Knowledge-Based Systems 209 (2020) 106450

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Predicting the effects of suspenseful outcome for automatic storytelling

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ARTICLE INFO

Article history:
Received 25 May 2020
Received in revised form 6 August 2020
Accepted 1 September 2020
Available online 17 September 2020

Keywords:
Automatic storytelling
Suspense
Predictive model
Genetic

ABSTRACT

Automatic story generation systems usually deliver suspense by including an adverse outcome in the narrative, in the assumption that the adversity will trigger a certain set of emotions that can be categorized as suspenseful. However, existing systems do not implement solutions relying on predictive models of the impact of the outcome on readers. A formulation of the emotional effects of the outcome would allow storytelling systems to perform a better measure of suspense and discriminate among potential outcomes based on the emotional impact. This paper reports on a computational model of the effect of different outcomes on the perceived suspense. A preliminary analysis to identify and evaluate the affective responses to a set of outcomes commonly used in suspense was carried out. Then, a study was run to quantify and compare suspense and affective responses evoked by the set of outcomes. Next, a predictive model relying on the analyzed data was computed, and an evolutionary algorithm for automatically choosing the best outcome was implemented. The system was tested against human subjects' reported suspense and electromyography responses to the addition of the generated outcomes to narrative passages. The results show a high correlation between the predicted impact of the computed outcome and the reported suspense.

1. Introduction

Suspense is a key component of storytelling. It is known to play a fundamental role in immersion, enjoyment and suspension of disbelief, which are essential elements in a wide range of narratives such as novels, films or video games [1,2]. Also, suspense is a matter of interest in psychology and cognitive science. In particular, event anticipation in suspenseful scenes and the forecast of the outcome is a creative problem-solving activity in which humans try to counteract the negative and stressful effects of the narrative [3,4].

The emotional impact of the outcome can be exemplified with many classic suspense movies [5–7]. For instance, in the scene of Hitchcock's *Psycho* in which the victim is about to be killed in the shower, the audience anticipates a fatal outcome and feels distress, even when the outcome is not rendered in full detail. The anticipation is mainly triggered by the audience's perception of the foreseeable threat [8]. Therefore, the nature and hazard of the outcome influences this "fear of victimization" [9].

Mainly contextualized in narratological and behavioral studies [10], the emotional impact of the outcome has been broadly analyzed in books and films [11–15]. However, although it has been qualitatively tested, a detailed quantitative model for predicting the suspense triggered by the expected outcome has not yet been implemented. This is probably due to the variability of human response to suspense and the difficulty of analyzing the complexity of the many aspects involved in the phenomenon. In the field of computational narrative, such a model would be of interest to storytelling systems: so far, automated storytellers have typically been based on narratological aspects, focusing on the task at hand and not providing a quantification of the emotional impact of the different features of suspense.

This paper presents an original model of the emotional impact of the outcome in a suspense setting and its development. This proposal is intended to provide a computational implementation for quantifying the suspense that the reader will experience in an automatic story generation system. As such, the model has been extracted and implemented from experimental data.

This study was carried out by: (a) gathering different types of outcomes from an analysis of narratives in suspense films, (b) running a preliminary study in which subjects report the level of suspense and the affective evaluation for each type of outcome, (c) computing a model that predicts the effect of suspense based on the reported values, (d) implementing an evolutionary algorithm to get the best-fit outcome for the desired suspense level to

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https://doi.org/10.1016/j.knosys.2020.106450

evoke, and (e) testing the system by analyzing subjects' responses and bodily EMG reactions.

2. Related work

The process of automatic story generation is mainly led by a high-level narrative planning system. The process generates a large set of states (the potential *events* of the story) from which the best candidates to compute the story are chosen, according with the planner's objectives. While this list of selected states covers the internal generation of the story-line (the *plot*), a different step is responsible of turning the plot into a comprehensible language for the audience (the *discourse*). To address the process of plot generation, the field of computational creativity covers different strategies [16–21]. These strategies include variations on the weight of the featured elements (events, context, characters, actions, sets) as well as specialized sub-processes for different aspects of storytelling (causality and coherence, classical predefined structures and events, inter-character affinity). Fig. 1 contains a schematic representation of an incremental, state-based plot generation process.

