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Adaptive virtual reality horror games based on Machine learning and player modeling

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ABSTRACT

Fear is a basic human emotion that can be triggered by different situations, which vary from person to person. However, game developers usually design horror games based on a general knowledge about what most players fear, which does not guarantee a satisfying horror experience for every-one. When a horror game aims at intensifying the fear evoked in individual players, having useful information about the fears of the current player is vital to promote more frightening experiences. This work presents a new method to create adaptive virtual reality horror games, which combines player modeling techniques and an adaptive agent-based system that can identify what individual players fear and adapt the content of the game to intensify the fear evoked in players. The main contributions of this work are: (1) a new method to identify individual player's fears using only gameplay data and machine learning techniques; and (2) a new agent-based adaptive game system that can track the horror intensity experienced by players and moderate the use of the horror elements feared by individual players in the game. The results show that the proposed method is capable of correctly identifying players' fears (average accuracy of 79.4% for new players). In addition, results of a user study and statistical significance tests (ANOVA and post-hoc analyses) suggest that our method can intensify the fear evoked in players and positively improve immersion and flow.

1. Introduction

Fear can be depicted as an emotion or reaction to the anticipation of threatening or painful situations [1]. In general, fear arises when the subject is facing a threat (real or imaginary). Damasio [2] upholds that the human brain possesses mechanisms for the recognition of harmful circumstances or threats. Once they are identified, the brain releases adrenaline, dopamine, dilates the veins and pupils, to prepare the body to flee or to fight against the detected menace. Damasio names this state as the "primary emotion" of fear. Furthermore, he also defines a "secondary emotion" that is more private and intimate [2]. While the primary emotion is natural and instinctive, the secondary arises from the negative experiences of each person. A threat or the awareness of a threat, can also arise from something that is not understood or imaginary. On this subject, Freud [3] places the threat or strange as something that was recognized, but now is unusual, or even threatening, causing therefore the sense of fear.

When analyzing fears, it is important not only to consider Freud's vision on terror and emotions, but also consider more recent theories about how the evolution of the species shaped and transformed our fears and anxieties. This evolutionary perspective on terror and emotions is exploded by Mathias Classen in his book "Why Horror Seduces" [4]. The main assumption is that with the evolution of the species, the objects of fear and anxiety that no longer represent a threat to us today, continue to unconsciously provoke fear in us. For example, although it is irrational in the urban world for people to be afraid of carnivorous predators or poisonous snakes, it is certain that such fear or anxiety exists. The evolutionary fear theory tells us that these were fears that grew and evolved within our genes for thousands of years. This is an important concept for horror writers, because by realizing this, they can achieve larger audiences for their works by exploring fears that have been "imprinted" in our genes for millennia, in addition to the common fears that can be located within a few biologically constrained categories or domains.

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Although fear is typically considered an unlikable feeling, it can be used for entertainment purposes. In the last decades, the game industry has widely explored players' fears in horror games. With the advent of emergent technologies, such as virtual reality, new techniques to use horror for entertainment have emerged. Due to its immersive capabilities, virtual reality is able to induce strong emotional responses in players that are comparable to those that occur in real scenarios [5,6,7]. Such a characteristic is useful for the treatment of phobias and anxiety disorders in serious applications [8,9], but can also be used to maximize the sense of fear in horror games [10].

Horror games are designed to provoke fear in players. Although there are similarities in physiological fears across humans [11], the situations that can trigger fear in players vary from person to person. Still, game developers usually design horror games based on a general knowledge about what most players fear, which does not guarantee a satisfying horror experience for every-one. In this context, the concept of adaptive games stands out. According to Streicher and Smeddinck [12], adaptive games "can react to the player and the respective individual prior experience or background by offering context-adaptive modifications". Generally, adaptive games rely on a player model to represent the characteristics and preferences of players, which is then used by an adaptive system to adjust gameplay variables according to player's preferences or abilities [13]. Although it is especially rare to see the use of adaptive game technology in commercial games, there are some very successful examples, such as Left 4 Dead (Valve, 2008), which dynamically manages the pace and difficulty of the game according to the emotional tension of players. Another famous example is Resident Evil 5 (Capcom, 2009), which employs heuristics to optimize the difficulty of the game according to individual player's abilities. Even though adaptive games have been extensively explored by academic researchers, there is a lack of techniques to adapt the content of horror games according to individual player's fears (see Section 2 for a detailed literature review on player modeling and adaptive horror games).

The main research question that motivates this work is: how can virtual reality games create adaptive horror experiences that explore the individual fears of players? We can initially divide this problem into two subproblems: (1) How can a computer system create a model to identify player's fears? (2) How can a computer system employ the fear model to adapt games according to the individual fears of players? Arguably, a third even more important question is (3) can adaptive virtual reality games balance horror and entertainment to provide players with a scary but still satisfying and entertaining experience?

With these questions in mind, we propose in this work a new method to create adaptive virtual reality horror games. The proposed system comprises two components: (1) a fear model, which uses machine learning and player modeling techniques to identify what players fear in a virtual reality horror game; and (2) an adaptive agent-based system, which uses the knowledge of the fear model and a dramatic pacing algorithm to adapt the content of the horror game in order to intensify the fear evoked in players.

This work is an extension of our paper "Towards the Design of Adaptive Virtual Reality Horror Games A Model of Players' Fears Using Machine Learning and Player Modeling" published in the *XIX Brazilian Symposium on Computer Games and Digital Entertainment* (*SBGames 2020*), where we originally presented the method to identify players' fears in a virtual reality horror game [14]. In the present work, we extend our method to support the actual application of the knowledge represented in the fear model to adapt the content of horror games (see Section 5). This article also presents a user study to evaluate the impacts of the proposed method in the overall game experience (see Section 6).

The main contributions of this work are: (1) based on the hypothesis that players who fear a certain horror element have a similar in-game behavior when playing virtual reality horror games, we present a new method that uses a machine learning algorithm to find behavioral patterns in past gameplay data, and therefore identify what new players fear; and (2) by combining the fear model with an agent-based architecture, we propose a new adaptive game system that uses specialized algorithms to track the horror intensity experienced by players, and a Finite State Machine to moderate the use of the horror elements feared by individual players in the game. By evaluating the proposed system in a user experiment and analyzing the results through statistical significance tests (ANOVA and post-hoc analyses), we found that adapting virtual reality horror games according to individual player's fears can intensify the fear evoked in players and positively improve immersion and flow.

The text is organized as follows. Section 2 presents related work. Section 3 describes how fear is explored in games and offers an overview on the main horror elements commonly used to scare players in horror games. Section 4 describes the proposed model to identify players' fears. Section 5 presents the new method to adapt the content of horror games using the fear model. Section 6 describes the evaluation of our method. Section 7 offers concluding remarks.

2. Related work

There are several previous works on adaptive and affective games that explore topics related to this work. Therefore, in the next subsections, we review the main approaches used in previous works to create general player models for adaptive games (Section 2.1), including specific solutions for horror games (Section 2.2).

2.1. Player modeling

The concept of player modeling emerged in the 90 s with notion of player types. In 1996, Richard Bartle [15] proposed his famous four player types (Achievers, Socializers, Explorers, and Killers) as one of the earliest attempts to represent player models. Following Bartle's work, Bateman and Boon [16] extended the original model using the Myers-Briggs personality indicator [17] to categorized players into four classes: Conqueror, Manager, Wanderer and Participant. Later, by empirically grounding Bartle's original model, Yee [18] found that the motivation of player can be described by three main components: achievement, social, and immersion. In a more recent work, Nacke et al. [19] proposed seven player archetypes taking inspiration from neurobiological research: Seeker, Survivor, Daredevil, Mastermind, Conqueror, Socializer, Achiever. Although player types were proposed as an early attempt to model players, type-based approaches are very limited as they provide only a superficial information about the player, which does not take into account players with blended types and transitions among types that can occur during a game [20].

Based on the seminal ideas of Richard Bartle, several other approaches for player modeling and profiling have been proposed over the years. Their applications include the use of player models for personalized content generation, playtesting analysis, game balancing, game authoring, and different ways of adapting player experiences. Similar to our method, most of these approaches rely on the use of machine learning techniques to create player models. The use of clustering and classification techniques to dynamically adjust the difficulty of a shooter game is explored by Missura and Gärtner [21]. Their method uses the clustering algorithm k-means and a classification method based on support vector machines to classify players into different types based on data extracted from the gameplay, which are then used as parameters to adjust the difficulty of the game. A similar approach is explored by Mahlman et al. [22], who use several supervised machine learning algorithms trained with gameplay data to predict when a player will stop playing the game Tomb Raider: Underworld (Crystal Dynamics, 2008). Another player modeling approach that also uses machine learning techniques is presented by Machado et al. [23], who apply support vector machines to create models of virtual agent's preferences according to gameplay data extracted from the game Civilization IV (Firaxis Games, 2005). A similar method is explored by Spronck and den Teuling [24], but instead of support vector machines, they use a sequential minimal optimization classifier to predict specific player preference values. A more dynamic solution that considers changes in the player model that can occur over time is presented by Valls-Vargas et al. [25], who propose a model to capture and predict play style using episodic segmentation of gameplay traces and sequential machine learning techniques. Their method uses multiple models that include predictions from previous time intervals to identify how players change play style over time.

In a more recent work, Lima et al. [26] propose a player modeling technique to create a model of the players' personalities and behaviors, which are used to generate interactive and adaptive narratives for games. Their method uses in-game dialog choices to assess players' personality traits according to the Big Five model [27]. In addition, an artificial neural network is used to predict player behaviors in real-time using past gameplay data. Lima et al. [28] also explore the use of player modeling and machine learning techniques to ascertain users' preferences for narrative events according to the personality traits and preferences of past users. The use of action model learning and data extracted from play traces is explored by Krishnan et al. [29]. Although their method was only validated in a simple puzzle game to estimate how well a player understands the mechanics of a game, the authors claim that their action models can be used to create player models for any game in which player actions can be represented in a planning formalism, such as STRIPS and PDDL. Another modeling approach is explored by Williams et al. [30], who propose a player profile framework that combines data-driven techniques in game analytics with the theoretical backing of demographic, psychometric, and psychographic measurements.

There are also works that explore alternative solutions to the player modeling problem, such as the approach proposed by Gray et al. [31], which uses the multi-armed bandits' optimization method [32] to model both the problem of exposing players to different situations in the game and the problem of adapting the game to maximize features of interest to the designer. Another recent example is the player profiling method proposed by Melo et al. [33], which uses provenance graphs and representation learning techniques to identify vector representations for each game element, which does not require feature engineering or the extraction of gameplay metrics. Their method uses a clustering algorithm to identify data patterns and clusters, which are then manually interpreted and labeled according to the underlying patterns found in the data.

