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Adaptive storytelling based on personality and preference modeling

Edirlei Soares de Lima[a,*], Bruno Feijó[b], Antonio L. Furtado[b]

[a] Universidade Europeia, School of Design, Technology, and Communication, Lisbon, Portugal
[b] Pontifical Catholic University of Rio de Janeiro, Department of Informatics, Rio de Janeiro, Brazil

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ABSTRACT

In almost all forms of storytelling, the background and the current state of mind of the audience members predispose them to experience a given story from a uniquely personal perspective. However, traditional story writers usually construct their narratives based on the average preferences of their audience, which does not guarantee satisfying narrative experiences for its members. When a narrative aims at providing pleasurable entertainment, having some information about the preferences of the current user for the narrative's content is vital to create satisfying experiences. This paper explores personality modeling and proposes a novel approach to generate individualized interactive narratives based on the preferences of users, which we model in terms of the Big Five factors. This paper presents and evaluates the proposed method in a web-based interactive storytelling system that explores the Little Red Riding Hood folktale. The results show that the proposed method is capable of correctly recognizing the preferences of users for story events (average accuracy of 91.9%) and positively improve user satisfaction and experience.

1. Introduction

In most cases, the narrator's success in achieving a desired impact on the audience depends strongly on the ability to accommodate different personal preferences of the individual audience members. While in traditional forms of storytelling (e.g., books, movies, and comics) authors generally have no access to this preference information, the very nature of interactive storytelling allows the system to obtain this information through the user-interaction process automatically. In this case, if the interactive storytelling system correctly infers the user's preferences, then well-suited elements of the story can be brought to the viewer's attention or even a completely different storyline can be generated to comply with the viewer's preferences.

The main question that motivates this work is: how can computer systems create interactive narrative experiences that satisfy users' preferences? We can initially divide this problem into two subproblems: (1) How can a computer system create a user model to describe the main characteristics of the user in real-time? (2) How can a computer system employ the user model to adapt narratives according to user's preferences? Arguably, a third even more important question is (3) how do user's characteristics correlate with his/her narrative preferences?

The starting point to investigate the questions above mentioned is to notice the strong relationship between personality and preferences. The following works are particularly revealing in this sense. Karumur et al. [1] correlate user preferences with personality traits in a movie recommender system. Rentfrow et al. [2] relate music preferences with people personalities. Mark and Ganzach [3] estimate the relationship between personality traits and internet use. Kraaykamp and Eijck [4] examine the impact of personality traits on media preferences (TV programs) and cultural participation (book reading and attending museums and concerts). Kuijpers et al. [5] investigate the relationships between personality traits, reading habits, and the experience of narrative absorption.

Some research works demonstrate that reader preferences can influence expectations for future narrative events [6]. Therefore, the user's personality is an essential factor to be considered when adapting narratives, because it exerts a significant influence on his/her preferences and, consequently, affects expectations about congenial outcomes. Personality is the combination of all characteristics that form a distinctive character, an individual style of thinking, feeling, and acting [7]. In this paper, we follow the tradition of descriptive personality trait models [8,9]. According to this tradition, the behavior is an integral part of the personality, and then we can consequently avoid most of the polemic questions of personality-behavior correlations (however, we recommend further reading on these questions in [10]).

To assess users' personality, researchers in psychology have developed several psychometric tests and measurement scales. Among the most widely accepted are those that follow the Big Five proposal [8].

* Corresponding author.
E-mail address: edirlei.lima@universidadeeuropeia.pt (E.S. de Lima).

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Further research works in psychology showed that if we ask human subjects a small set of well-designed questions, applied in one minute or less, then we can successfully ascertain their personality traits [11,12].

This paper explores the use of personality modeling to adapt interactive narratives according to users' preferences. We propose a novel approach to create individualized narrative experiences which consider the personality of the users in terms of the Big Five factors. In this approach, the system suggests plot events at story branching points according to the user's personality traits, after assessing these traits through a new Big Five inventory process specially tailored for gaming environments.

The input for the proposed system can be either a story with multiple branching points already predefined by the author, or a set of linear story variants from various authors with no branching points at all. By employing a method that we proposed in a previous work [13], linear variants are unified and condensed into a story network with multiple branching points. In these two types of input, we are considering a branching narrative structure, which explicitly defines all possible storylines. On the other hand, in interactive storytelling systems based on planning techniques, stories are created by the planning algorithm, guided to some extent by the user's interactions, in such a way that it is not easy (and, sometimes, not feasible) to predict all the possible storylines that can emerge. For example, the decision of removing a magic potion bottle from its usual cabinet may cause dramatic unforeseen consequences in future (possibly many events ahead), which the author has not planned explicitly. The generalization of the model we propose in this paper can handle this type of situation, in which there are no explicit branching points.

The main objective of this paper is to present our method, evaluate its precision, and assess its effects in the overall user experience. Although the basic ideas of our method were previously presented in a conference paper [14], here we expanded it with a more general approach and conducted a more comprehensive evaluation.

The paper is organized as follows. Section 2 reviews related work. Section 3 describes the plot generation method used to compose stories in our system. Section 4 presents our strategy to obtain and build a model for the personality of users. Section 5 describes the proposed method to create the preference model. Section 6 shows how the processes of adapting interactive narratives consider the personality of a user and his/her preferences. Section 7 presents an evaluation of our method, including a technical assessment and a user study. Section 8 offers concluding remarks.

2. Related work

In recent years, user modeling is usually traced back to seminal research works in the late 70 s and has mainly been using in human-computer interaction and web personalization [15,16]. More recently, machine learning has been an increasingly popular approach to user modeling [17]. Among the several application areas, we can find some implementations of user modeling in interactive storytelling systems, which we review in this section.

Barber and Kudenko [18] present an interactive story generator system that learns the personality of its users by applying predefined increments or decrements to a vector of personality traits, such as honesty and selfishness, in response to the users' decisions. Based on a similar approach, Seif El-Nasr [19] presents an interactive storytelling system where both player behavior and personality are modeled to allow users to participate in a more engaging drama. The system tracks the user's actions to adjust a vector of values representing tendencies toward character traits (heroism, violence, self-interestedness, and cowardice), via pre-specified annotations on player actions. For example, if a player chose to flee from a confrontation, the model's representation of the player's cowardice would increase.

Another interactive storytelling system that models player personality using a vector of traits is PaSSAGE [20]. The system uses player modeling to automatically learn a model of the player's preferences through observations of the player in the virtual world, and then uses the model to select the content of an interactive story dynamically. This system models the player with the help of a vector where each dimension is the strength of one of the stereotypes proposed by Laws [21]. As the player performs actions, dimensions are increased or decreased by predefined annotations on player actions. Ramirez and Bulitko [22] use this player model with a reward function in such a way that, when the system generates several narratives, the one that maximizes this function is automatically selected.

All works above share a common characteristic: they model users' personalities using vectors of traits, whose values are updated according to predefined annotations on user actions. Although the use of a vector to represent personality traits is widely accepted (even the Big Five dimensions is represented in vector format), the application of manual annotations on specific actions or events to determine how the personality traits will be updated is problematic. It requires extra authorial work and extensive studies to correctly measure the impacts of each action on the personality of users.

A different approach is explored by Sharma et al. [23], who use a database of interest-annotated logs of past users to infer the preferences of current users (a Case-Based Reasoning approach). By combining past captured narrative traces and current user survey data, they manage to create user models to dynamically determine the next plot point that is best suited to specific users. Their system uses a database of logs of the experiences that previous users had with the stories and attempts to infer the interests of its current user by matching his/her trajectory through the space of possible story events with the trajectory of similar users. One explicit limitation of their proposal is that it requires some user interactions before the system starts to have some information about how the decisions of a current user match the decisions of similar users.

Although the present work shares some similarities with this last proposal, the initial assumptions and the strategies adopted to solve the problem are entirely different. Indeed, while Sharma et al. (*op. cit.*) assumes that users with similar gameplay characteristics will have similar narrative interests, we argue that personality is a better descriptor to group users with similar preferences. Besides, we rely on machine learning techniques to find correlations between personality and user's preferences for future narrative events.