In automatic storytelling systems oriented to the generation of suspense, the planner's objective is to compute sequences of states that lead to situations that are harmful to the protagonists of the story [16,22–24]. In this regard, the relevant literature supports the importance of outcome as a key factor in evoking suspense [24–28]. For instance, [29] introduces suspense as an affective concomitant of an answering event with two logically opposed outcomes (morally correct but unlikely versus evil and likely). [30] view suspense as a high degree of certainty of a negative outcome. [31] relate suspense to how much is at stake on the outcome. [32] defends that suspense implies feared probable outcomes that threaten protagonists liked by the audience.

This fear of victimization is key for media production, since audiences tend to enjoy frightening stories based on it [33]. These stories generally increase their evoked arousal by threatening or showing graphic victimization related to the expected outcome for characters [34–36]. According to [37], perceived seriousness of the result of the outcome (e.g., a crime) is an important predictor of this fear [e.g.,[38–43]]. Similarly, several studies have compared different hazardous outcomes in terms of apprehension. [44] analyze how *afraid* the subjects were of becoming the victim of several types of crimes in their daily life (such as being murdered, or beaten up by someone known). Likewise, [45–47] show that, in a threat situation, people prioritize their most fearful emotions in a certain order, such as: attacked with a weapon, kidnapped, murdered, sexually assaulted, and victim of a burglary while at home [45]. Additionally, the field of fictional narrative covers the study of unreal threats: mutations as the fear of the destruction of humanity, diabolic possession as the fear of losing self-control of self-degradation, being injured by a vampire as the fright of "returning" as another inhuman threat [48–51], also involve expectations of an undesirable event [52].

Although this is an extensively researched issue (e.g., [38,53–57], in addition to the authors noted above), results may be considered only partially valid for the purposes of modeling and predicting the effects of the outcome in suspense. Information about how outcomes quantitatively influence suspense is still missing from the relevant literature. Therefore, an analysis of the emotional effects of these outcomes (real or fictional) which may improve automatic story generation has not been provided yet. The implementations of current automatic storytelling systems focused on suspense barely consider neither a variability of outcomes nor its emotional impact [16,22–24].

Table 1
Distribution of participants among the different stages of the study. The three first stages cover the preliminary study, and the last stage covers the evaluation of the implemented model (see Section 6).

Code	Stage	Males	Females	$mean_{age}$	SD_{age}
OE	*Outcome extraction*	11 (55.00%)	9 (45.00%)	20.05	3.02
SA	*Suspense evaluation*	21 (53.85%)	18 (46.15%)	20.28	3.99
AE	*Affection evaluation*	21 (53.85%)	18 (46.15%)	20.21	3.79
ME	*Model evaluation*	22 (53.66%)	19 (46.33%)	19.90	3.12

3. Preliminary study of suspense ratings and affective evaluation

This section details how the list of suspenseful outcomes was obtained, and the process for assigning a quantitative metric to each outcome. This metric was gathered for computing the predictive model.

3.1. Participants

The study was publicly announced, and those wanting to take part in it voluntary enrolled. $N = 138$ subjects participated, 75 men (54.35%) and 63 women (45.65%), with ages ranging from 17 and 37 years ($mean = 20.12$, $stdev = 3.49$). All of them were native Spanish speakers.

Each participant was assigned an internal code (from 001 to 138). This code was stored along with its age, gender and contact method. Participants were manually, anonymously distributed in a way that limited the variability of number of participants, age and gender between the different stages of the study. Table 1 shows this distribution.