Deep learning methods also have been recently explored in the context of player modeling. Pfau et al. [34] demonstrates the applicability of deep learning algorithms to create models of players in the online multiplayer game Lineage II (NCSOFT, 2003), which can be used to analyze and explain the behaviors of individual players. In a subsequent work, Pfau et al. [35] applied their deep player behavior modeling approach to automate the process of balancing the options available to players in the game Aion (NCSOFT, 2008). More comprehensive literature reviews on player modeling and adaptive games are presented in [36,37], and [38].

As most of previous works on general player modeling, the present work also relies on the use of machine learning techniques to find behavioral patterns in gameplay data. However, to the best of our knowledge, this is the first work to use these techniques to identify individual player's fears using only data extracted from gameplay sessions (without relying on surveys or any special hardware to obtain additional information about players). In term of structure, the proposed model is similar to the model presented in [26] to identify player behaviors, but instead of mapping gameplay data to personality factors, our model is designed to identifies the fears of players.

2.2. Analysis of Players' fears and Adaptive horror games

In the last decade, several studies have explored the analysis of fear in games. In the context of immersive virtual reality horror games, Lin [9] analyses the fright reactions of players according to Slater's theory of virtual reality [58] and its two dimensions of fear elements: (1) the fear of place illusion (PI); and (2) the plausibility illusion (PSI). Slater's theory states that the PI is the sense of being in a real place, and PSI is the illusion that an actual scenario is happening [58]. Lin's research revealed that the fear of PSI elements has a stronger effect in the overall fear [9]. Furthermore, the study presents a self-help strategy, that consists in a monologue that is stated as an effective method to deal with emergent dangers or fear situations in virtual reality games.

In a similar context, Freytag and Wienrich [59] conducted another study that evaluates the assessment of emotions, such as horror, in virtual reality environments through self-reported ratings. The authors evaluate emotional reactions through a virtual experience that combines narrative and game-oriented objectives. Freytag and Wienrich implemented a test pilot where players self-reported their emotions. A pertinent contribution of their work is that virtual reality and self-reported assessments proved suitable for detecting emotional states.

The application of biometric sensors to assess emotions and reactions in games and virtual reality also gained importance in both research community and game industry [60–63]. For example, Vachiratamporn et al. [63] uses physiological and behavioral data (brainwave signals, heart rate and keyboard-mouse activity) to monitor the suspense level of a survival horror game. The results indicate that "players are more likely to experience fear from a scary event when they are in a suspense state compared to when they were in a neutral state" [63]. Although biometric sensors are a well-known method to identify emotional responses in games, virtual reality scenarios impose additional constraints related to users' movement that can create signal noises. Hence, Otsuka et al. [64] presented a solution that embedded vital signs collection in the head-mounted display through a phototransistor sensor capable of measuring the arterial pulse of players, which is then used to calculate the heart rate.

In the context of adaptive games, Nogueira et al. [65] present an adaptive horror game that directly interprets physiological data of players as an emotional state, mapping it to a set of rules that adapt the behavior of enemies, the level structure, character attributes, sound, light, and item placement. Another example of a solution that also relies on physiological data is the game Bring to Light (Red Meat Games, 2018), which adapts the game's level of fear based on the player's heart rate that is monitored in real time by a chest band [66]. A similar approach is explored by Inazawa et al. [67], who use optical pulse and thermopile sensors attached to the head-mounted display to measure the player's tension and excitement. Based on this information, their virtual reality horror game adapts the field of view of the player.

In general, most of the previous works try to identify fear and other emotional reactions using biometric sensors or user surveys. In contrast, our approach is based on the hypothesis that players who fear a certain horror element have a similar in-game behavior when playing horror games in virtual reality. In this way, machine learning algorithms can be used to discover behavioral patterns in past gameplay data, and therefore identify what new players fear, allowing games to adapt their horror levels in real time.

A recent solution that does not rely on biometric sensors is presented by Palma et al. [68], which maps predefined player actions within the environment of the game to different values for traits related to empathy, morality, cautiousness, and search for strong emotions. Based on these player trait values and a set of predefined rules, their game modifies some elements of the environment (such as colors, paintings, objects, and traps) in accordance with the level of fear that the player is expecting to experience. Although the approach proposed by Palma et al. (*op. cit.*) shares some similarities with our work, the strategies adopted to solve the problem are entirely different. While we adopt a machine learning algorithm to automatically identify player's fears, Palma et al. (*op. cit.*) rely on predefined player actions and choices in a tutorial level to identify traits that can indicate the level of fear that the player is expecting to experience (for example, the action of searching for lights to turn on contributes to a cautiousness factor). Their adaptation strategy is also limited to a set of predefined environment modifications that occur in the beginning of the game according to predefined levels of fear. In contrast, we propose a dynamic and intelligent agent-based system that continuously modifies the game in response to players' fears.

3. Fear and horror elements in games

The terms "horror" and "terror", in the entertainment industry, are often complementary and comprehended as equal, however, both have different definitions. Terror is defined by Cavallaro [39] as the fear that is generated by unidentified entities, while the horror itself is the fear of the visible gore. Stephen King, in his book [40], also presents a definition for these terms, classifying terror as "the best of elements – the feeling of tension before the monster is revealed", and horror as "the moment when one sees the creature that causes the terror, provoking a shock in the observer".

The relevance and relation between human beings and horror has been the topic of several studies, such as the one presented by Carroll [41]. Carroll's study depicts curiosity as the main factor that draws human attention, especially because the threat (referred as the "monster") is one of the representations of the unknown, which humans both fear and are attracted to. The study of Andrade and Cohen [42] analyzed the attraction to fear through an experiment with a room of students that rated the degree of negative and positive feelings they sense during the exhibition of three different types of films. Through the results of the Andrade and Cohen's study, it was possible to conclude that the moments of more horror were also the most enjoyable moments. This happens because dopamine is released into the body during times of stress. The high levels of dopamine prepares the body for the threat, however when the brain identifies a false threat, the stimulated body feels a sensation of pleasure.

Hence, video games create new horror opportunities to the entertainment industry. In games, players can become active agents in a virtual world with strong influence on what can happen on screen, instead of being just passive observers. In this context, Perron [43] conducted a study to analyze how survival horror games appeal to players according to three general characteristics associated with player's immersion: presence, agency, and embodiment. Results indicate that horror games have worlds intrinsically capable of creating the feeling of presence, as they represent threatening and frightening places, full of sensory incentives that focus the players' attention. Agency can also innately emerge in horror games, because fear is the perfect emotion to provoke the player to act. Another finding of Perron's study [19] is that horror games have a strong relation with embodiment, allowing the player to have the same range of feelings that the avatar has.

Numerous techniques to incite fear in horror games have been created and applied through the years, which affect the aesthetic aspects of the game's atmosphere, the game's narrative, and the audio of the game. Demarque and Lima [44], state that most of these techniques are inspired by the approaches used by cinematographers to create horror movies. Hence, in this work, we named these techniques as "horror elements", which are elements that create feelings of horror or terror, either through a real or imagined menace, or by elements that carry discomfort and tension.

Darkness is one of the most common elements used to create frightening atmospheres for horror games and horror movies, which is directly related with the fear of the unknown. In this respect, Howard Phillips Lovecraft, the famous American writer, wrote that "the oldest and strongest emotion of mankind is fear, and the oldest and strongest kind of fear is fear of the unknown" [45]. According to Carleton [46], the fear of the unknown is an important fear of the human being and the components that derive from it also have related features, such as voices and sounds that originate from unknown sources. One famous example of game series that constantly uses unknown sounds and voices to provoke fear in players is Silent Hill (Konami, 1999–2012).

Two other elements that are typically present in several horror games, such as P.T. (Konami, 2014) and Dead Space 3 (Frictional Games, 2013), are creatures and ghost-like apparitions. The human fear for these elements can be explained by the theories of Carroll [41] and Freud [3] as they represent unfamiliar beings and dangers that attract and strike fear at the same time.

Evolutionary theory and physiological studies provide evidence on the existence of innate and learned fears [47–49]. Although some authors suggest the existence of "fundamental fears", such as the fear of the unknown [46], other authors argue that innate fears tend to decrease over time [50]. For example, studies have shown that innate fears that are frequent in children, such as the fear of darkness, tend to gradually diminish with time as result of the habituation phenomenon [51,52]. Although there are similarities in physiological fears across humans [11], the differences in learned fears among individuals is important when establishing personal fears in games [53]. These personal differences can be associated with past experiences, such as phobias [47] and trauma [54], or with individual characteristics, such as gender and age [55,56]. Regarding this topic, Martin [57] presents a review of research works that study the psychological reactions of individuals to different horror elements.

4. Identifying Players' fears in virtual reality

The famous psychologist Paul Ekman identified fear as one of the six universally experienced emotions [69]. In the last decades, several computational techniques have been proposed for identifying emotions. Typical emotion recognition techniques usually rely on the collection vital signs [70], audio signals [71], or image capture [72], to identify certain emotions. Still, we reason that these methods are not appropriate for virtual reality games as the head-mounted display blocks part of the player's face and make it hard to recognize facial expressions. Moreover, vital signs collected by wearable or body sensors might suffer from noise due to the usual physical movement of the player. Also, audio signals are rare, because players usually do not speak while playing.

Instead of relying on dedicated hardware or sensors, the proposed method to create a computational model able to identify players' fears comprises the use of machine learning algorithms to ascertain how horror elements affect players. Based on the response and statistical gameplay data of previous players, we aim at predicting what future players fear in a virtual reality horror game. As a general player model based on machine learning, the proposed fear model uses data extracted from past gameplay sessions to identify patterns in the behavior of players that have similar fears. By training an Artificial Neural Network to identify these behavioral patterns according to a set of predefined horror elements, the fear model becomes capable of predicting in real time the horror elements that can intensify the fear evoked in individual players.

As described in the introduction (Section 1), the fear model was originally proposed in our previous conference paper [14], and in this work we extend our method to support the application of the knowledge represented in the fear model to adapt the content of horror games. The architecture of the proposed adaptive game system is modeled as an agent-based system (see Section 5.2), where two main agents (*Horror Director* and *Game Manager*) are responsible for maintaining the fear model, tracking the game's pace according to the horror intensity that the player is experiencing, and deciding when and how to introduce new horror elements into the game. The next subsections present an overview of the prototype game and the process of creating the fear model.

4.1. Game prototype

The game used to test and validate our method isa virtual reality horror game developed in the context of an undergraduate student project (Fig. 1). In the game, the player assumes the role of an investigator that is investigating reports of unusual events that are occurring in a mysterious house. Upon arriving at the house, the player discoveries four unusual “teddy bears” (Fig. 2). The main game loop consists in the search for clues to uncover the mysteries that surround the “teddy bears”. The game was developed using the Oculus Rift Headset SDK[1] and Unity.[2]

The horror elements used by the game to fright players include apparitions, unknown voices/sounds, and darkness. Apparitions are represented by unexpected advents of ghost-like mannequins and “teddy bears” that occur as result of some narrative events. Unknown voices/sounds are represented by sounds that play from certain places of the environment. Lastly, darkness is triggered by light sources that turn off unexpectedly, leaving the player in a partial or complete darkness. More details about the horror elements used by prototype game are presented in our previous work [14].