Another topic closely related with this work is the identification of personality traits according to user's choices in interactive storytelling scenarios. In this context, Paradeda et al. [24] present a method to predict user's personality traits according to the Myers-Briggs Type Indicator (MBTI) using the language of the interactive experience itself (i.e. without using questionnaires). As done in our previous work on personality modeling [38], Paradeda et al. [24] also present the user's decisions as interactive scenes that are related to MBTI questions. However, their method assumes a story that is composed only of user choices that are related with MBTI questions, without considering how user decisions and personality could be predicted in general interaction points.

Personality and preference modeling also have been explored in the context of games. Rivera-Villicana et al. [25], use a player profile to guide the behavior of a generic player model based on the Belief-Desire-Intention model of agency, aiming to simulate player's choices in game events. In a similar context, Ferro [26] conducted a study to evaluate if a player's personality type, established with the Australian Personality Inventory (API), can be used to predict the player's preference for game elements or mechanics. Although the author concluded that it is not possible to use personality types to predict the player's preferences, his research was limited to statistical data collected through surveys (i.e. no tests in practical game scenarios were conducted).

3. Plot generation from linear story variants

Our plot generation strategy is based on the reuse of already existing stories that follow the same narrative pattern [27–29]. By combining a chosen set of story variants into a network-structured pattern, we conveniently expose their coinciding, diverging, and converging subsequences of events. Consequently, we can generate new alternative versions of the story by traversing the network, besides the possibility of reproducing the original variants. The reader can find more details about this plot generation method in one of our previous work [13].

3.1. Story network

In our model, *events* are the building blocks of a story. They have the form $e_i(p^i_1, p^i_2, \ldots, p^i_n)$, where e_i denotes a class of event, and the values of the p^i_j parameters serve to characterize different instances of this class. An example of a story event is meet('Little Red Riding Hood', 'Wolf'), which is an instance of the event class *meet*(*X*,*Y*). An *event sequence S* is a time-ordered set of events, which we represent concisely as $[e_1, e_2, \ldots, e_m]$. As an example of event sequence, consider:

```
[ask_to_take('Mother', 'Little Red Riding Hood',
'cake and butter', 'Grandmother'), go('Little Red Riding
Hood', 'the woods'), meet('Little Red Riding Hood',
'Wolf'))]
```

involving three classes of events: *ask_to_take*, *go*, and *meet*.

The story network is modeled as a directed, connected, labeled graph $G = (N, E, \alpha)$, where N is a finite set of nodes, $E \subseteq N \times N$ is a finite set of edges, $\alpha{:}N \rightarrow \Sigma_N$ is a node labeling mapping, and Σ_N is a set of node labels, such that a node is associated with a story event $e_i(p^i_1, p^i_2, \ldots, p^i_n)$. Sometimes we use e_i only (i.e. with no parameters) as the node label for the sake of simplicity.

The first step to create a story network involves the transformation of the chosen repertoire of story variants into event sequences $[e_1, e_2, \ldots, e_m]$. Then, two general border events (called *begin* and *end*) are added to each variant and grouped as a network structure, in which e_i are node labels (Fig. 1).

In the next step, we transform the initial network (Fig. 1) into a reduced form called *condensed network*, by applying two basic processes of unification repetitively (called *Fusion by equality* and *Condensation by similarity*). Our previous work [13] describes these unification processes in detail. Fig. 2 illustrates the process of generating a final condensed network from an initial one.

3.2. Story domain

The story domain chosen to exemplify our interactive storytelling system is based on the folktale of Little Red Riding Hood (LRRH for short). After a brief survey of classic variants of this folktale, we selected four strikingly divergent variants that tell the little girl's story with entirely different outcomes, and we combined them into a network which happened to offer a fair number of branching nodes (i.e., a reasonable number of opportunities for user interaction).

The first chosen variant is the classic *Le Petit Chaperon Rouge* (Little Red Riding Hood), composed in France in 1697 by Charles Perrault [30]. In this variant, the little girl, going through the woods to see her grandmother, is accosted by the wolf who reaches the grandmother's house ahead of her. The wolf kills the grandmother and takes her place in bed. When the girl arrives, she is astonished at the "grandmother"'s large ears, eyes, and mouth, until she finally asks about the long teeth, whereat the wolf gobbles her up.

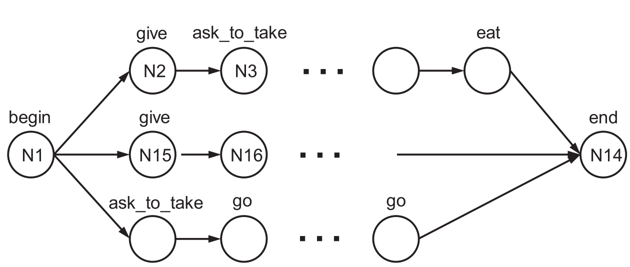

Fig. 1. Example of an initial network with 3 story variants.

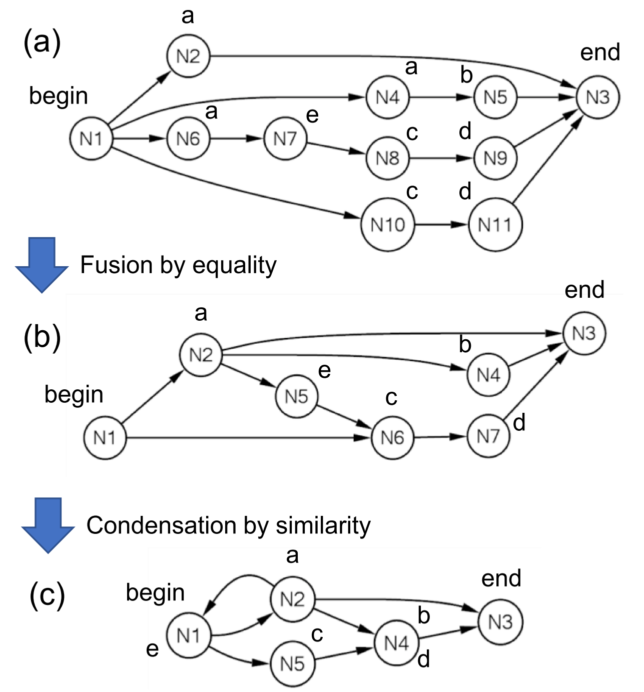

Fig. 2. An example of event unification. First, the network is transformed by *equality* (e.g., N2, N6, and N4 in Figure (a) are unified as N2 in Figure (b) because they represent the same event a). Then the network is condensed by *similarity* (e.g., the events b and d in Figure (b) are condensed into N4 in Figure (c) because they are similar and produce the same main effects).

The second variant, perhaps even more influential, is that of the Brothers Grimm (Jacob and Wilhelm), written in German and entitled *Rotkäppchen* (Little Red Cap) [31], first published in 1812. This tale complements Perrault's variant, including an imaginative episode of rescue, which is performed by a hunter, who finds the wolf sleeping and cuts his belly, allowing the girl and her grandmother to escape. The wolf has his stomach filled with heavy stones fetched by the girl, wakes up (surprisingly still alive despite the wounded belly), tries to run away, and falls dead, unable to carry the weight.

The third chosen variant is the *Conte de la Mère-grand* (The Story of Grandmother), collected by folklorist Achille Millien in the French province of Nivernais, 1870, and later published by Paul Delarue [32]. In this variant, the villain is a "bzou" (a werewolf). After killing and partly devouring the grandmother's body, he stores some of her flesh and fills a bottle with her blood. When the girl comes in, he directs her to eat and drink from these ghastly remains. Then he tells her to undress and lie down on the bed. When the question about the "big mouth" is asked, the Bzou gives the conventional reply: "All the better to eat you with, my child!" – but this time the action does not immediately follow the words. What happens instead is that the girl asks permission to go out to relieve herself, which is a ruse whereby she ends up outsmarting the villain and safely going back to her mother's home.

The last variant used to compose our story network is the *Zio Lupo* (Uncle Wolf) [33], collected by Italo Calvino. In this variant, the girl does not resist the temptation to eat and drink all that her mother was sending to Uncle Wolf in return for the loan of a skillet, offering him an ugly mess composed of donkey manure, dirty water, and lime instead. As revenge, Uncle Wolf sneaks into the little girl's house and eats her.