3.2. Outcome extraction (OE)

A selection of the best films for a preliminary extraction was made based on four on-line magazines specialized on movies: Rotten Tomatoes, IMDb, Movie Lens, and FilmAffinity. All four magazines present a clear genre segmentation and an active community with a high number of evaluations per film. These sources have been used as the base for other studies involving automatic generation of predictive models [e.g., [58–64]].

A search was carried out for each magazine to get films classified as *crime*, *suspense*, *thriller*, *terror* and/or *horror* (according to the classification found in each magazine), and the results were ordered by magazine punctuation resulting in a total of five lists of 150 films each.[1] Once the lists were composed, any film not typified as crime, suspense, thriller, terror or horror by at least three of the four magazines was discarded. The result was a final list of 93 films categorized either as horror or thriller.

Once the films were collected, each movie was randomly assigned to the $N = 20$ participants (see Table 1, stage *OE*). In order to get a peer review, the assignment ratio was of two participants per film, with a total of nine to ten films per participant, to meant identify suspense scenes and their corresponding outcomes.

The terms that each participant reported were checked in order to create the list of outcomes. Table 2 shows the resulting types and analysis of occurrences.

[1] Rotten Tomatoes differences audience score from critics' score, so both evaluations were collected separately.

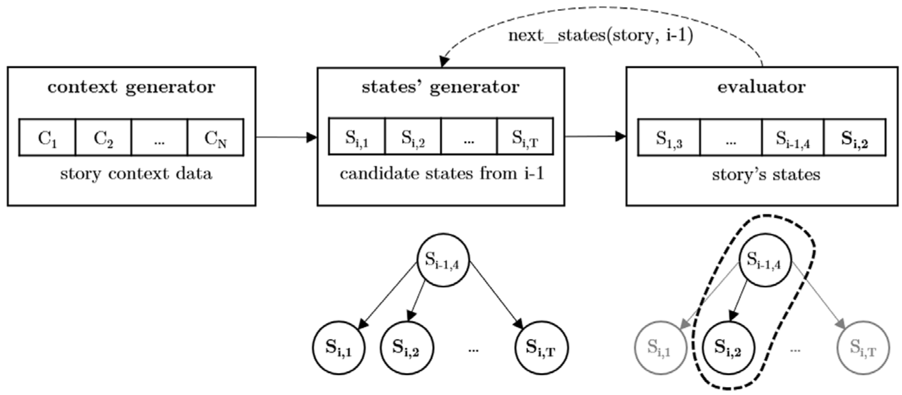

Fig. 1. General scheme of a planning system for generating the plot. From a preliminary context (descriptions, characters' features, environment), the states' generator computes a set of potential new states. Following, a second process evaluates them and select the best candidate. This sequence between states' generation and best candidate selection iterates until the plot is completely created.

Table 2
Film information and reported outcomes along the percent of films in which they appear. The list of outcomes includes *death*, *confinement* (for an indefinite period), *loss of a limb*, *loss of a loved one*, *madness*, *material losses*, *non-lethal physical wound*, *returning* (as ghost or a living-dead), *sexual assault*, and *torture*.

Characteristic	Thriller	Horror	Total
Films			
Genre	49 (52.69%)	44 (47.31%)	93
Year (mean)	1985.42	1971.55	1978.86
Year (stdev)	26.61	24.82	25.76
Types of outcome			
Death	95.92%	97.73%	96.74%
Confinement	32.65%	38.64%	35.48%
Loss of a limb	6.12%	2.15%	5.38%
Loss of a loved one	34.69%	43.18%	38.71%
Madness	6.12%	9.09%	7.53%
Material loss	20.41%	4.55%	12.90%
Non-lethal physical wound	34.69%	31.82%	33.33%
Returning	2.04%	45.45%	22.58%
Sexual assault	16.33%	29.55%	22.58%
Torture	40.82%	45.45%	43.01%

3.3. Suspense evaluation (SA)

In a second stage, the reported perceived suspense of the collected outcomes was obtained. $N = 39$ participants (see Table 1, stage *SA*), eighteen women (53.85%) and twenty-one men (46.15%), were queried about the relative suspense they perceived in each term. The process took place in a single room, where paper-and-pencil surveys were randomly distributed among the participants. The outcomes were shuffled beforehand. Prior to this, a set of instructions in paper informed the participants about the purpose of the evaluation.