4.2. Fear modeling

Fig. 3 presents the proposed *general fear model*, which includes three main components: input, output, and function. The model’s function is the core of the model, as it maps the input data into the output horror elements. The model’s input includes a set of observations extracted from the gameplay data, which must include enough information about the player’s behavior in reaction to different horror events. The model’s output represents the set of horror elements that can provoke fear in players and can be predicted by the model based on the input data.

Due to the dynamic nature of virtual reality horror games, players’ fears can change over time. Therefore, the fear model must be constantly used to identify and update the elements that provoke fear in the current player. This dynamic process is performed using time frames, which are constant intervals where the gameplay data is collected and then used to predict which horror elements cause more fear in the current player. The length of the time frame is a vital variable to control the accuracy of the model. Too short frames may provide only a limited amount of information about the player’s behaviors, however excessively long frames can fail in capturing transitions and produce blurred data. In order to determine the best length for the time frame, we performed several tests with time frame sizes of varying lengths. These experiments and their respective results are presented in Section 6.1.

The fear model’s input data is built of a set of statistical features extracted from the gameplay during a time frame. The gameplay features that are used as inputs to our model are described in Table 1.

The output of the model comprises a set of classes that characterize the horror elements that can be identified and used by the game to provoke fear. Table 2 describes the four horror elements used as output of our model, which were identified and selected based on our research on the main techniques used by horror games to provoke fear in players (see Section 3). Although these elements are commonly found in most horror games, they still are effective when it comes to evoking fear in players [73].

The model’s function is responsible for the process of mapping the input data to the output classes, which is built with data samples extracted from previous game sessions in which the player’s fears were known. In this way, the model can identify patterns and use them to predict what future players will fear (a multiclass classification problem [74]).

In the proposed model, we implemented the classification function using an Artificial Neural Network, which was selected after several preliminary tests conducted in the Weka framework.[3] Results of tests showed that the Neural Network classifier produced better accuracy in comparison to all other algorithms available in the framework. For the model development, we adopted the FANN library,[4] which is an open-source library that implements multilayer Neural Networks in C. The model’s classification function uses a single hidden layer Neural Network with 36 neurons in the hidden layer. The Neural Network was trained by an incremental backpropagation learning algorithm using a sigmoidal activation function.

4.3. Data collection

Considering that our method employs a supervised machine learning algorithm to create the general fear model, samples of gameplay sessions need to be captured and annotated with labels describing the horror elements that caused more fear in players during the game.

The procedure to collect training samples was divided in three steps. First, all participants filled a consent form and a pre-test survey where they provided general demographic information. After this first step, participants were allowed to play our virtual reality game freely until they decided to stop or until they complete the game. After playing the game, participants filled a post-test questionnaire, in which they were asked to rate how much fear they have experienced with each horror elements that they faced during the game (darkness, apparitions, unknown voices, and unknown sounds). Each horror element was rated in a five-point Likert scale ranging from “not scared at all” (1) through “moderately scared” (3) to “extremely scared” (5).

A total of 18 volunteers participated in the study (fifteen bachelor’s students, one master’s student, one designer, and one game developer). All participants were male, and their ages ranged from 19 to 36 years (mean of 22.2). Nine of them play horror games regularly. During the tests, three subjects stopped the experiment before completing the game and fifteen completed the entire game. Each game session lasted, on average, 10.5 min (standard deviation of 2.3 min). Fig. 4 shows the rate of fear that participants indicated that they have experienced with each horror elements during the game sessions.

During the game sessions, the system automatically captured all statistical features required to train our model (Table 1) in six time frames of different lengths (1, 3, 5, 10, 15, and 20 s). As mentioned above, different time frames are being used to determine its best length for the time frame.

Following the data collection, we executed a preprocessing phase to label the samples and create the final datasets to train and test our model. For the labeling process, we used the players’ answers to the post-test questionnaire to identify the horror element that caused more fear during the game session. Since every horror element was rated by each player in a five-point Likert scale, the element with the highest rate was selected and then used to label all samples collected from the game session of each player. Although players were exposed to multiple horror elements in a single game session, our objective was not to identify their response to specific game moments, but to identify the general behavior of players that share similar fears. In this way, the fear model can be used even when players are not being exposed to any horror element.

After labeling the samples, we divide the samples into six datasets (one for each time frame). The numbers of samples of the datasets are: (1) time frame of 1 s – 9507 samples; (2) time frame of 3 s – 3178 samples; (3) time frame of 5 s – 1906 samples; (4) time frame of 10 s – 950 samples; (5) time frame of 15 s – 631 samples; and (6) time frame of 20 s – 470 samples.

The results obtained with the proposed model for different time frames are presented in Section 6.1.

5. Adaptive virtual reality horror games

The proposed method to identity players’ fears in real time provides

[1] https://developer.oculus.com/.
[2] https://unity.com/.
[3] https://www.cs.waikato.ac.nz/ml/weka/.
[4] https://leenissen.dk/fann/.

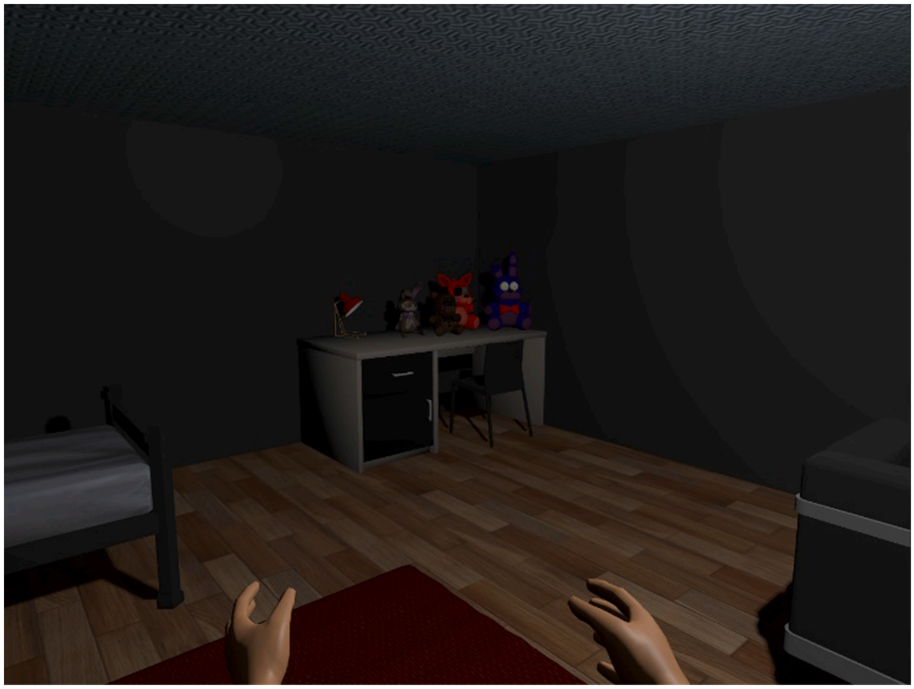

Fig. 1. Scene of the prototype game: player finds four unusual "teddy bears".

Fig. 2. Scene of the prototype game: player finds the first note left by the "teddy bears".

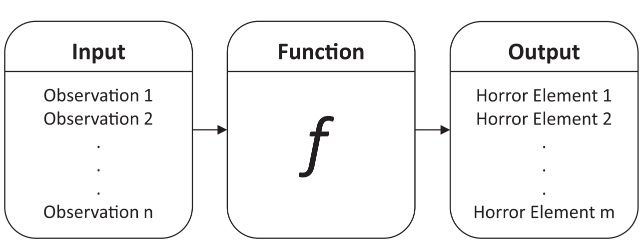

Fig. 3. General fear model.

game designers with new ways to enhance the gameplay of virtual reality horror games. However, the actual application of the method requires intelligent decisions about "when" and "how" to use the model's knowledge to adapt the horror elements of the game. Although one could easily use the fear model's output in predetermined moments of the game to decide which horror element to activate, such type of integration would be a weak form of adaptation that does not scale very easily for a fully adaptive game [75]. A more general solution requires the implementation of an intelligent agent capable of automatically identifying the best moments to use the horror elements feared by the

Table 1
Input features of the fear model. T is the length of the time frame in seconds.

	Description
F_1	Percentage of time that the player is standing still (in relation to T)
F_2	Percentage of time that the player is walking (in relation to T)
F_3	Percentage of time that the player is colliding (in relation to T)
F_4	Average walking speed
F_5	Standard deviation of the walking speed
F_6	Average rotation speed
F_7	Standard deviation of the rotation speed
F_8	Average position of the right-hand controller on the x-axis
F_9	Average position of the right-hand controller on the y-axis
F_{10}	Average position of the right-hand controller on the z-axis
F_{11}	Standard deviation of the position of right-hand controller on the x-axis
F_{12}	Standard deviation of the position of right-hand controller on the y-axis
F_{13}	Standard deviation of the position of right-hand controller on the z-axis
F_{14}	Average position of the left-hand controller on the x-axis
F_{15}	Average position of the left-hand controller on the y-axis
F_{16}	Average position of the left-hand controller on the z-axis
F_{17}	Standard deviation of the position of left-hand controller on the x-axis
F_{18}	Standard deviation of the position of left-hand controller on the y-axis
F_{19}	Standard deviation of the position of left-hand controller on the z-axis
F_{20}	Average rotation of the player's head on the x-axis
F_{21}	Average rotation of the player's head on the y-axis
F_{22}	Average rotation of the player's head on the z-axis
F_{23}	Standard deviation of the rotation of player's head on the x-axis
F_{24}	Standard deviation of the rotation of player's head on the y-axis
F_{25}	Standard deviation of the rotation of player's head on the z-axis

Table 2
Output classes of the fear model.

Horror Element	Description
Darkness	Lack of illumination or dimmed lighting conditions created when some or all artificial light sources are turned off.
Apparitions	A remarkable and unexpected appearance of someone or something, such as ghost-like images and inanimate objects.
Unknown voices	Voices whose source is unknown or originates from specific places, such as walls, rooms, or inanimate objects.
Unknown sounds	Recognizable or unrecognizable sounds that come from specific places but without a known cause, such as bangs, footsteps, claps, and whistles.

player. When designing the artificial intelligence for such agent, the concept of pacing stands out as one of the key components for a successful horror experience [76,77]. While the constant exposure to horror elements can be exhausting, long periods of inactivity can be boring. The natural pacing of a horror game is "spiky", with periods of quiet tension punctuated by moments of intense horror. Therefore, a horror game that can adapt its content according to player's fears must also be able to track and control its own pace in order to create compelling horror experiences.