The condensed network for the four LRRH variants is composed of 47 nodes (story events), 5 fork nodes (branching points or interaction points), and 5 join nodes. A full resolution image of this network is fully accessible in an online document.[1] However, the reader may also have a

[1] http://www.icad.puc-rio.br/~logtell/fullnetwork1.pdf

glimpse of this network if he/she anticipates the appreciation of the bottom part of Fig. 4 in Section 5. The total number of plots that can be generated by traversing all possible paths across the network is 378, but, after grouping together the plots that, despite minor differences, comprise the same sequence of basic episodes (characteristic event subsequences: 'Preparation', 'Villainy against Grandmother', 'Girl's gluttony', 'Girl as cannibal', 'Girl fools villain', 'Villainy against Girl', 'Girl suffers retaliation', 'Safe return home', 'Rescue'), the number of fundamentally distinct alternatives is reduced to 13.

4. Personality modeling

Personality plays an essential role in influencing individual preferences for game genres [34], heroic roles in games [35], and cultural participation [4].[2] While traditional forms of storytelling cannot create individual and personalized experiences, an *interactive* storytelling system can take advantage of its communication capability to learn about the personality of its users and use this information to adapt stories according to their individual preferences.

The personality traits of an individual can be determined through a variety of tests and measurement scales. Among the most widely accepted are those that follow the Five Factor Model (also known as "Big Five") [8]. Big Five is a dimensional representation of human personality structure, which claims that, by examining five personality traits, it can suitably account for personality diversity.

The five dimensions of the human personality structure are supported by several questionnaires, inventories, and adjective rating scales designed to measure each dimension (e.g.: [12,36,37]). Personality classification is then achieved by assigning five numerical scores (one per dimension) that account for how well each factor describes the person. The attribution of the scores is typically performed with questionnaires that consider observable behavior and characteristics of the individual.

The Big Five factors (also called dimensions) are:

1. **Openness**: those who are high on this factor are imaginative, curious, and receptive to new ideas. In contrast, those who score low on this factor are indifferent and uninterested;
2. **Conscientiousness**: the ones that display a high degree of this factor are meticulous, efficient, and systematic. Who scores low is careless, chaotic and disorderly;
3. **Extraversion**: high scorers are characterized by enjoying social activities. On the opposite side, low scorers are reserved and shy.
4. **Agreeableness**: a high score on this factor characterizes helpful, cooperative, and friendly people. In contrast, low score characterizes selfish and hostile people.
5. **Neuroticism**: those who score high on this factor are emotionally unstable, anxious, and aggressive. In contrast, those who score low are well-adjusted and calm.

In this paper, we assess the user's personality with an adaptation of the method we used in previous work [38]. For the sake of a better understanding of this adaptation, we present an overview of adequate strategies for personality assessment (Section 4.1). Also, we explain how we adapted one of these strategies to the present work (Section 4.2).

4.1. Strategies for personality assessment

In psychology research, the Big Five dimensions are usually assessed through long questionnaires (60 or 44 items). However, forcing users to answer such long questionnaires in interactive storytelling applications indeed produces adverse effects in the general user experience. Therefore, a better solution is to adopt simplified questionnaires, such as the BFI-10 [11], which is one of the shortest questionnaires that, as its denomination implies, measures the scores of the Big Five factors with only 10 questions.

In BFI-10, the subject answers the following 10 questions "I see myself as someone who …": (1) is reserved; (2) is generally trusting; (3) tends to be lazy; (4) is relaxed, handles stress well; (5) has few artistic interests; (6) is outgoing, sociable; (7) tends to find fault with others; (8) does a thorough job; (9) gets nervous easily; (10) has an active imagination. The answers (L values) are given in a five-point Likert scale: 1 (disagree strongly), 2 (disagree a little), 3 (neither agree nor disagree), 4 (agree a little), and 5 (agree strongly).

For each Big Five dimension, BFI-10 calculates the average score of two poles, which correspond to a true-scored item and a false-scored item respectively. The false-scored item must be reverse scored before calculations are made, so that the values 1, 2, 3, 4, and 5 become 5, 4, 3, 2, and 1 respectively, i.e.:

$$reversed\ \ score = 6 - score \tag{1}$$

For instance, for the Neuroticism dimension, BFI-10 evaluates how much one "gets nervous easily" (say, L = 4 for question 9) and "is relaxed, handles stress well" (say, L = 5 for question 4), that is, Neuroticism would be in this case (4 + 1)/2 = 2.5 (where 1 is the reversed score of 5). The scored items for each dimension are defined as follows (where R indicates a reversed-scored item): Extraversion (6 and 1R), Agreeableness (2 and 7R), Conscientiousness (8 and 3R), Neuroticism (9 and 4R), and Openness (10 and 5R).

Another well-known short measurement scale is the *Ten-Item Personality Inventory* (TIPI) proposed by Gosling et al. [12], which also uses two items associated with each personality dimension. However, we favored BFI-10 over TIPI for the following reasons: (1) BFI-10 uses a five-point Likert scale rather than the seven-step scale of TIPI – which makes BFI-10 simpler and slightly faster (both take about a minute to complete); (2) BFI-10 uses statements representing both extremes of the same dimension clearly, which are more aligned with actions and attitudes than the more generic opposite adjectives of TIPI; (3) the BFI-10′s authors (cf. [11]) have shown that BFI-10 is psychometrically superior to TIPI; (4) BFI-10 was successfully tested in more than one idiom, besides the original version in English and German [39,40] – which suggests that BFI-10 might be particularly adequate for multi-language storytelling applications.

There are two standard methods to integrate Big Five questionnaires into interactive storytelling applications: (1) integrating the questionnaire statements into the narrative through story-related dialog choices; and (2) directly asking users to answer a questionnaire when they begin to interact with the system. In a previous work [38], we explored the first approach by creating an introductory narrative for a game with 10 story-related scenes followed by decision-making points (one for each BFI-10 question), where players make decisions that are equivalent to answering BFI-10 questions. Each scene creates a situation that stimulates users to react in a way that makes evident their answer to the BFI-10 question that defined the scene. The second approach was explored in another previous work [14], where we directly integrated the BFI-10 questionnaire into an interactive storytelling system. By asking users to fill in the BFI-10 questionnaire when they first access the system, we were able to directly establish their personality before generating the initial plot for the story. Although the second approach is a more straightforward and precise solution, it may cause adverse effects on the general user experience since the original BFI-10 statements are not directly related to the narrative. In the present work, we return to the first method, as explained in the next section.

[2] For example: TV programs, book reading, attending museums and concerts. Games are not mentioned in [38], but we can speculate on similarities with exciting or unconventional cultural activities.

4.2. A personality inventory for interactive storytelling

In our previous work on personality modeling [38], we proposed a new Big Five inventory to assess players' personalities in a game environment, which we called Big Five Game Inventory (BFGI-10). The proposed inventory is based on the structure of the BFI-10, but includes more than just questions and measurement scales. The BFGI-10 comprises 10 story-related interactive scenes followed by decision-making points (one for each BFI-10 question), where players make decisions that are equivalent to answering BFI-10 questions. Each scene creates a situation that stimulates players to react in a way that makes evident their answer to the BFI-10 question that defined the scene. All scenes are presented to players at the beginning of the game as a single interactive cutscene. At the end of each scene, the player must inform how he/she would react to the presented situation by choosing between five options, which are equivalent to the Likert scale of BFI-10, but with descriptions that are related with the scene.

In order to apply the BFGI-10 with the present interactive storytelling system, we adapted the original scenes that were designed in our previous work (a zombie survival genre) to the story domain of our current example (Little Red Riding Hood). The interactive scenes tell a short story about the events that took place the day before the traditional storyline, which include events such as the little girl going to school and interacting with her friends and family. For example, for the BFI-10 question 9 ("I see myself as someone who gets nervous easily"), we created a scene where Mia – a clumsy friend of Anne (Little Red Riding Hood) – accidentally spills sauce on Anne's most beloved blouse. After showing the scene, the system asks what the user would do if he/she were Anne. In this case, the five options that are equivalent to answer the BFI-10 question 9 are: do nothing ($L = 1$), forgive Mia ($L = 2$), ask for Mia's apologies and then forgive her ($L = 3$), get nervous and rebuke Mia ($L = 4$), and get very nervous and strongly rebuke Mia ($L = 5$).