To avoid potential effects derived from the term's ambiguity, we facilitated the definition of suspense by [30, p. 325]: "a high degree of certainty of a negative outcome". The list of outcomes was presented to the subjects along with the task: *In a scene of a thriller movie in which a character is under an imminent threat (any of the following), report how much suspense you would feel as spectator.* The words were randomly shuffled for each participant to avoid sequence effects.

Participants were asked to use a 9-point rating scale (where 1 corresponds to *no suspense* and 9 corresponds to *extremely suspenseful)*, presented as a pictographic scale based on the SAM model [65]. This scale was chosen to simplify the analysis, since it is also used by the comparative affective set, as detailed in Section 3.4.

3.4. Affective evaluation (AE)

To find out the amount or intensity of each outcome and compare it against the reported suspense, $N = 39$ participants (see Table 1, stage *AE*), eighteen women (46.15%) and twenty-one men (53.85%), were asked to rate a set of terms according to their emotional dimensions, as described below.

The model for quantitatively predicting the effect in readers of suspenseful outcomes was based on affective evaluations. It relies on the Affective Norms of English Words (ANEW) [65], an extensive list that contains a number of emotional aspects of 1,034 terms evaluated in a 9-point rating scale represented by the Self-Assessment Manikin (SAM). ANEW measures the emotion by conceptualizing it in three dimensions: valence (or pleasure, ranging from *unpleasant* to *pleasant*), arousal (or intensity of the emotion, ranging from *calm* to *excited*) and dominance (or degree of control over the stimulus, ranging from *out of control* to *in control).* Since the study features Spanish speaking evaluators, we use the Spanish version of ANEW [66], containing the same set of words than the original ANEW.

This stage was designed as a paper-and-pencil test. The subjects were given the list of the ten outcomes to be rated. In order to avoid the potential skewing of affection due to the expected decreasing valence because of the consecutive occurrence of negative terms with respect to the ANEW experiments, a set of 140 new words from ANEW collection were added resulting in a total of 150 terms. The added words were obtained by sorting the set of ANEW by ascending valence and taking the terms that adjust to the formula $p \bmod \left\lfloor \frac{1034}{140} \right\rfloor = 0$, where p is the position of the word in the sorted list, and 1,034 the number of words. Due to the potential difficulty in understanding the difference between the dimensions, any doubts were solved following the method described in [66, p. 601], after the participants read the instructions and before they rated the words.

4. A predictive model for outcome emotional effect

To validate and quantify the relation between the emotional impact of outcomes and the reported suspense, it was necessary: (a) to ensure that the type of outcome influences suspense (by analyzing the results of the stage *SA*); and (b) to find a significant correlation between reported suspense and reported affectivity of the terms representing the outcome (using the results of stage *AE).*

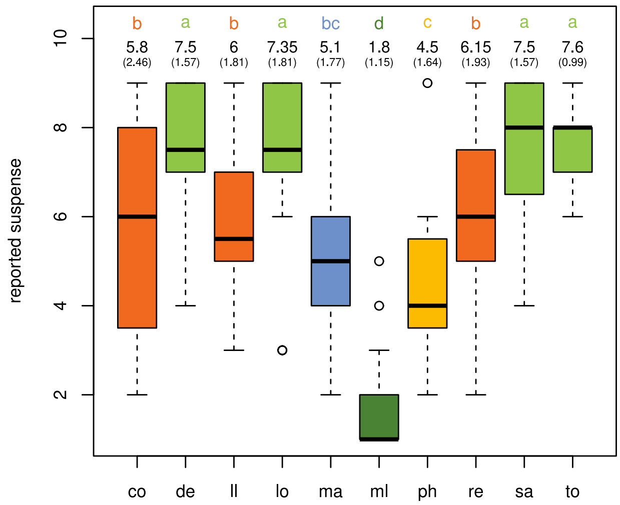

Fig. 2. Reported suspense by type of outcome. The outcomes are presented by: *co* (confinement), *de* (death), *ll* (loss of a limb), *lo* (loss of a loved one), *ma* (madness), *ml* (material losses), *ph* (non-lethal physical wound), *re* (returning), *sa* (sexual assault), and *to* (torture).