5.1. *Pacing in horror games*

In general, the concept of pacing (also known as rhythm, tempo, or flow) can be described as the relationship between the intensity of an activity and the duration of that activity. The term is commonly used in the game industry to describe the rate of progression players experience in a game. Although the interactive nature of games naturally associates the term with level design and game progression, it can also be connected with the game's narrative and be used to describe how players experience the dramatic tension of the narrative. When it comes to narrative pacing, the concept of story arcs stands out as a normative way to represent narrative structures as dramatic arcs. The concept of story arcs dates back to 1863, when Gustav Freytag proposed a model to represent the narrative structure of a classical five-act tragedy, which was later enhanced by subsequent theorists and today is known as Freytag's Pyramid or Freytag's Triangle (Fig. 5 – *a*). Another popular story arc is the three-act structure (Fig. 5 – *b*), which is commonly used by the film industry and is divided into Setup (1/4 of the story time), Confrontation (2/4 of the story time), and Resolution (1/4 or less of the story time) [78]. Story arcs add emotional tension as a new dimension to the concept of pacing. Therefore, narrative pacing is not only related with the speed at which a story is told, but also with how much each event contributes to the emotional tension of the story.

In the context of horror games, pacing can also be associated with the rate of horror intensity that players experience over time. Similar to narrative pacing, horror pacing is not only about the speed at which horror elements are presented to players, but also about how each horror element will contribute to the horror intensity that will be experienced by players. The way the horror intensity changes over time can be compared to how the emotional tension of a story is expected to progress in a story arc, but instead of a single tension peak (the climax), the horror intensity in a horror game is expected to follow a sequence of peaks and valleys, as illustrated in Fig. 6 (i.e., moments of intense horror followed by periods of quiet tension). Although there is lack of studies on horror patterns for games, this pattern can be easily observed in many successful horror games, such as Silent Hill (Konami, 1999), Fatal Frame (Tecmo, 2001), Amnesia: The Dark Descent (Frictional Games, 2010), and Outlast (Red Barrels, 2013).

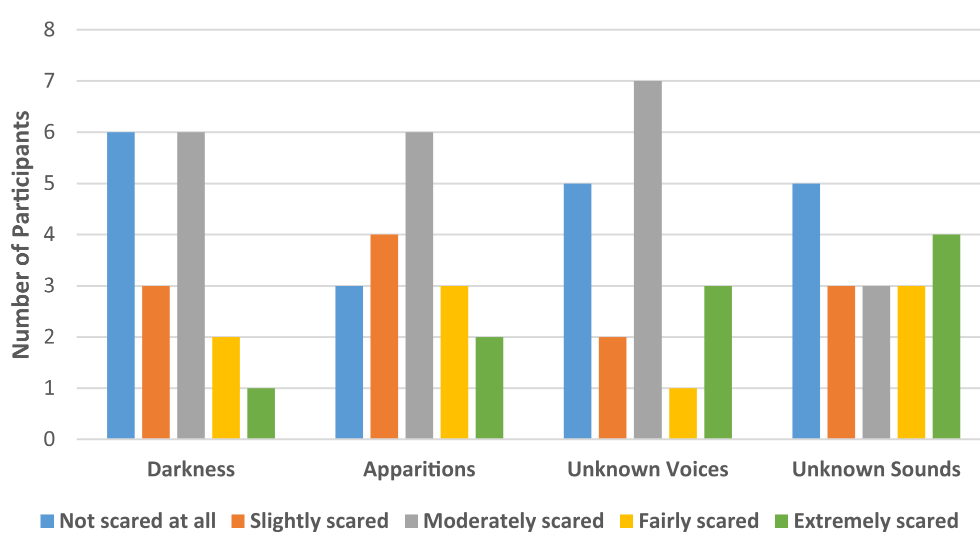

Fig. 4. Rate of fear that participants indicated that they have experienced with each horror elements during the game sessions.

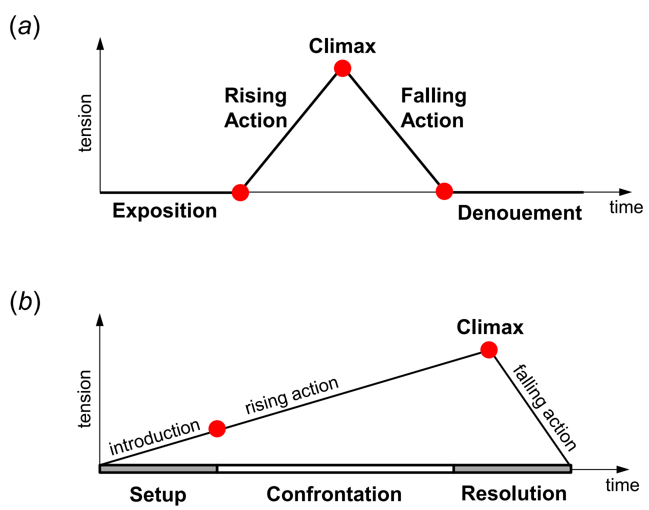

Fig. 5. Examples of story arcs: (*a*) Freytag's Pyramid; and (*b*) Three-act Structure.

deciding when and how to introduce new horror elements into the game; and (2) the *Game Manager*, which works as an interface between the *Horror Director* and the *Game World*. The *Game Manager* handles the process of collecting gameplay data, identifying player's fears, and instantiating the horror elements that are requested by the *Horror Director*.

The *Horror Director* is controlled by a Finite State Machine (*FSM Controller*) and has access to a library of horror elements (*Horror Elements Library*),[5] which includes the specification of all horror element's variants and the resources associated with them (3D models, animations, and sound files). The *Horror Director* also maintains the *Player Fear Model*, which is a structure that represents the fears of the current player. The *Player Fear Model* is encoded as a multidimensional variable that comprises all fear dimensions considered by the system to establish the horror elements of the game. The *Player Fear Model* is regularly updated with observations (player's fears) provided by the *Game Manager*, which uses the *General Fear Model* (described in Section 4) to identify what the player fears based on data extracted from the gameplay. More details about the *Player Fear Model* are presented in Section 5.3.1.

The *Game Manager* constantly captures gameplay data to provide the input data used by the *General Fear Model* to identify what the player

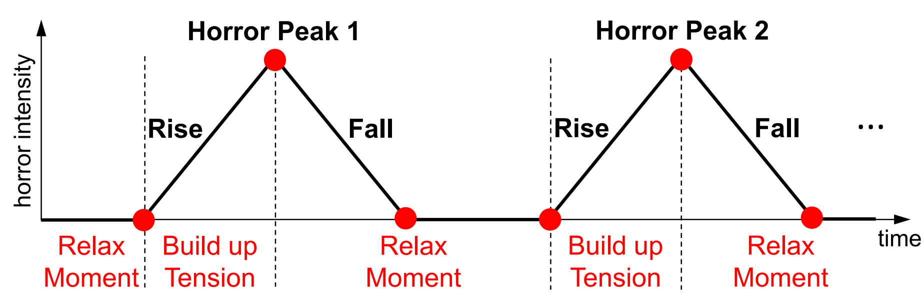

Fig. 6. Horror intensity arc.

5.2. The architecture of the Adaptive horror game system

The proposed system to track the game's pace and use the fear model's output to dynamically adapt the horror elements of the game is modeled as an agent-based system (Fig. 7), where the system's tasks are shared between two main agents: (1) the *Horror Director*, which is responsible for maintaining the fear model, tracking the game's pace according to the horror intensity that the player is experiencing, and

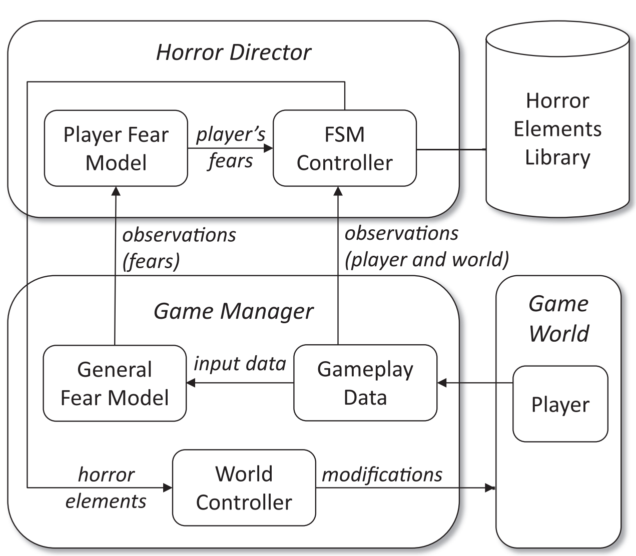

Fig. 7. Architecture of the adaptive horror game system.

fears. In addition, the *Game Manager* also provides the *Horror Director* with observations about the game world, such as the player location and the location of the next objective, which are used by the *Horror Director* to find the best way to introduce new horror elements. When the *Horror Director* requests the instantiation of a new horror element into the game, the *World Controller* performs all modifications in the game world to introduce the new horror element, such as turning lights off, instantiating 3D objects, or playing sound sources. More details about the process of instantiating dynamic horror elements in the game are presented in Section 5.4.

5.3. Horror Director

The concept of the *Horror Director* is inspired by the famous AI Director of the game Left 4 Dead (Valve, 2008), which focus on managing the pace and difficulty of the game by placing enemies and items in varying positions and quantities in the game world based on the emotional intensity of each survivor (player character) [79]. However, instead of generating enemies and items, the proposed *Horror Director* aims at evoking fear in individual players by introducing new horror elements into the game. By tracking the horror intensity (as described in Section 5.3.2), the *Horror Director* is capable of automatically adjusting the game's pace in real-time to maximize the horror experienced by the player. Similar to the AI Director of Left 4 Dead, the proposed *Horror*

[5] In our implementation, the *Horror Elements Library* comprises a set of Unity's ScriptableObjects, which are data containers that store the resources associated with the horror elements. An example of *Horror Elements Library*, in XML format, is available at: https://edirlei.com/projects/adaptive-horror/horror-elements-library.xml.

Director is also controlled by a Finite State Machine (Fig. 8), which modulates the use of horror elements to create periods of quiet tension followed by moments of intense horror.

As illustrated in Fig. 8, the Finite State Machine of the *Horror Director* is composed of four states: (1) *Relax*, which maintains the player relaxed by not exposing him/her to new horror elements for α seconds (maintaining the horror intensity low); (2) *Build Up*, where new horror elements are gradually introduced into the game until the horror intensity crosses the peak threshold β; (3) *Sustain Peak*, which maintains the horror intensity above the threshold peak β by adding new horror elements or maintaining the existing elements active for γ seconds (duration of the horror intensity peak); and (4) *Peak Fade*, where active horror elements are gradually removed and the horror intensity is monitored until it decays out of peak range δ. The variables α, β, γ, and δ must be defined according to the general pace of the game. In our prototype game, we used $\alpha = 25$ seconds, $\beta = 0.9$, $\gamma = 5$ seconds, and $\delta = 0.1$. These values were selected based on the average time that players needed to explore the environment and progress through the narrative events of the game, which were obtained by analyzing the gameplay data that was previously collected to train the neural network to identify player's fears (see Section 4.3).