During the adaptation work above mentioned, we fixed some bias problems found in the evaluation of our first experiment using BFGI-10. More specifically, in the present work, we avoided designing scenes in which fantasy situations or the lack of backstories of characters could influence the decisions made by the players. The full description of the BFGI-10 scenes and questions designed for the LRRH domain is available in a separate online document.[3]

After obtaining the user choices for all 10 decision-making points in the interactive scenes, the final scores of the Big Five dimensions can be calculated. In order to prepare the scores for the preference model (presented in the next section), we normalize the score bf_i of the i-th dimension in the interval [0, 1] instead of [1,5], i.e.:

$$bf_i = \frac{\bar{bf_i} - 1}{4} i = 1, 5 \tag{2}$$

where

$$\bar{bf_1} = \bar{bf}_{extraversion} = \frac{L_6 + L_1^R}{2} \tag{3a}$$

$$\bar{bf_2} = \bar{bf}_{agreeableness} = \frac{L_2 + L_7^R}{2} \tag{3b}$$

$$\bar{bf_3} = \bar{bf}_{conscientiousness} = \frac{L_8 + L_3^R}{2} \tag{3c}$$

$$\bar{bf_4} = \bar{bf}_{neuroticism} = \frac{L_9 + L_4^R}{2} \tag{3d}$$

$$\bar{bf_5} = \bar{bf}_{openness} = \frac{L_{10} + L_5^R}{2} \tag{3e}$$

and L_j and L_k^R are the Likert scale values of the true-scored item and the reversed-scored item of each dimension respectively.

5. The proposed preference model

Although the scores of the Big Five factors can be directly used to describe the personality of users, an important question remains: how personality can be related to narrative preferences? We propose the use of machine learning techniques to ascertain the preferences for the narrative content of past users based on their personality. This knowledge can then be used to predict the preferences of future users. There are two possible ways to formulate this problem using machine learning. First, we could create a model to classify user preferences for entire plots, that is, by using each possible plot as a class in a classification problem. The second formulation takes a more in-depth approach by creating several models to classify user preferences for specific story decisions. That is, each model would represent the predilections of users for the possible choices of a branching point in the story network. Again, we have a classification problem, this time using the branching points' choices as classes. We adopted the latter formulation because Section 7.2 shows that it is far superior to the first formulation based on entire plots.

Fig. 3 illustrates the proposed model to map users' personalities to narrative preferences. For each branching point in the story network (user decision points $b_1, b_2, \ldots, b_M$), we utilize an artificial neural network trained to predict the best choice to satisfy user's preferences. Distinct neural networks are necessary because each decision point involves completely different choices. For example, in the LRRH domain, the first branching point involves the decision of which path the girl should take to go to her grandmother's house (crossroad, forest, or uncle wolf's house). The second branching point refers to the reaction of the girl when she arrives at grandmother's house (lay down on the bed, question the villain, or eat something). Therefore, each neural network is trained to recognize how the personality of users affects their preferences for the choices presented at each branching point.

Our model uses single hidden layer neural networks trained by a standard back-propagation learning algorithm using a sigmoidal activation function. The input for all neural networks comprises the five scores of the Big Five factors (vector $\vec{F}$). Their output is defined by the possible choices available for their respective branching points (b_i). For example, the first branching point of the LRRH domain (decision of which path the girl should take to go to her grandmother's house) offers three possible choices: (1) crossroad; (2) forest; or (3) uncle wolf's house. Accordingly, the neural network for this branching point has three neurons in the output layer. The hidden layer is composed of 12 neurons, which was selected after testing the neural network with different numbers of neurons (from 5 to 25).

Since our method employs a supervised machine learning technique, training samples are necessary to teach the neural networks how the personality of users is related to their preferences for narrative choices. The process to recognize user's preferences is executed in real-time, but the training procedure can be performed offline.

The method to collect training samples uses the authoring tool described in [13], which was initially designed to assist professional and non-professional writers in composing narrative variants interactively. As illustrated in Fig. 4, the tool displays the network for the story domain in the bottom side of the screen. On the upper left side, the user is prompted to create his plot by making decisions at branching points. The resulting path is automatically drawn in colors over the network. As soon as the plot is ready, a storyboard is shown on the upper right-side.

The procedure to collect training samples consists of two steps. First, participants answer the BFI-10 questionnaire, which is integrated into the authoring tool and is displayed as soon as they start the application. The system then computes the scores of the Big Five factors of each

[3] http://www.icad.puc-rio.br/~logtell/interactive-quests/bfgi-10-lrrh.pdf

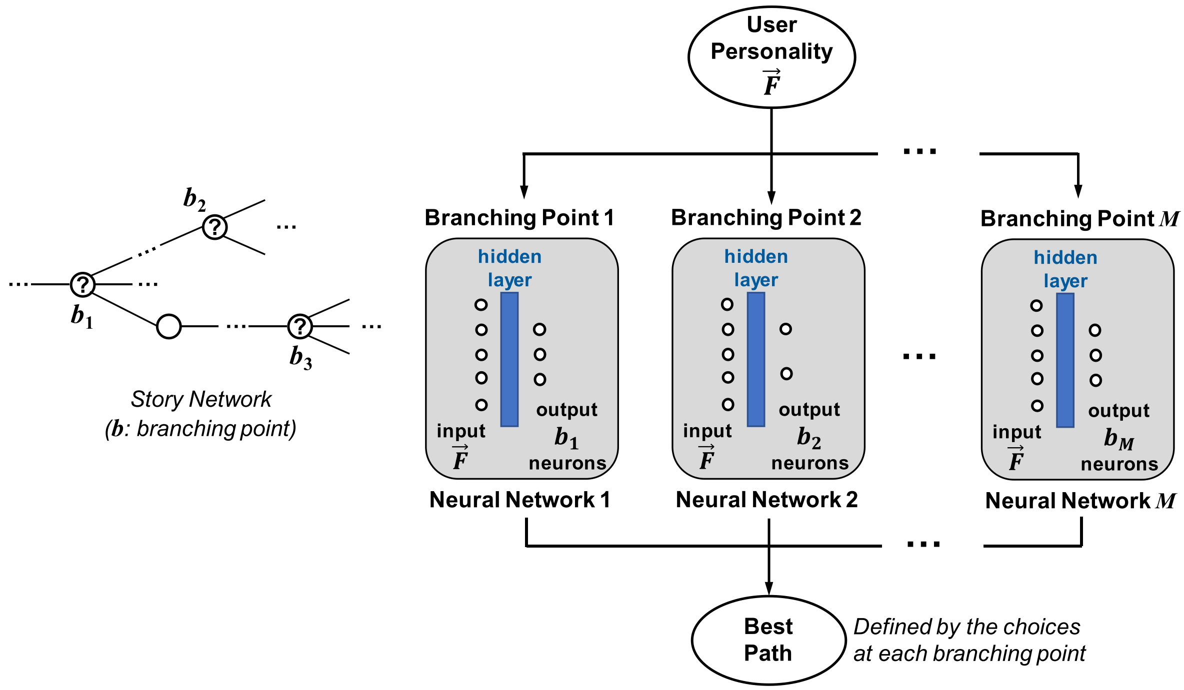

Fig. 3. Model to map users' personalities to narrative preferences: $\vec{F}$ is the vector with the five scores of the Big Five factors and b_i is the number of choices in the i-th branching point of the story network. The neural networks have only one hidden layer.