4.1. Results of reported suspense evaluation

The resulting reported suspense shows relevant differences among the outcomes ($\chi^2_9 = 90.286$, $p < 0.000$). Likewise, an analysis of variance (ANOVA) was conducted for the means, resulting in a similarly significant result ($F_{9,199} = 22.350$, $p < 0.000$). Fig. 2 illustrates these differences.

4.2. Results of affective evaluation

The reported suspense per type of outcome appears to influence the affective evaluation in its three dimensions: valence ($\chi^2_9 = 30.12$, $p < 0.000$), arousal ($\chi^2_9 = 25.25$, $p < 0.005$), and dominance ($\chi^2_9 = 20.05$, $p < 0.01$). The analysis evidences a strong downhill correlation of suspense against valence ($\rho = -0.816$, $p < 0.000$), moderately strong uphill with arousal ($\rho = 0.5597$, $p < 0.000$), and downhill with dominance ($\rho = -0.637$, $p < 0.000$), as shown in Fig. 3. These correlations seem to validate the existence of an influence of expected outcome on the perceived suspense, which is in line with the reviewed literature.

Regarding the subjects' gender, affectivity analysis reported no differences between male and female scores in valence ($Z = -0.214$, $p > 0.8$), arousal ($Z = -0.410$, $p > 0.6$) or dominance ($Z = 0.76$, $p > 0.4$). Similar results were found when examining the effect of the context in which the terms were evaluated as neutral or suspenseful, as explained in Section 3.4 (valence, $Z = -0.870$, $p > 0.4$; arousal, $Z = 1.300$, $p > 2$; dominance, $Z = -0.382$, $p > 0.7$).

Regarding the correlation with the original ANEW [66] scores, no significant differences were found ($t = -0.45$, $p > 0.5$ for valence; $t = 0.74$, $p > 0.1$ for arousal; $t = -1.17$, $p > 0.05$ for dominance).

4.3. Computing the predictive model

Given the suspense ratings provided by the subjects, a multiple regression analysis was conducted with suspense mean ratings as the dependent factor, and the rated three affective dimensions as independent factors. A function describing the model, $M : \mathrm{R}^3 \to \mathrm{R}$, was computed. The obtained best fit formula was multiple linear, where ($\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$, RMSE) = (8.20, − 1.02, 0.14, − 0.26, 1.32), $\beta 1$ to $\beta 3$ being the coefficients for the valence (V), the arousal (A) and the dominance (D) parameters, respectively, as shown in Eq. (1):

$$M = -1.02 \cdot V + 0.14 \cdot A - 0.26 \cdot D + 8.20 \tag{1}$$

5. Implementing the predictive model

A library implementing the model was developed in Java. This library selects the best combination of elements for a suspenseful story based on the previously described model for predicting of the intensity of evoked suspense. Although this research aims to predict the effect of the different outcomes (avoiding collateral effects because of other narrative strategies, such as managing the environment or the threat resources [67]), the algorithm has been conceived to cover a broader set of suspenseful features and their corresponding models, beyond the influence of outcome alone.[2]

The implemented library uses the Java Genetic Algorithms Package (JGAP) [72]. Each chromosome is defined by a cluster of genes. Each cluster U_i contains a set of genes $G_{i,[1..n]}$ respectively representing terms (such as *fog*, *tall*, or *death*) for a specific feature that can be manipulated to evoke suspense (such as *environments*, *characteristics of the threat*, or *outcomes*) [73]. Since suspense is affected by each type of feature in several ways, all the genes of each cluster U_i are related to a particular predictive model $M_i : \mathrm{R}^3 \to \mathrm{R}$. This ensures, for example, that changes on the environment or the characters' resources affect suspense differently from the way in which the outcome does. This way, the gene phenotype term is an instance of the feature represented by its cluster U_i, and the genotype is obtained by applying M_i to the affective dimensions of the term.