5.3.1. The player fear model

When introducing a new horror element into the game, the *Horror Director* uses the fears of the current player (predicted by the *General Fear Model*) to select the best horror element to add to the game. However, instead of using the direct output of the *General Fear Model*, the *Horror Director* maintains and uses a structure that represents the average fears of the current player during a time period (the *Player Fear Model*). This structure comprises all fear dimensions considered by the system to establish the horror elements of the game, which are regularly updated according to the fears identified by the *General Fear Model*. The frequency in which the *Player Fear Model* is updated depends on the time frame used by the *General Fear Model* to predict the player's fears. Considering that our prototype game uses a time frame of 10 s for the *General Fear Model*, which is the time frame that provides the highest accuracy (see the evaluation results in Section 6.1), the *Player Fear Model* is also updated every 10 s.

The length of the time period in which the predicted fears are accumulated in the *Player Fear Model* is a parameter of the system. While a short period can provide a more recent perspective on the player's fears, it also is susceptible to classification errors that can occur due to the imperfect accuracy of the *General Fear Model*. On the other hand, a long period is less affected by classification errors, but the model takes more time to adapt to changes in the player's fears that can occur during the game. In our prototype game, the classification results are maintained in the *Player Fear Model* for a maximum time period of 3.5 min, period in which they will be contributing to the calculation of the average fear.

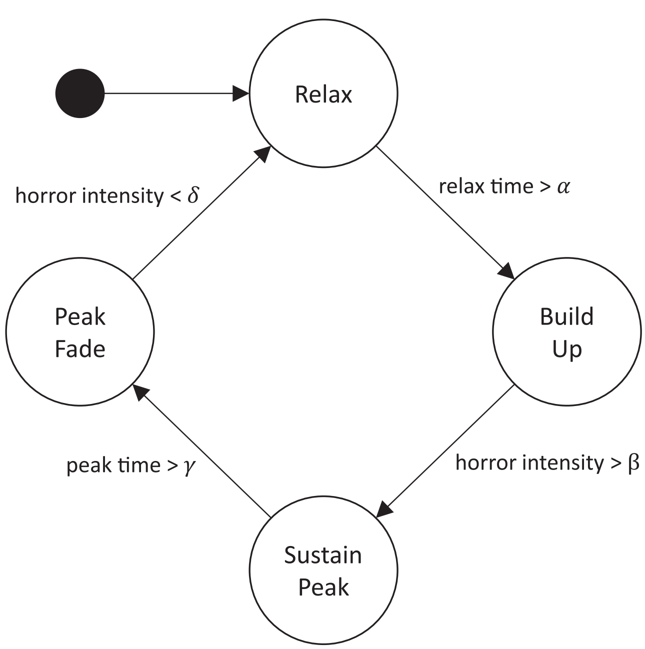

Fig. 8. Finite State Machine of the *Horror Director*.

Considering the four horror elements e_i used in our prototype game ($e_1 = darkness$, $e_2 = apparitions$, $e_3 = unknownvoices$, $e_4 = unknownsounds$) and a sequence of n predicted fears p_i, the four dimensions of the player's fears f_i are given by:

$$f_{darkness} = \frac{\sum_{i=1}^{n} \begin{cases} 1, if\, p_i = e_1 \\ 0, otherwise \end{cases}}{n}$$

$$f_{apparitions} = \frac{\sum_{i=1}^{n} \begin{cases} 1, if\, p_i = e_2 \\ 0, otherwise \end{cases}}{n}$$

$$f_{unknownvoices} = \frac{\sum_{i=1}^{n} \begin{cases} 1, if\, p_i = e_3 \\ 0, otherwise \end{cases}}{n}$$

$$f_{unknownsounds} = \frac{\sum_{i=1}^{n} \begin{cases} 1, if\, p_i = e_4 \\ 0, otherwise \end{cases}}{n}$$

For example, considering the sequence of 15 predicted fears p_i shown in Table 3 (captured from an actual player during a game session), the player's fears can be calculated as:

$$f_{darkness} = \frac{3}{15} = 0.20,$$

$$f_{apparitions} = \frac{9}{15} = 0.60,$$

$$f_{unknownvoices} = \frac{2}{15} = 0.13,$$

$$f_{unknownsounds} = \frac{1}{15} = 0.07,$$

where each dimension of the player's fears f_i will be a value in the range [0, 1]. The combination of all fear dimensions provides an overview on the player's fears, which can be visualized in a radar chart (as illustrated in Fig. 9).

When introducing a new horror element into the game, the *Horror Director* uses the player's fears to associate a probability of selection to

Table 3
Sequence of 15 fears predicted by the General Fear Model during a game session.

ID	Game Time	Predicted Fear
p_1	1:30	Apparitions
p_2	1:40	Apparitions
p_3	1:50	Apparitions
p_4	2:00	Darkness
p_5	2:10	Darkness
p_6	2:20	Apparitions
p_7	2:30	Apparitions
p_8	2:40	Unknown Voices
p_9	2:50	Unknown Voices
p_{10}	3:00	Unknown Sounds
p_{11}	3:10	Darkness
p_{12}	3:20	Apparitions
p_{13}	3:30	Apparitions
p_{14}	3:40	Apparitions
p_{15}	3:50	Apparitions

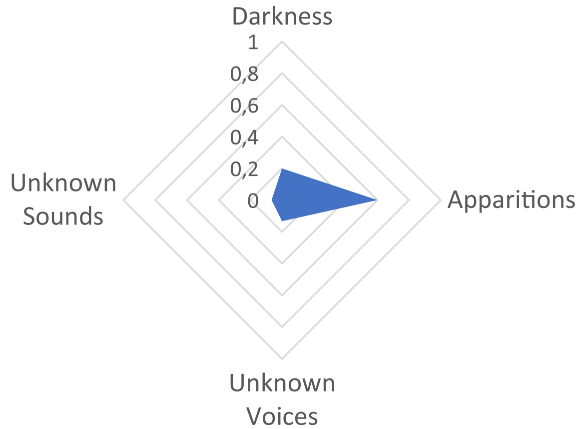

Fig. 9. Example of player's fears visually represented in a radar chart, which indicates that the player is mainly scared by apparitions.

each horror element. Considering that the player's fears are values in the range [0, 1] that add up to 1, the player's fears can be directly used as selection probabilities. For example, the selection probability s_i of the horror elements used in game prototype, according to the player's fears illustrated in Fig. 9, are:

$$s_{darkness} = 0.20 = 20\%$$

$$s_{apparitions} = 0.60 = 60\%$$

$$s_{unknownvoices} = 0.13 = 13\%$$

$$s_{unknownsounds} = 0.07 = 7\%$$

In this case, when selecting a new horror element to introduce into the game, the *Horror Director* will prioritize apparitions (60 % of selection probability), but also giving a chance to other horror elements (especially darkness, with the probability of 20 %). This probabilistic selection method is important to reduce the predictability that could be associated with the decisions of the *Horror Director*, and also to increase the variety of the horror events that can happen during the game.

5.3.2. Tracking the horror intensity

Besides maintaining the *Player Fear Model* and selecting horror elements, the *Horror Director* is also responsible for tracking the horror intensity of the game, which is used by its Finite State Machine to moderate the use of the horror elements. The horror intensity is represented by a single value in the range [0, 1] that tries to estimate how intense is the feeling of horror experienced by the player at a given time. As a time-dependent variable, the horror intensity is automatically updated over time according to the following rules:

1. Increase the horror intensity when:
   a. The player is experiencing a horror element instantiated by the *Horror Director*;
   b. The player is experiencing a horror element introduced as result of a narrative event;
   c. The player is visiting a new location for the first time (the natural fear of the unknown).
2. Decrease the horror intensity over time, except when:
   a. The player is experiencing a horror element (introduced by *Horror Director* or by a narrative event);
   b. The player is visiting a new location for the first time;

The updates to the horror intensity occur in intervals of t seconds (in our experiments, we used $t = 1$). While decrements take place over time based on a default decrement amount μ, increments are given by:

$$Intensity(i) = \max(\lambda, \theta \times f_i)$$

where i is a horror element type that is being experienced by the player (*darkness*, *apparitions*, *unknownvoices*, or *unknownsounds*), λ is a minimum increment, and θ is the increment rate, which is multiplied by the player's fear for the horror element of type i (f_i). In this way, the *Horror Director* uses the *Player Fear Model* not only to select the best horror elements to introduce into the game, but also to estimate how each horror element affects the horror intensity. The values of λ, θ, and μ must be defined according to the pace of the game and will influence on how fast/slow the horror intensity changes over time. In our experiments, we used $\lambda = 0.1$, $\theta = 0.2$, and $\mu = 0.05$.

5.4. Dynamic horror elements

In order to allow the system to take full advantage of the knowledge about the player's fears, the implementation of the horror elements must be dynamic and adaptive to different situations that can occur during the game. In addition, any horror element that usually would be triggered by static player actions or narrative events must be dissociated from these events (except the ones that are essential for the narrative development). In this way, the *Horror Director* will be in charge of controlling the horror intensity of the game by automatically introducing new horror elements at any given time.

For the validation of the proposed adaptive horror game system, we adopted the same prototype previously used to capture gameplay data for the creation of the fear model (see Section 4.1). The game was originally designed without the concept of a *Horror Director* entity to control the horror elements; therefore, all horror events of the game were associated with static narrative events or player actions. Thus, the first step to transform the game into an adaptive horror game involved the process of dissociating the horror elements from any static event. Only elements that are essential for the narrative were kept, such as the apparitions of "teddy bears" and some unknown sounds that are important to guide the player towards the next story event.

The implementation of the horror elements as dynamic events that can occur at any given time and location requires some adaptations to the internal structure of game's environment, such as the identification of all individual areas of the game (so it becomes possible to identify the area where the player is or where the next narrative objective is), the creation of links between all light sources and the area where they are located (so the *Horror Director* can turn on/off all light sources of a certain area), and the creation of at least one audio source in every area (so unknown sounds and voices can be played at any given area). The game's areas are defined as 3D bounding boxes that encompass all the objects that are in a certain location. Considering that our prototype game takes place in the interior of a house, the areas are naturally associated with the rooms and corridors of the house (Fig. 10).

The identification of the environment areas is also important to the process of instantiating apparitions during the game, which must be dynamically placed inside of a certain area without colliding with existing objects. Therefore, when calculating the position for an apparition entity, candidate positions are randomly generated within the ranges of the area's bounding box (also considering the extents of the entity's bounding box). Each candidate position is then tested for possible intersections between the entity's bounding box and the bounding boxes of other objects that are within the area. When no intersections are detected, the candidate position is considered valid and is used to define the final position for the apparition entity.