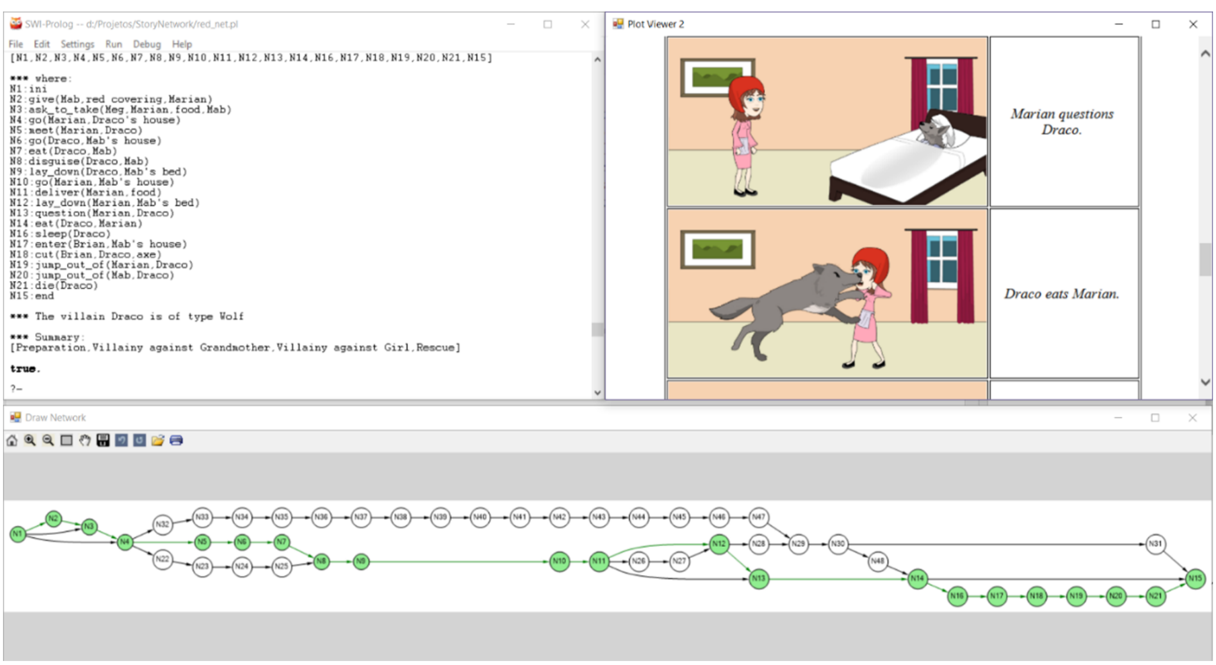

Fig. 4. Authoring tool used to collect training samples: plot creation (top left window), storyboard dramatization (top right window), and the full story network for the LRRH domain (bottom window).

participant. In the second step, the participants use the authoring tool to create a story they like. Participants can freely explore all possible storylines and take the time they need to find the one that best suits their personal preferences. After a story is composed, the system stores the final scores and the composed plot in a text file.

After collecting the data from all participants, the training datasets for the neural networks associated with each branching point are created. The training sample is the participants' scores of the Big Five factors and the respective branching point decision. Thus, each training sample comprises five numerical values (scores for the Big Five factors) and a class C (which is a number representing a choice at a branching point). These samples are assembled in training datasets that encompass all participants' decisions for each specific branching point, as illustrated in Fig. 5.

Note that not all plots include decisions for all branching points (e.g., in Fig. 3, a plot with b_1 and b_2 may not include b_3), that is, some branching points may occur only because of specific decisions in previous branching points. In Fig. 5, we indicate a missing branching point with "$-$". Therefore, a different number of training samples (n_j) is expected for each training dataset.

		Datasets						
		1	2	3	…	j	…	M
1	$\vec{F}_1$	C_1^1	–	C_1^3				
2	$\vec{F}_2$	C_2^1	–	–				
3	$\vec{F}_3$	C_3^1	C_3^2	–				
…	…							
i	$\vec{F}_i$	C_i^1	–	–		C_i^j		
…	…							
P	$\vec{F}_P$	C_P^1	–	–				
		n_1	n_2	n_3	…	n_j	…	n_M

Fig. 5. Training datasets are organized for each participant i ($i = 1, P$) and each branching point j ($j = 1,M$). A training sample is a pair ($\vec{F_i}$, C_i^j), where the first element is the Big Five factors of participant i and the second element is the choice made by the participant i at the branching point j. The number of samples of dataset j is n_j.

In our experiments, the training procedure was conducted with 58 computer science students with ages ranging from 17 to 26 years (mean of 19.1), who created a total of 8 different plots using the authoring tool (from a total of 13 possible plots). As the story network for the LRRH domain has five branching points (i.e., $M = 5$), five different datasets were created to represent the participants' decisions for each interaction point. The numbers of samples of the datasets are (we named each dataset to express the decision that users make at each branching point): (1) *girl's path*, $n_1 = 58$ samples; (2) *girl's reaction when arriving at grandmother's house*, $n_2 = 38$ samples; (3) *girl's reaction to the disguised wolf*, $n_3 = 38$ samples; (4) *wolf's action after eating the girl*, $n_4 = 35$ samples; and (5) *girl's action after escaping*, $n_5 = 50$ samples.

After creating the datasets, the neural networks can be trained offline and then used to predict the narrative preferences of new users in real-time. An evaluation of the precision and performance of the neural networks is presented in Section 7. Section 7 also discusses the statistical limitations of our experiments, followed by further discussions in the part of concluding remarks (Section 8).

6. Adaptive storytelling using preference models

6.1. Different ways of applying preferences

The personality and preference models can be used to adapt interactive narratives in a variety of ways depending on how users interact with the story. In interactive storytelling systems based on active user interactions, such as Façade [41] and PaSSAGE [20], the user is continuously interacting with the story (in a game-like manner). In this case, the preference model can be used to change how characters react to specific situations (considering how the user prefers that they react) or to bring well-suited elements of the story to the user's attention (i.e., by focusing on specific events of the ongoing story).

In systems based on object-oriented interactions [42,43], the user interacts with the story indirectly by handling objects to the characters or by manipulating elements of the virtual world. In this case, the preference model can be used to adapt the effects that objects and world changes have over the story (considering the user's preference for a set of possible effects).

Perhaps an even more intuitive application of the personality and preference model lies in interactive storytelling systems based on passive user interactions, such as Logtell [44] and Pinter [45], where users are free, at each point, to choose whether or not to interact with the story. In this type of system, an entire storyline can be generated based on the user's preferences, which allows the user to enjoy a personalized narrative without being distracted or forced to interact with the story. A negative effect of "forced interaction" can be observed in reviews of the recent Netflix movie Black Mirror: Bandersnatch (2018) [46], where many users stated that they just wanted to sit on the couch, relax and enjoy the movie, but were constantly pestered by the film asking them to interact. Although this approach goes against the own nature of "interactive" storytelling, it provides ways to cater for a broader audience that may include members that still prefer to assume more passive roles in the experience.

6.2. Applying the model to a story network

In order to validate the proposed model in the context of story networks, we developed a simple web-based interactive storytelling system that offers a storyboard-like comic strip representation for the generated stories, where each event gains graphical illustrations and speech balloons. The system runs on a web browser and allows users to freely scroll the horizontal comic strip to see and read the narrative. Comic panels that represent events situated at branching points in the story network include interactive thought balloons (Fig. 6), where users can interact and interfere in the story by choosing the decisions to be made by virtual characters (indirectly selecting different branching paths to follow). As a result of user interaction, the plot and the visual representation of its events are automatically updated to reflect the new storyline. The system was implemented in Lua using the Löve 2D framework.[4]

The interactive scenes and decision-making points of the adapted BFGI-10 were implemented and integrated into the system as interactive comic panels, where images and narration balloons are used to present the situations, and interaction balloons allow users to choose how they would react to the situations (Fig. 7). All interactive scenes are presented at the beginning of the narrative, which allows the system to assess the user's personality before generating the initial plot for the story.

After assessing the user's personality, the system uses the neural networks of the established preference model to compute the initial decisions for all branching points, that is, it selects the best branching paths based on the output of the model. Then, the initial plot for the story is generated by traversing the story network and using the predicted decisions to define the path to follow in the branching points. In this way, the default story presented to users when they first access the system will be the one that best seems to match their personal preferences for narrative content. Still, they are freely allowed to interact and explore other possible storylines when desired.

7. Evaluation and results

In order to evaluate the results produced by applying our method, we performed three tests: (1) An evaluation of the *personality model*, with the purpose of verifying how well the modified BFGI-10 replicates the results of BFI-10 in a storytelling application; (2) An evaluation of the *preference model*, for assessing the accuracy and performance of the Neural Networks used to recognize the users' preferences for narrative events; and (3) A user evaluation test to check the overall *user experience* provided by our method from a Human-Computer Interaction (HCI) perspective.

[4] https://love2d.org/.

