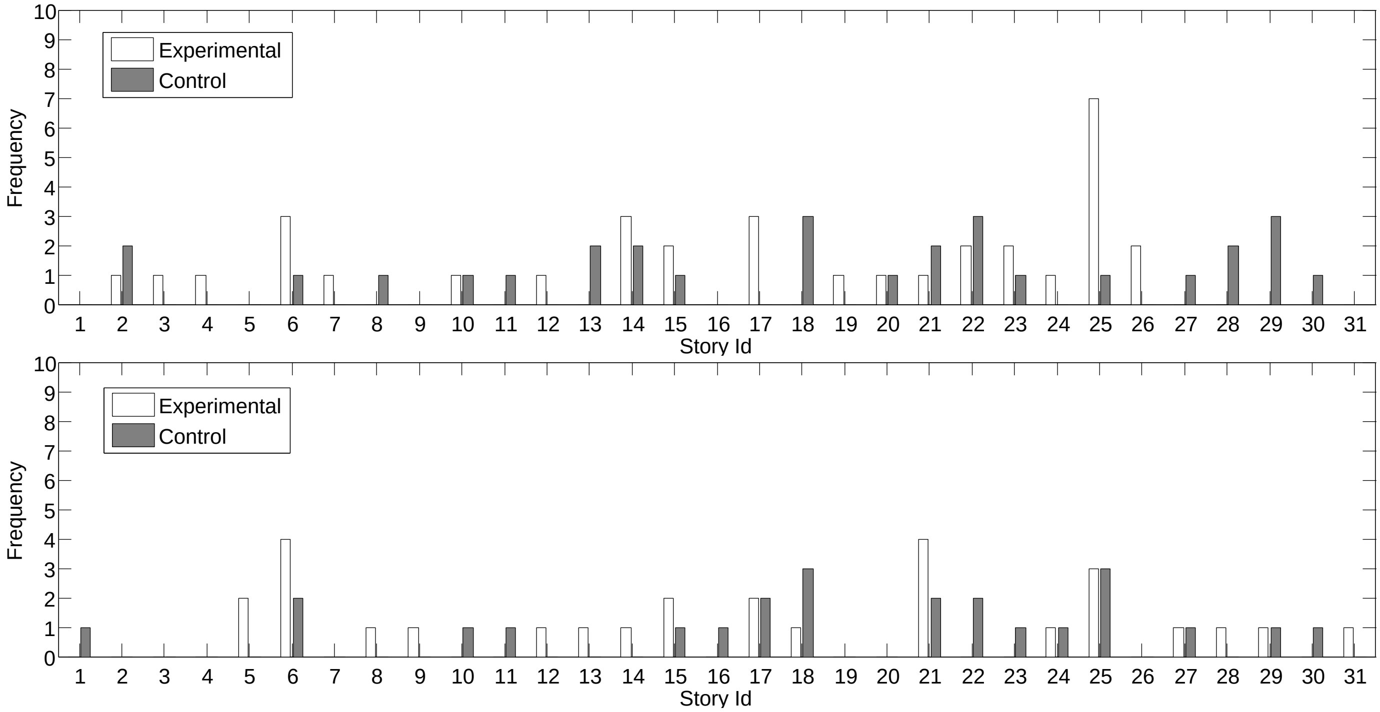


Fig. 10. Story distribution for user studies 2-A (top) and 2-B (bottom).

A. Applicability and Future Work

We expect PAST to be applicable in interactive digital experiences including commercial video games in the manner described in this paper. We also envision PAST to be an AI helper to a narrative designer as it allows to explore the narrative space and estimate the feeling of agency the different players will experience in a game. Most promising areas of the narrative space can then be fleshed out with multimedia content in the course of a game development.

Future work will study the effectiveness of our approach in larger narrative spaces and more participants to achieve statistically significant results. Additional player modelling outside of the play-style scope should also be studied. Poo Hernandez and Bulitko [37] proposed expanding our approach with explicit modelling of the player emotional state. While PAST was presented as a tool for video game developers and players, its applications to interactive learning should also be studied: interactive tutors could benefit from a modelling approach around pedagogical goals [38].

VII. Conclusion

Given a formally specified narrative domain, our approach, PAST, allows the player to rupture the original exemplar narrative without violating the authorial goals. It does so by automatically generating new narrative to accommodate the player's actions and yet satisfy the author's intentions. Furthermore, whenever several new narratives can be generated, the one that is expected to maximize the player's perception of agency is automatically selected.

This work made the following contributions. First, a seminal planning-based experience manager (ASD) was formally evaluated for the first time, with results that suggest that accommodating ruptures increases agency and fun in text-based narratives. Second, we proposed a new experience manager and found that player modelling combined with AI planning appears promising.

Acknowledgments

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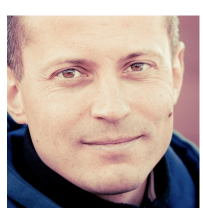

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