Each type of horror element has a set of parameters that affect how it is presented in the game, which are arbitrarily selected by the *Horror Director* to improve variety and reduce predictability.

Darkness is triggered by light sources that turn off or flicker for a certain time in the area where the player is. Therefore, two parameters are available: (1) *behavior*, which defines if the lights sources will turn

Fig. 10. The areas of the prototype game in a top-view perspective: (A) parent's bathroom; (B) parent's office; (C) corridor 1; (D) kitchen; (E) parent's bedroom; (F) corridor 2; (G) corridor 3; (H) bathroom; (I) child bedroom; and (J) living room.

off or flicker; and (2) *duration*, which establishes for how many seconds the lights will remain off/flickering. In our prototype, the duration is randomly selected from the range [2, 6].

Apparitions are represented by unexpected appearances of ghost-like entities or the occurrence of unusual visual events in the game, which are dynamically created according to three general parameters: (1) *target location*, which defines where the apparition takes place (the current player area or the area where the next narrative objective is located); (2) *type of apparition*, which defines whether the apparition will consist of ghost-like entities or unusual visual events (represented in our prototype by TVs that turn on and off mysteriously); and (3) *duration*, which establishes for how many seconds the apparitions will remain active (randomly selected from the range [4, 10] in our prototype). When creating ghost-like entities, four extra parameters must be selected: (1) *entity type*, which is selected from the set of entities available in the game (in our prototype, we used four entity types: mannequins, scary kids, zombie-like creatures, and shadow ghosts); (2) *number of entities*, which defines the total of entities that will be created (randomly selected according to the minimum and maximum number of entities defined for each entity type); (3) *placement type*, which establishes whether the entities will be randomly placed inside of the target area or if they will be placed around the player (the last is only available when the target location is the current player area, allowing the entities to surround the player); and (4) *entity behavior*, which defines whether the entities will be completely static or if they will abruptly move towards the player when being looked at (disappearing right after touching the player).

Unknown sounds and unknown voices are implemented in a similar way as both are represented by sound sources that play at specific locations of the environment without a known cause. The different between them lies in the sound files used: while unknown voices are based on human voices, unknown sounds include the sounds produced by any animate or inanimate object. For both types of horror elements, two parameters are available: (1) *location* where the sound will be played, which is randomly selected among the available areas of the game (Fig. 10); and (2) *sound effect*, which is also randomly selected from the set of unknown sounds or unknown voices available in the game. In our prototype game, we used 8 different unknown sounds (e.g., door knocking, glass breaking, footsteps, moving chains) and 10 different unknown voices, which vary from unintelligible whispers to demonic threats.

6. Evaluation and results

Considering the research questions of this work, which revolve around the identification of players' fears and its uses to adapt horror games, we conducted two experiments to evaluate the proposed solution: (1) a technical test to assess the precision and performance of the general fear model when identifying the fears of individual players, which is important to ascertain the applicability of our model; and (2) a user evaluation test to analyze the impacts of the proposed method in the overall game experience, which is essential to determine if our method can provide players with satisfying and entertaining experience.

6.1. Accuracy and performance of the fear model

To evaluate the accuracy of the general fear model, we performed two experiments: (1) a general accuracy test, where we used the six datasets of different time frames to train and test our Neural Network following a 10-fold cross-validation strategy; and (2) an accuracy test for new players, where we removed all samples of one player from the training datasets and used them to create testing datasets (repeating the process for all combinations of players in training and testing datasets), which were then used to train and test the Neural Network. The accuracy test for new players is important to evaluate how the model reacts to samples of unknown players. Fig. 11 shows the results of the accuracy tests.

As the results of the precision test indicate, the best length for the time frame is 10 s, where the general accuracy obtained for the cross-validation test is 81.58 % and the average accuracy obtained when classifying new players is 79.47 %. Given the similar accuracies obtained in both tests, we can also conclude that the model has learned what it was intended to and is capable of recognizing players' fears.

To evaluate the performance of the proposed model, we tested the model during a normal gameplay session, wherein a total of 62 predictions were performed (time frame of 10 s). For each prediction, we computed the time necessary to calculate the input features and to use the Neural Network to identify the horror elements feared by the player. The computer used to run the experiment was an Intel Core i7 2630QM, 2.0 GHZ CPU, 16 GB of RAM, NVIDIA GTX 1070 8 GB GPU, using a single CPU core to process the Neural Network. As a result, we got an average time of 3.1 ms (standard deviation of 0.8 ms), which indicates the applicability of the proposed method in highly interactive virtual reality games without noticeable delays.

6.2. User evaluation of the Adaptive horror game system

Although horror games are designed to provoke fear in players, they are also expected to provide players with a satisfying and entertaining experience. The balance between horror and entertainment within a virtual reality game is essential to create enjoyable experiences for players. Therefore, the evaluation strategy adopted in this work consists of analyzing the impacts of the proposed method not only in the fear evoked in players, but also on the overall game experience.

6.2.1. Participants and procedure

For the user evaluation study, we conducted a test with 42 volunteers (38 bachelor's students and 4 master's students). Thirty-three subjects were male and nine female. Ages ranged from 18 to 27 years (mean of 20.8). Thirty-one of them play video games at least weekly. Seventeen of them enjoy playing horror games. None of them had participated in the previous experiment to collect data to train the general fear model (described in Section 4.3).

For the experiment, we created three version of our virtual reality horror game: (1) *Base Version*, which does not use the proposed method to identify player's fears (all the horror events are associated with static narrative events or player actions); (2) *Random Adaptive Version*, which uses the proposed agent-based system to track and control the horror intensity of the game, but without using the player's fears to select the horror elements to be introduced into the game (the horror elements are randomly selected); and (3) *Intelligent Adaptive Version*, which fully uses the proposed architecture and method to adapt the content of the game according to the identified player's fears. By comparing the player experience in these three versions of the same game, we can: (1) assess the impacts of proposed adaptive game architecture in the player experience (comparing the *Base Version* with the *Intelligent Adaptive Version*); and (2) evaluate the real impact of the fear model when selecting the horror elements to be introduced into the game (comparting the *Intelligent Adaptive Version* with the *Random Adaptive Version*).

The subjects were divided into three groups: 14 of them were arbitrarily selected to play the *Base Version*, other 14 participants played the *Random Adaptive Version*, and the remaining 14 participants tested the *Intelligent Adaptive Version*. Before testing the game, all subjects filled a

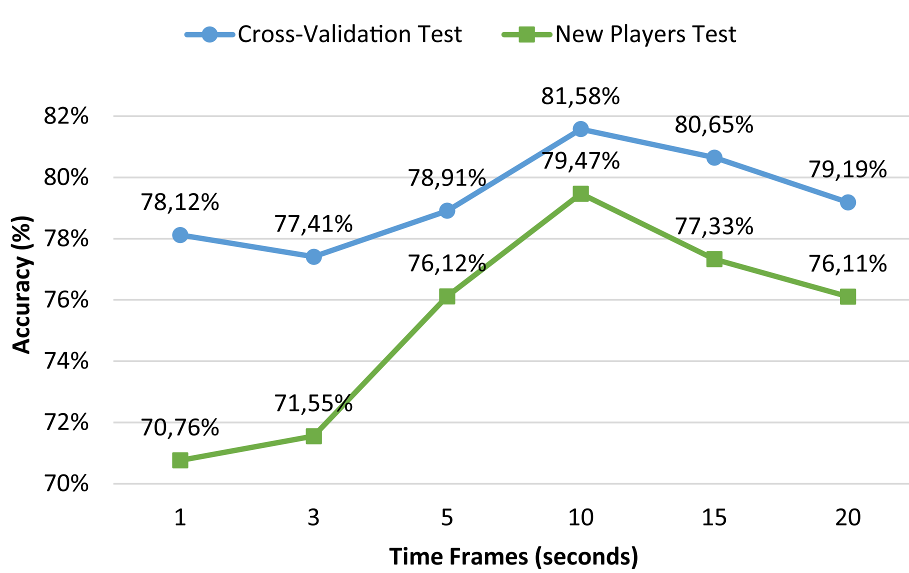

Fig. 11. Average accuracy of the proposed model for different time frames (cross-validation test and new players test).

consent form, answered a basic demographic questionnaire, and then were asked to play our virtual reality horror game. To avoid biased experiences, we did not mention to participants that the system was analyzing their fears or adapting the content of the game. After playing the game, all participants filled out a questionnaire with 33 questions derived from Game Experience Questionnaire (GEQ) [80], which is a self-reported questionnaire widely used to assess core elements of the player experience in virtual reality games [65,81]. Each statement was given on a five-point Likert scale ranging from “not at all” (0) through “moderately” (2) to “extremely” (4). All seven components of the GEQ Core Module were evaluated: *Competence*, *Sensory and Imaginative Immersion*, *Flow*, *Annoyance*, *Challenge*, *Negative Affect*, and *Positive Affect*. The scores of each component were calculated according to GEQ scoring guidelines [80]. The minimum score for each component is 0, and the maximum score is 4. A higher score is better for all components, except for *Annoyance* and *Negative Affect*, where a lower score is better.

In addition to the GEQ, participants were also asked to fill out the post-test questionnaire used in our first experiment to collect data to train the fear model (as described in Section 4.3), where they rated how much fear they have experienced with each horror element during the game. As in the previous experiment, each horror element was rated in a five-point Likert scale ranging from “not scared at all” (1) through “moderately scared” (3) to “extremely scared” (5).

6.2.2. Results and discussion

On average, each session of the *Base Version* lasted 11.2 min (standard deviation of 3.1), each session of the *Random Adaptive Version* lasted 12.7 min (standard deviation of 2.9), and each session of the *Intelligent Adaptive Version* lasted 13.2 min (standard deviation of 3.2). Thirty-eight subjects completed the game and four stopped before reaching the end. Out of the four participants that interrupted the session: two reported motion sickness (one was playing the *Base Version* and the other was playing the *Random Adaptive Version*); one considered the game “too scary to continue” (the subject was playing the *Intelligent Adaptive Version*), and the other one was not able to solve a puzzle to complete the game (in the *Random Adaptive Version*).

In order to analyze the variety of the sample, we checked if the fears reported by participants in the post-test questionnaire exhibited a minimum diversity. For this test, we verified if the fears reported for any pair of participants were significantly different (considering the four horror elements used in our game: darkness, apparitions, unknown voices, and unknown sounds). For this verification, the distance between two sets of values was calculated as being the *root mean square deviation*, that is:

$$RMSD(i,j) = \sqrt{\left(\sum_{k=1}^{4}\left(p_k^i - p_k^j\right)^2\right)\Big/4}$$

where p_k^i is the rating of horror element k reported by participant i and p_k^j is the rating of horror element k reported by participant j. Considering that fears are rated between 1 and 5, our sample exhibited all distances between 0.5 and 3.24, which is an indication of diversity. Table 4 shows the differences in the distances for the groups of participants that tested each version of our game.