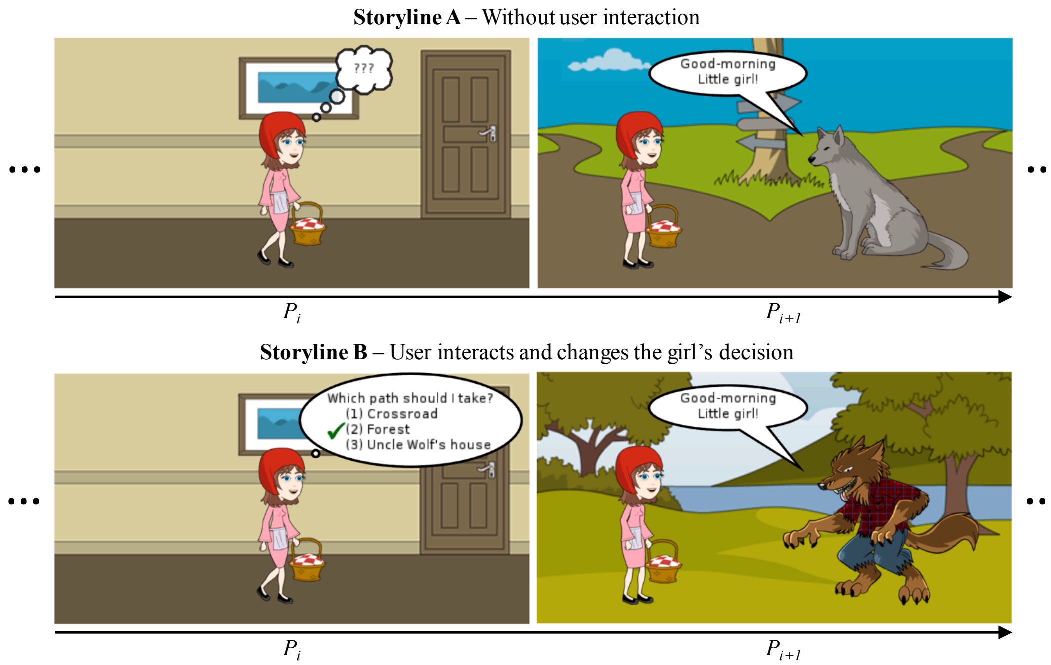

Fig. 6. User interaction process: by clicking on the thought balloon, the user can change the decision made by the virtual character.

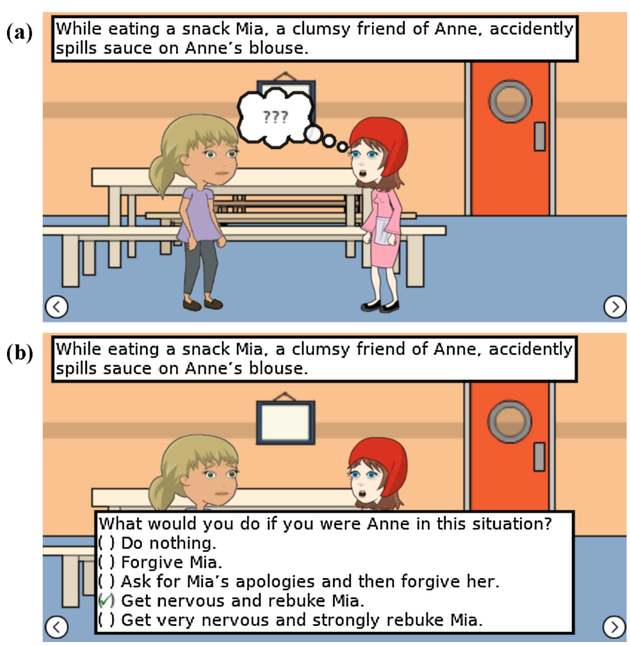

Fig. 7. BFGI-10 scene: (a) a situation is presented to the user; (b) the user interacts and decides how he/she would react to the situation.

7.1. Personality model evaluation

To evaluate the personality model, we performed a correlation analysis between the modified BFGI-10 and the BFI-10 questionnaire. With this test, we aim at evaluating: (1) how well the proposed interactive scene questions represent the BFI-10 scales; (2) how well the scenes create the right situations to support the decision-making process; and (3) whether or not the users react to the situations presented in the interactive scenes in ways that are consistent with their real-world tendencies.

The test was performed in conjunction with the user experience test (described in Section 7.3), where 56 volunteers tested our system. While the participants were interacting with the BFGI-10 scenes, the system automatically recorded the users' choices for each decision-making point. After completing the interview for the user experience test, the participants were asked to fill out the traditional BFI-10 questionnaire. At the last phase, the participants were interviewed and inquired about possible contradictions between their choices in the decision-making points and the BFI-10 questions.

On average, users spent 5.5 min (standard deviation of 1.1) interacting with BFGI-10 scenes. As expected, the traditional BFI-10 questionnaire was completed in less than a minute (average of 58.3 s).

The results of the test are shown in Fig. 8, where each bar represents the *root-mean-square error* (*RMSE*) calculated according to the participants' answers to the BFI-10 questions (observed values) and their answers to our BFGI-10 interactive questions (predicted values), both defined in a Likert scale ranging from 1 to 5. Although there were some differences between participants' answers to the questionnaires, the *RMSE* was relatively low (considering that the RMSE ranges between 0 and 4) and for the most part resulted from small divergences in the Likert scale levels (e.g. some participants who chose an alternative equivalent to "disagree strongly" in the game scene sometimes chose

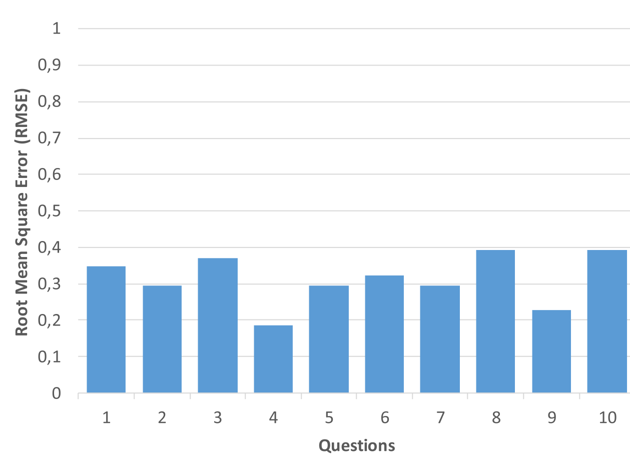

Fig. 8. Average root-mean-square error (*RMSE*) between participants' answers to the BFI-10 questionnaire (observed values) and their answers to our BFGI-10 interactive questionnaire (predicted values).

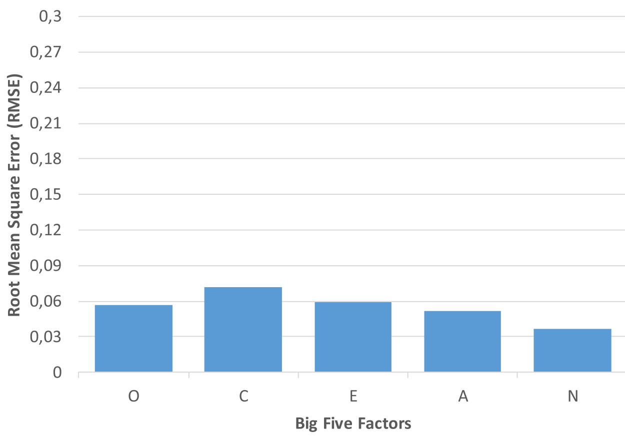

Fig. 9. Average root-mean-square error (*RMSE*) for the computed scores of the Big Five factors between the BFI-10 and BFGI-10 tests (Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N)).

"disagree a little" in the BFI-10). Another excellent result was the perfect match between the answers of 35 subjects (60.34% of the participants) to the two questionnaires.

In order to evaluate how much the differences between participants' answers to the BFI-10 and BFGI-10 tests affect the final scores of Big Five dimensions, we calculated the scores for both questionnaires and then computed the *RMSE* of each dimension. The results of this test are shown in Fig. 9. As we can observe, the final *RMSE* is relatively low (less than 0.08) in all dimensions, which is a promising indication of the accuracy of the personality model.