The algorithm performs in a similar way to a Simple Genetic Algorithm (SGA) [74]. It works by using mutation, crossover, and worst candidates' re-placement. The mutation operation consists in the substitution of a single term of only one cluster by another term corresponding to the feature represented by such cluster. This way, the new term can match with another term already existing in the cluster. Concerning the single-point crossover operation, the point is also randomly chosen and each operation also affects only one cluster.

As previously explained, the specific model M_i corresponding to its cluster U_i is applied to obtain each gene ($G_{i,j}$) genotype. In order to compute the predicted suspense Φi for the terms of a cluster U_i, the mean of applying the model to all the genes of such cluster is calculated, $\Phi_i = \sum_j^{n_i} M_i(G_{i,j})/n_i$, where n_i is the number of genes of the cluster U_i. Likewise, the predicted suspense for the complete chromosome is obtained through the formula $\sum_i^m \Phi_i/m$, where m is the number of clusters of the chromosome. The fitness function compares this value with the desired value of suspense to be evoked. The lower the difference is, the better the chromosome is considered.

6. Evaluating the system through adapted stories (EM)

To test the model, a list of narrative texts was adapted so that they would include the predicted outcomes. Based on the adaptation of these passages and in order to collect a paper-and-pencil survey and EMG facial reactions when reading the suspenseful excerpts, we carried out an experiment. The resulting data was compared against the suspense values predicted by the model.

To compose the texts, eight excerpts were collected from novels published in Spanish. Four of them ($N_e = 4$, experimental excerpts) were randomly selected from thriller/horror books. The other four ($N_c = 4$, control excerpts) were obtained from

[2] Other models have been addressed in previous studies [67–71].