To compare the fear experienced by players in the different versions of our game, we analyzed how players rated each horror element that they faced during the experiment. Fig. 12 shows the average fear ratings reported by participants for each horror element in the three versions of our game. As can be observed, the *Intelligent Adaptive Version* obtained higher ratings for darkness, apparitions, and unknown voices in comparison with the other two versions of the game. For unknown sounds, all three versions received similar ratings, with a slightly advantage for the *Random Adaptive Version*. Although unknown voices and sounds are implemented in a similar way in our system (the only difference is related to the sound files used by each element), the results point to a higher effectiveness of unknown voices when such fear is identified by the system. Apparitions were the horror element with the highest difference between the *Intelligent Adaptive Version* and the other two versions of the game.

A two-way analysis of variance (ANOVA) was conducted to test the effect of the game version and horror element on the fear ratings reported by participants (Table 5). For the analysis of the results, we considered a significance level $\alpha = 0.050$. The ANOVA revealed a main effect for the game version on the fear ratings: F(2, 156) = 4.133, $p = 0.018$, $\eta_p^2 = 0.050$. There was no significant effect for the horror element (F(3, 156) = 2.514, $p = 0.060$, $\eta_p^2 = 0.046$), and no significant interaction between game version and horror element (F(6, 156) = 0.883, $p = 0.509$, $\eta_p^2 = 0.033$). A post hoc comparison using the Tukey HSD test on the game version indicates that the mean fear ratings for the *Intelligent Adaptive Version* were significantly different from the *Base Version* ($p = 0.016$, CI = [0.10, 1.19]). There was no statistically significant difference in mean fear ratings between *Intelligent Adaptive Version* and *Random Adaptive Version* ($p = 0.113$) or between *Random Adaptive Version* and *Base Version* ($p = 0.720$). These findings suggest a significant difference on the fear ratings reported by participants for the three version of our virtual reality horror game, which is mainly driven by the difference between the *Intelligent Adaptive Version* and the *Base Version*.

In order to check the correlation between the fear ratings reported by participants after the experiment and the fears predicted by our model during the game sessions, we compared the ratings of the 14 participants that tested the *Intelligent Adaptive Version* with their history of predicted fears, which was automatically recorded by the system. Considering that participants rated every horror element in a five-point Likert scale, we selected the elements with the highest rates and compared them with the dominant fears present in the individual player’s fear models that were created during the game sessions (as described in Section 4.3.1). The result of this comparison indicates a direct correlation between the highest fear ratings and the predicted fears in 93 % of the cases (13 participants), which is positive indication that our method contributes to the process of increasing the horror intensity of the game.

By analyzing the history of predicted fears and the player fear model created for each participant that tested the *Intelligent Adaptive Version* of our game, we observed two different behaviors in the model: (1) the model remains stable during the whole game session (i.e. there are no substantial changes in the player’s fears); and (2) the model gradually changes during the course of the game (i.e. there is a transition in the player’s fears). Fig. 13 shows an example of fear model history of one participant that had no considerable variations during the game session (with apparitions being identified as the main fear of the player during the entire game). Fig. 14 show an example of participant that had a gradual transition in the fear model (the player started with darkness as the main fear and then changed to unknown voices over the course of the game). In our experiment, stable models were observer in 12 cases (86 %).

In order to assess the overall game experience, we analyzed the results of the GEQ, which are summarized in Fig. 15. As can be noticed, the three versions received similar grades for *Competence* and *Challenge*, which was expected considering that players perform the same in-game tasks in all versions of the game. In addition, low scores for the *Challenge* component were also expected as the game does not include complex obstacles or enemies that could challenge the player. The *Intelligent Adaptive Version* received slightly higher scores than the other versions on *Immersion*, *Flow*, and *Positive Affect*.

Table 4
Minimum, maximum, and mean distances for the groups of participants that tested each version of our game.

	Base Version	Random Adaptive Version	Intelligent Adaptive Version
Minimum	0.5	0.5	0.5
Maximum	2.73	3.24	2.69
Mean	1.62	1.74	1.49

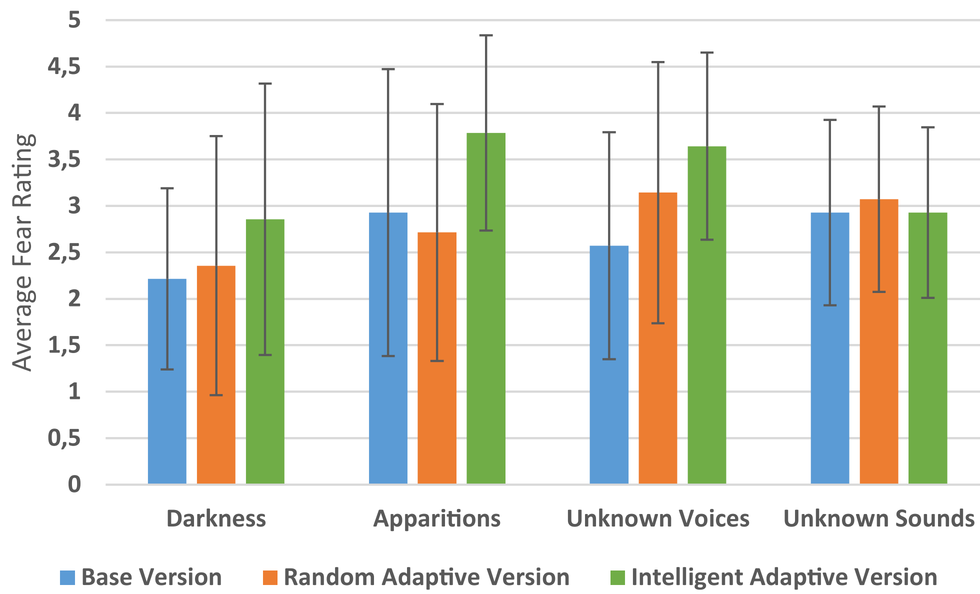

Fig. 12. Average and standard deviation of the fear ratings reported by participants for each horror element in the three versions of our game.

Table 5
Two-Way ANOVA statistics for two independent variables: game version and horror element. The statistics are: sum of squares (SS), degrees of freedom (*df*), mean square (MS), F-ratio (F), p-value (*p*), and effect size/partial eta squared (η_p^2).

	SS	*df*	MS	F	*p*	η_p^2
Game Version (A)	12.333	2	6.167	4.133	0.018	0.050
Horror Element (B)	11.256	3	3.752	2.514	0.060	0.046
A × B	7.905	6	1.317	0.883	0.509	0.033
Error	232.786	156	1.492			

For a more detailed analysis of the game version's effect on the score of the GEQ components, we conducted a one-way analysis of variance (ANOVA) for each component of the GEQ. As shown in Table 6, the ANOVA revealed a significant main effect for the game version on the scores of *Immersion* (F(2, 105) = 11.164, $p < 0.001$, $\eta_p^2 = 0.175$), and *Flow* (F(2, 87) = 11.902, $p = < 0.001$, $\eta_p^2 = 0.215$). There was no significant effect for the scores of *Competence* (F(2, 87) = 0.098, $p = 0.907$, $\eta_p^2 = 0.002$), *Annoyance* (F(2, 51) = 3.084, $p = 0.054$, $\eta_p^2 = 0.108$), *Challenge* (F(2, 87) = 0.203, $p = 0.817$, $\eta_p^2 = 0.005$), *Negative Affect* (F(2, 69) = 2.257, $p = 0.112$, $\eta_p^2 = 0.061$), and *Positive Affect* (F(2, 87) = 1.653, $p = 0.188$, $\eta_p^2 = 0.037$).

A post hoc comparison using the Tukey HSD test on the *Immersion* component indicates that the mean score of the *Intelligent Adaptive Version* was significantly different from the *Base Version* ($p = 0.002$, CI = [0.16, 0.89]) and *Random Adaptive Version* ($p < 0.001$, CI = [0.33, 1.06]). There was no statistically significant difference in mean scores between the *Base Version* and the *Random Adaptive Version* ($p = 0.525$). Similar results were obtained for the Tukey HSD test on the *Flow* component: the mean score of the *Intelligent Adaptive Version* was significantly different from the *Base Version* ($p < 0.001$, CI = [0.39, 1.28]) and *Random Adaptive Version* ($p < 0.001$, CI = [0.29, 1.18]), and no statistically significant difference in mean scores between the *Base Version* and the *Random Adaptive Version* ($p = 0.854$) were identified. The Tukey HSD test on the other components of the GEQ showed no significant difference in mean scores between the three version of the game.

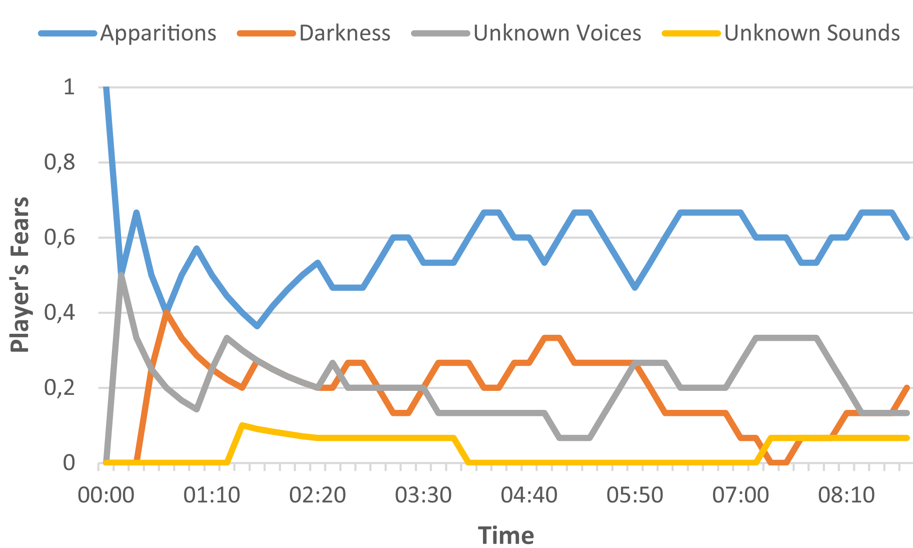

Fig. 13. Example of stable fear model for a participant that had no considerable fear changes during the game session. A gameplay video recording of this session is available at: https://www.youtube.com/watch?v=3phk_WMEoPM.