In order to analyze the personality variety of the sample and thereby confirm the accuracy of the personality model, we checked if the results from the BFI-10 test exhibited a minimum of personality diversity from two points of view. First, we verified if the five personality traits for any pair of users were significantly different. For this verification, the distance between two sets of values was calculated as being the *root mean square difference*, that is:

$$distance(i, j) = \sqrt{\left(\sum_{k=1}^{5} (p_k^i - p_k^j)^2\right)/5}$$

where p_k^i is the k-th factor of user i and p_k^j is the k-th factor of user j. Our sample exhibited all distances between 0.12 and 0.76, which is an indication of diversity. From a second viewpoint, we calculated the coefficient of variation for each Big Five factor:

$$V_k = \sigma_k/\mu_k$$

where σ_k is the sample standard deviation and μ_k is the mean of the k-th factor observed for all users. The coefficient of variation is a measure of the variability of the data around the mean, which is a dimensionless value. In our sample, V_k was between 38.3% and 45.3% around the mean, for the 56 users and the 5 factors – which is another indication of personality diversity amongst the users. Table 1 shows μ_k and V_k for the five factors and Fig. 10 shows the sets of scores for the factor with minimum value of V_k (Openness) and the maximum V_k value (Neuroticism). Furthermore, the means for the five factors are around 0.5, which also confirms the good personality variety of the sample.

Table 1
Mean and coefficient of variation for the five factors (Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N)).

		O	C	E	A	N
Mean	μ	0.49	0.54	0.46	0.50	0.47
Coefficient of Variation	V	38.3%	40.7%	40.2%	41.3%	45.3%

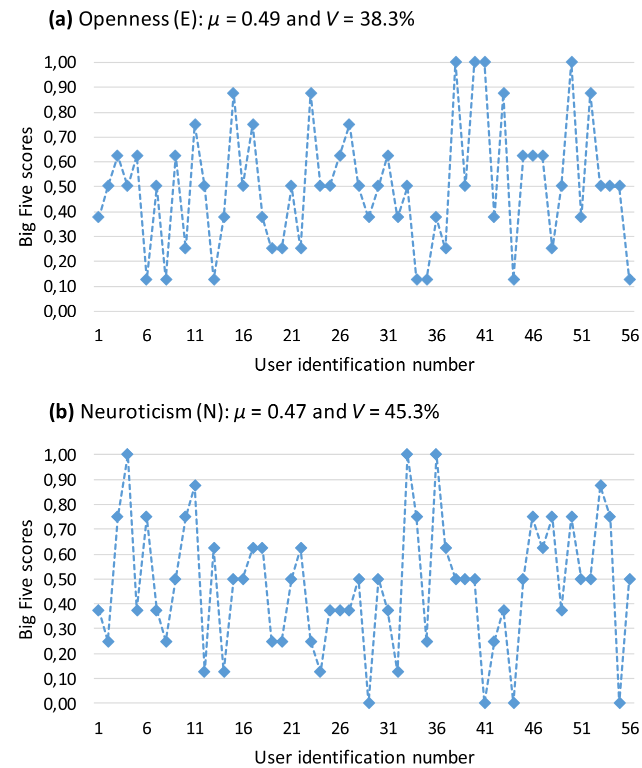

Fig. 10. (a) Openness scores for 56 users (minimum V value); (b) Neuroticism scores for 56 users (maximum V value).

7.2. Preference model evaluation

As anticipated in Section 5, there are two possible approaches to create a model to map the personality of users into preferences for narrative events: (1) by classifying the user's preferences for entire plots; or (2) by classifying the user's preferences for specific story decisions. In order to evaluate and compare these approaches, we performed two tests: (1) a precision test to check the accuracy of the model; and (2) a performance test to evaluate the real-time performance of the neural networks used by the model. For both models, we used the data collected from 58 users obtained through the procedure to collect training samples described in Section 5.

For Model 1 (to classify the user's preferences for entire plots), we grouped the samples of users that created equal plots, that is, we assigned a unique class label to all samples that represent the same plot. In our experiment, the 58 users created a total of 8 different plots. Thus, the dataset for this model comprises 58 samples of 8 classes, where each sample includes the user's scores for the Big Five factors (feature vector) and a class representing the plot created by the user.

For Model 2 (to classify the user's preferences for specific story decisions), we jointly considered the users' scores of the Big Five factors and the users' decisions for each branching point, and then stored this information in separate datasets (one for each branching point). Therefore, each sample comprises the user's scores for the Big Five factors (feature vector) and a class that represents a choice at a branching point. As the story network for the LRRH domain contains 5 branching points, 5 different datasets were created for Model 2 (see Fig. 5).

In order to evaluate the precision of the models, we used the datasets of both models to train and test the neural networks. First, we divided the datasets into training and testing sets (66% of the samples were used for training and the remaining samples were used for testing). Next, we trained the neural networks of both models with the training sets and used them to predict the plot for the samples of their respective testing sets. Then, we compared the entire plots and the

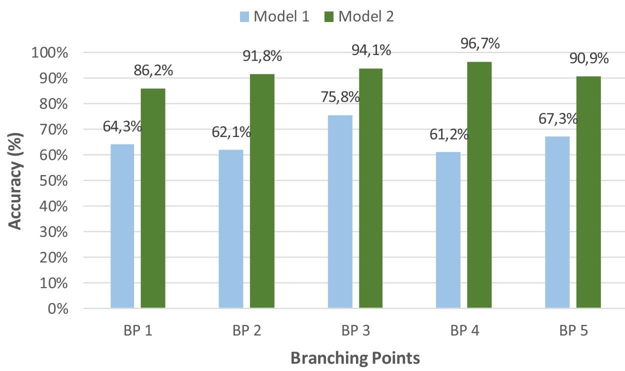

Fig. 11. Average accuracy of the models (Model 1 and Model 2) for each branching point of the story network (BP 1 to BP 5).

individual decisions at branching points generated by each of the two approaches (for Model 2, we combined the output of all neural networks to compose the full plot; and for Model 1, we divided the full plots into individual decisions at all branching points). Following a 10-fold cross-validation strategy, this process was repeated 10 times (varying the samples used for training and testing) and then the average accuracy was calculated.

The results of the precision test are shown in Fig. 11, where the bars represent the average accuracy of the models (Model 1 and Model 2) for each branching point of the story network (BP 1 to BP 5). The results indicate that Model 2 is far superior to Model 1, being able to correctly recognize the preferences of users for all story decisions in most of the cases (overall average accuracy of 91.9%). Similar results are obtained when comparing the full plots produced by the combination of all story decisions: average accuracy of 39.3% for Model 1 and 81.3% for Model 2.

To evaluate the computational performance of Model 2, we computed the average time to: (1) train all five neural networks of our model; (2) load precomputed models of all five neural networks that were created offline during the training process; and (3) predict a story path using the neural networks (five decisions). Each test was performed 100 times and then the average time was calculated. The equipment used to run the experiments was an Intel Core i7 7820HK, 2.9 GHZ CPU, 16 GB of RAM using a single core to process the neural networks.

The results of the performance test show that the average time required to train all neural networks is 663.48 *ms* and the process of loading the precomputed models requires 1.03 *ms*. The average time required to predict a story path using the neural networks is 0.04 *ms*. It is important to notice that the training process is performed offline and the storytelling system only needs to load and use the precomputed models. These results confirm that the proposed method can be applied in real-time interactive storytelling applications without affecting the performance of system.

7.3. User experience

In order to evaluate how much our method affects the overall user experience, we conducted a user evaluation test with 56 volunteers (17 Design students and 39 Game Development students). Forty-three subjects were male and fifteen female. Ages ranged from 17 to 25 years (mean of 20.2). Fifty-two of them play video games at least weekly. Twenty-nine of them had previous experience with interactive storytelling systems.[5]

For the experiment, we created two versions of our comics-based interactive storytelling system: *V1*, which uses our method to select the default story path (i.e., the system automatically selects the path in the absence of choice made by the user) based on the output of the personality and preference models; and *V2*, which randomly selects the paths at branching points. In both versions, we tracked the number of interactions in which users changed the default story paths as they progressed through the story for the first time, as well as the total number of interactions of the entire session (as the users are free to scroll back and try out a new path at any time). We hypothesized that subjects testing *V1* should perform fewer interactions than those using *V2*, since the choices of the former were expected to coincide with those predicted by our method.

The subjects were divided into two groups: 28 of them were arbitrarily selected to use V1, and the remaining 28 participants interacted with V2. Before testing the system, all subjects answered a basic demographic questionnaire and then were asked to interact with the system freely. To avoid biased decisions, we did not mention to participants that the system was measuring their personality. After using the system, all participants filled out a questionnaire with 30 questions derived from the IRIS Evaluation Toolkit for interactive storytelling [47,48], with which we aim to evaluate the system usability, user satisfaction, and user experience (flow, enjoyment, and curiosity). Each statement was given on a five-point Likert scale ranging from “strongly disagree” (1) through “neutral” (3) to “strongly agree” (5). After completing the questionnaire, the subjects were interviewed about their experience.

On average, each session of *V1* lasted 20.3 min (standard deviation of 3.5), and each session of *V2* lasted 22 min (standard deviation of 4.2). Table 2 shows the statistical data of the tracked user interactions in both versions of the system. As can be noticed, our initial hypothesis was confirmed, because the subjects testing *V1* performed clearly fewer interactions as they progress through the story for the first time (1st Pass Interactions). We observed a reduced number of interactions even when the entire session is considered (Total Interactions), which includes interactions done by curious users trying different paths after completing the story for the first time.

Fig. 12 summarizes the results of the questionnaire. As can be noticed, both V1 and V2 received similar grades for system usability, probably because both versions share the visual interface and interaction method. Since the IRIS Evaluation Toolkit measures usability by how easy it is to handle the system, similar scores were already expected in this regard. However, when comparing user satisfaction with user experience, *V1* received higher grades for both topics. In the IRIS Evaluation Toolkit, user experience is measured in terms of flow (how engaged users are in their activity), enjoyment (how pleasurable the experience is) and curiosity (how intense is the users’ desire to progress through the story and try out other possibilities). On the other hand, user satisfaction is determined by how closely the system capabilities meet the users’ expectations. By analyzing the quantitative data, it appears that adapting the default story presented to users according to their personality and preferences positively improved the overall experience.

As far as the interviews are concerned, none of the participants declared that they noticed the effects of their personalities or preferences in the first story that they visualized (they thought that it was the default story). When participants who tested *V1* were questioned why they did not change the default branching paths as they progressed through the story for the first time, 21 participants (75%) declared that the default options were already the ones they would choose; and 7 participants (25%) stated that they wanted to know how the default story would end before interacting. The participants that interacted and changed the default options, as they progressed through the story for the first time (only 5 participants changed 1 of 5 possible branching points), stated they preferred to try out the option they chose instead of the default one.

In terms of general user experience, twenty-four of the participants (85.7%) that tested *V1* reported during the interview only positive

[5] We are not considering games as interactive storytelling systems.

Table 2
Statistics of user interactions in both versions of the system (*V1* and *V2*). The column "1st Pass Interactions" represents user interactions in which the user changes the default story paths (while they were progressing through the story for the first time). The column "Total Interactions" represents the user interactions for the entire session (which includes first pass interactions and additional interactions done by users trying different paths after completing the story for the first time).

	1st Pass Interactions		Total Interactions	
	V1 (adapted path)	V2 (random path)	V1 (adapted path)	V2 (random path)
Minimum	0	0	3	4
Maximum	1	4	9	11
Average	0.20	1.41	5.58	6.51
Standard Deviation	0.40	1.03	1.56	1.84

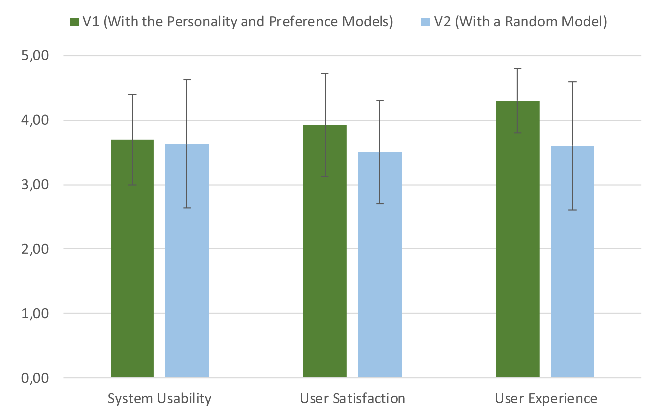

Fig. 12. Average and standard deviation of questionnaire topics for the two versions of the system (*V1* and *V2*).

feelings and effects resulting from the experience (e.g., enjoyment, excitement, pleasure, curiosity). Four (14.3%) mentioned some negative feelings (boredom and frustration), which originated from not liking the story, considering it too childish, or wanting more freedom and interaction options. In comparison with the group that tested *V2*, seventeen of them (60.7%) mentioned only positive feelings (similar to those reported by *V1* users) and eleven (39.3%) revealed some negative feelings regarding the story quality/genre, lack of interaction freedom, and expectations for a more game-like experience.

8. Concluding remarks

Storytelling is a universal social phenomenon, like music. Many questions arise concerning such an essential human activity. In particular, how we can improve people's experience in listening, watching, and interacting with stories is a complicate question, with no consensual answer. In this paper, we scratched the surface of this intriguing issue by examining user preferences in interactive storytelling. We presented a new approach to create personalized narrative experiences based on the personality of individual users. The proposed method can adapt interactive narratives according to the users' preferences for narrative events, which enhances the system's ability to deliver customized narrative experiences. Besides, it also caters for passive users, who can enjoy their favorite plot without being forced to make decisions during the story.

The results of user evaluation tests suggested that our method can improve the general user satisfaction and experience. Although the study involved a small number of participants, it provides a good indication that adapting the default story presented to users according to their personality and preferences significantly improves the overall experience.

The study of human personality has been the focus of many philosophers and scientists throughout centuries. Today, the Big Five model stands as a widely accepted way to capture and represent the main traits of human personality, having been validated across different languages and cultures [49]. We felt thus justified, in the present work, to adopt the Big Five model, and combine it with Neural Networks to directly relate personality traits with narrative preferences.

We are continuously trying to extend our work by borrowing from other possible approaches to obtain user preferences in narrative domains, particularly those centered on attempts to classify personality types. On this matter, a recent scientific work by Gerlach et al. [50] applied clustering techniques to analyze the personality of more than 1.5 million participants, which resulted in the identification of four distinct clusters of personality types: average, reserved, self-centered, and role model.

Since the work of Gerlach et al. [50] represents a promising result for psychology research, we performed a preliminary experiment to verify how well the proposed personality types could be related with user preferences for narrative events. By using the approximate clustering information provided by Gerlach et al. [50], we classified the personality types for all users of our training dataset (58 users). Then, we tried to find a correlation between the personality types and users' preferences for the decision-making points of our story. However, no significant relationship between the four personality types and user preferences was found (the results were similar to what would be produced by a random model). Therefore, we are led to suspect that such broadly encompassing personality types are too generic to account for the individual users' preferences for narrative events. However, we are aware that a more in-depth investigation is required to reach a more reliable conclusion.

On the other hand, although our method presented good results in the LRRH domain, some limitations must be pointed out. First, considering only the experiments conducted in the course of this work, we cannot guarantee that our model can achieve the same success when trying to correlate users' personalities with all possible interaction choices in all story domains. Testing the applicability and extensibility of our method to other story domains and contexts and incorporating other features that may prove necessary for this purpose, represents a paramount commitment in our current research agenda. Another immediate concern is that we have relied on a small and homogeneous sample (young university students as research subjects). Future work is needed to use a larger and more representative sample, representing a broader range of ethnic and socioeconomic groups.

Apart from the application and validation of our method in other story domains, another promising future work that caught our attention is the automatic extraction of the Big Five factors from the user's decisions in the story. Since we were able to use the values of the Big Five factors to predict user's preferences for interaction choices, it might be possible to apply a regression algorithm to estimate the values of the Big Five factors for a user based on his/her interactions at the decision-making points. In this way, the personality model could be automatically created by the system without using a personality inventory. Furthermore, this would allow psychology researchers to use the storytelling application to assess personality traits without relying on long questionnaires.

Lastly, all and all, we firmly believe that interactive narratives that automatically adapt their content to individual preferences reduce the gap between linear storytelling and interactive storytelling. This approach enables passive and active users to enjoy personalized experiences, increasing their engagement and encouraging them to progress in the ongoing story.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.entcom.2020.100342.

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