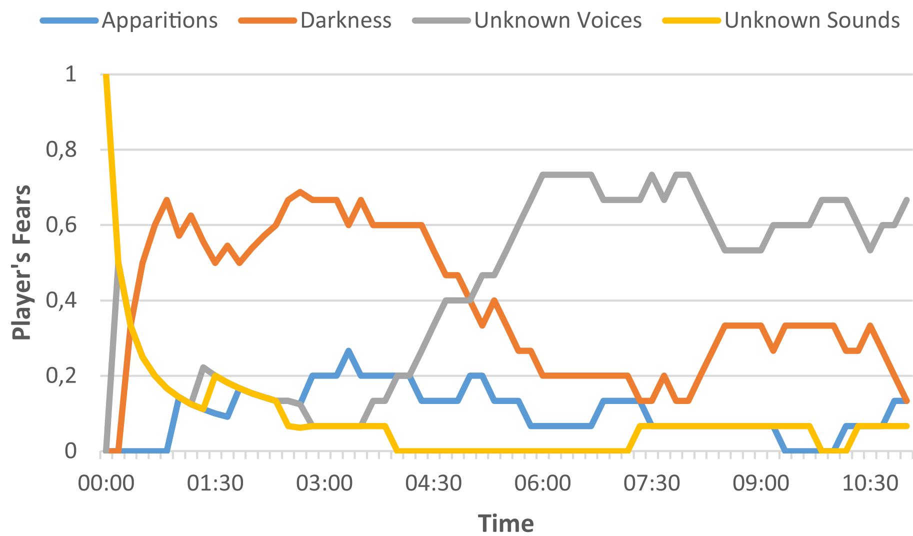

Fig. 14. Example of fear model for a participant that shows a gradually transition of fears during the game session. A gameplay video recording of this session is available at: https://www.youtube.com/watch?v=4NMXxC4hQ68.

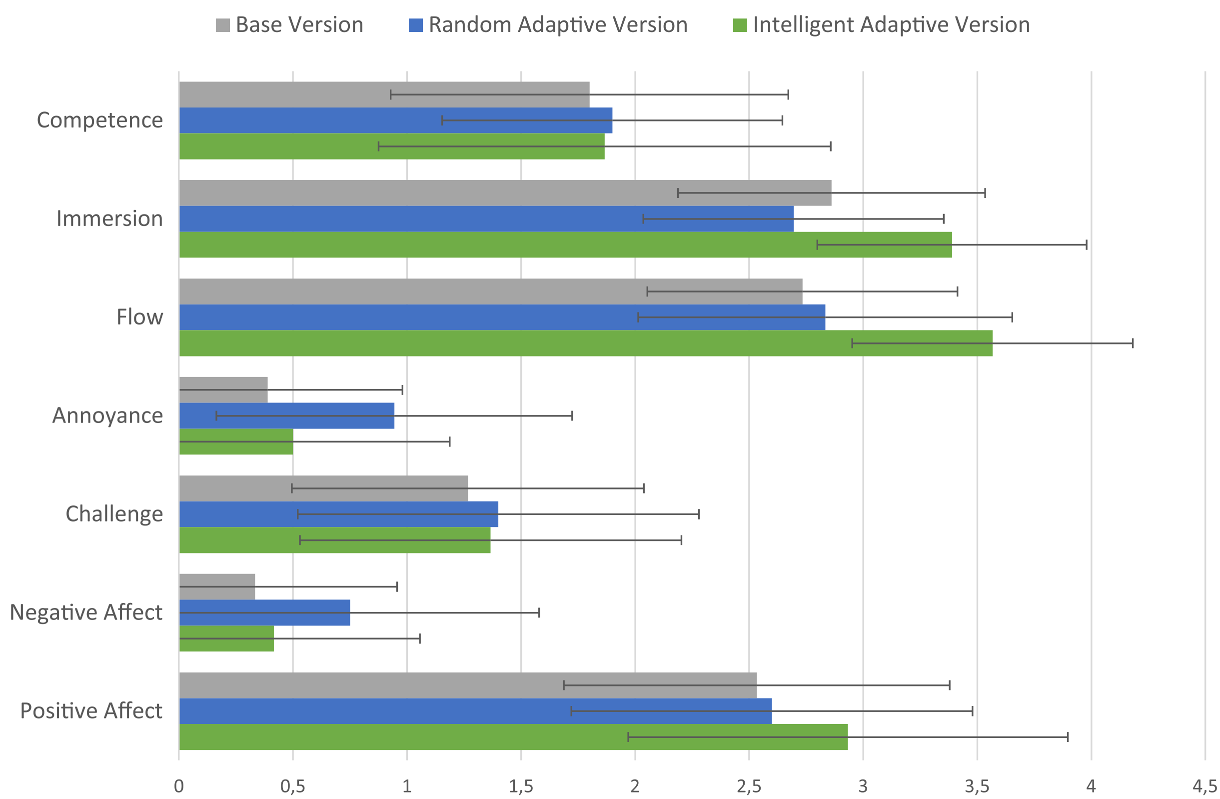

Fig. 15. Average and standard deviation of the seven components of the GEQ Core Module (*Competence*, *Immersion*, *Flow*, *Annoyance*, *Challenge*, *Negative Affect*, and *Positive Affect*) for the three versions of our game (*Base Version*, *Random Adaptive Version*, and *Intelligent Adaptive Version*).

The results of the ANOVA and post hoc comparisons suggest that our method can positively improve two important elements of the player experience: *Immersion* and *Flow*. While *Immersion* represents the mental involvement of the player with the game, *Flow* accounts for the players' motivation, sense of enjoyment, and connection with the game world, which are very important aspects for virtual reality games.

7. Concluding remarks

In this article, we presented a novel method to create adaptive virtual reality horror games, which combines a player model capable of identifying players' fears with an adaptive agent-based system that uses the knowledge of the model to adapt the content of horror games.

As the main contributions of the present work, we can highlight our method to identify behavioral patterns related to players' fears in gameplay data without relying on biometric sensors or any special hardware. As discussed in Section 2, most of the previous work on fear modeling and adaptive horror games focuses on the identification of emotional reactions based on the use of biometric sensors, which restricts the applications of these method to well-controlled laboratory

Table 6
One-Way ANOVA results for each component of the GEQ Core Module on the three versions of our game. The statistics are: sum of squares (SS), degrees of freedom (*df*), mean square (MS), F-ratio (F), p-value (*p*), and effect size/eta squared (η^2).

	SS	*df*	MS	F	*p*	η^2
Competence						
Between Versions	0.156	2	0.078	0.098	0.907	0.002
Within Versions	68.967	87	0.793			
Immersion						
Between Versions	9.463	2	4.731	11.164	< 0.001	0.175
Within Versions	44.500	105	0.424			
Flow						
Between Versions	12.422	2	6.211	11.902	< 0.001	0.215
Within Versions	45.400	87	0.522			
Annoyance						
Between Versions	3.111	2	1.556	3.084	0.054	0.108
Within Versions	25.722	51	0.504			
Challenge						
Between Versions	0.289	2	0.144	0.203	0.817	0.005
Within Versions	62.033	87	0.713			
Negative Affect						
Between Versions	2.333	2	1.167	2.257	0.112	0.061
Within Versions	35.667	69	0.517			
Positive Affect						
Between Versions	2.756	2	1.378	1.653	0.188	0.037
Within Versions	72.533	87	0.834			

experiments. In contrast, our method relies only on machine learning algorithms to discover behavioral patterns in past gameplay data, and therefore does not require any extra hardware to identify players' fears.

Another important contribution of this work is the proposed agent-based adaptive game system, which uses the knowledge of the fear model and specialized algorithms to track the horror intensity experienced by players to moderate the use of horror elements in the game. As demonstrated by the results of our user study, the proposed system can positively improve the player experience in virtual reality horror games, balancing horror and entertainment for an immersive and enjoyable game experience.

In our experiments, the proposed method revealed encouraging results. The accuracy of the fear model obtained even with a small training dataset is a promising indication that the model can be further improved by using larger training datasets. Results from our user study also suggest that our method can positively improve the overall player experience (*Immersion* and *Flow*). Although future work and more representative user studies still are needed to evaluate other aspects of our method, such as replayability factors, the positive feedback we received from players, especially the enthusiasm demonstrated by them when they were told that the game was adapting its content according to their fears, is a welcome stimulus for the continuation of our work.

As suggested by the results of the user study and statistical significance tests (ANOVA and post-hoc analyses), the proposed system is capable of balancing horror and entertainment. The results obtained when comparing the player experience in the *Base Version* with the experience provided by the *Intelligent Adaptive Version* suggest that adapting horror elements according to players' fears can positively increase the sense involvement and enjoyment of players. At the same time, when comparing the fear ratings reported by participants that tested these versions of the game, we can also conclude that the *Intelligent Adaptive Version* was the one that provided players player with scariest experience. The comparison between the *Random Adaptive Version* and the *Intelligent Adaptive Version* revealed no significant differences in the fear ratings reported by players, but the *Intelligent Adaptive Version* was the one that provided players with a better game experience (improving *Immersion* and *Flow*). These results suggest that selecting the correct horror elements (the ones feared by individual players) can positively improve the overall player experience in virtual reality horror games.

The results obtained in our study are in agreement with the recent finding of Andersen et al. [82], which suggest an optimal fear level (a "sweet spot") in which enjoyment is maximized (pointing to an inverted-U-shaped relationship between enjoyment and fear). Although we cannot conclude that our system has achieved such optimal fear level only with the studies conducted for this work, the results suggest that we are at least on the way to an optimal level of fear. On this matter, future studies can focus on finding the optimal parameters to optimize the fear levels in order to maximize player enjoyment. In terms of limitations, it is important to point out that we have relied on a small and homogeneous training dataset created with samples collected mainly from game sessions of young male university students, which serves as an indication that our method is capable of recognizing players' fears, however future work still is needed to validate our method with more representative datasets. Another important limitation is related to the labeling process, where labels for the samples of our datasets were defined using only the information provided by players, which is subject to noise considering that not all players are able to precisely measure their fear levels. Although we did not observe any issues related to this problem in our experiments, it is something to take into consideration when creating larger datasets. In this respect, a promising direction for future work is the use of sensors to obtain biometric data of players when collecting gameplay data to train the fear model, which can be used to replace the questionnaire where players manually rate their fear levels in the training phase. The use of sensors can also be useful to assess the levels of fear evoked in players when evaluating the impacts of our method in an adaptive horror game.

Apart from the validation of our model with more representative datasets and more comprehensive user studies, another promising direction for future work that caught our attention involves the adaptation of other game elements that can be used to intensify the fear evoked in players. In particular, the adaptation of the game's narrative according to players' fears represents a potential aspect to be explored in future works. On this matter, our previous works on the development of adaptive narratives based on personality and preference modeling [14,26,28,83,84] can offer some insights on how interactive narratives can be automatically adapted in response to user preferences, which are inferred from the user's personality. In this context, future work is needed to evaluate if there are any relations between players' personalities and their fears for certain narrative events in horror games. Future studies to further analyze different types of fears and different horror theories, such as the evolutionary perspective discussed by Classen [4], also represent a paramount commitment in our current research agenda.

Lastly, we firmly believe that horror games that automatically adapt their content to players' fears represent the next step in the evolution of this genre. Besides proving players with personalized experiences, this approach also allows game designers to explore new and creative ways to scare players in horror games.

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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