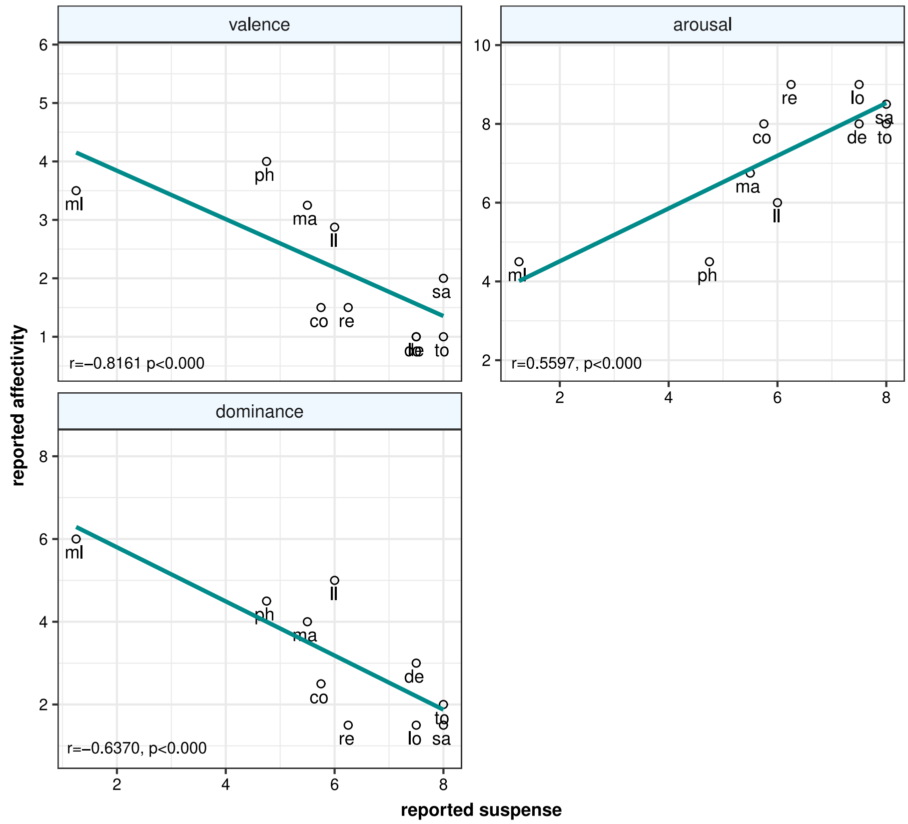

Fig. 3. Reported suspense by reported affectivity in the three affective dimensions.

literature of other different genres (neither thriller nor horror). The method to review the books was based on recommendation lists gathered from search engines inputting the terms "modern thrillers", "thrillers", "horror tales", and "classical horror" for suspense passages; and "adventure story", "romantic novel", "biography live story", and "classical literature" for control excerpts. Table 3 shows the books and passages finally chosen through a comparative analysis to check that there was no inconsistency between the passages, as described below.

The readability of all passages was classified as *normal* or *quite easy* according to the FS index and the INFLESZ scale, without significant differences between suspense and control passages ($t = 0.38$, $p = 0.72$). According to the Semantria score for automatic sentiment analysis [75], suspense passages ranged from negative to neutral-negative emotions ($mean = -0.189$, $std = 0.134$), while control excerpts ranged from neutral-positive to positive ($mean = 0.270$, $std = 0.105$). The results yield a difference ($t = -5.39$, $p < 0.002$).

Regarding the lexical/syntactical characteristics, suspense passages similarly have a lower number of words ($mean = 376.00$, $std = 33.67$) and syllables ($mean = 759.25$, $std = 57.75$) compared to neutral passages (words: $mean = 435.50$, $std = 17.94$; syllables: $mean = 854.75$, $std = 7.39$), although having a small difference ($twords = -3.12$, $pwords < 0.03$, $tsyl = -3.30$, $psyl < 0.05$). In any case, suspense passages had to be completed with the information of each possible outcome. In terms of the number of phrases, no significant differences were found ($tphr = 0.78$, $pphr < 0.47$).

6.1. Participants

$N = 41$ participants (see Table 1, stage *EM)*, nineteen women (46.33%) and twenty-two men (53.66%), took part in this stage. The assignment was carried out according to the same methodology described in Section 3.1.

6.2. Material

The words to be inserted for the suspense passages were computed by the predictive algorithm. The probabilities of mutation and crossover were both fixed to 0.6, population size and offspring were set to 100, and iterations were set to 200. The cluster representing the outcomes contained four genes, one for each suspenseful passage. The algorithm was run $N = 41$ times, once for each participant. For each execution, the first population and the desired average suspense were randomly set after reading all passages. Clusters related to features that were not outcomes were excluded since they were not necessary. Once the process was completed, the passage-outcome-gender ratio was balanced so that every element appeared with similar frequency. This was achieved by selecting among the best results for each execution.

After this stage, a number of Microsoft® PowerPoint™ blank files were filled with eight different adapted passages, one per novel. Each passage was divided into three slides that included sets of complete paragraphs, avoiding to break any sentence, and balancing the resulting length of the texts. Outcomes were introduced in the third (last) slide of each passage. Although the outcomes were automatically computed, the inclusion of some of them required a manual fix in the texts to keep the consistency of the plots. Specifically, for the narratives The Spirits' Mountain, The Ice Princess and Shadowfires, the adaptation involved the addition of a new block of content at the end of the passage that included a placeholder to be automatically filled with the selected outcome, because the original excerpt did not include any sentence referring to an expected, immediate outcome that could be replaced. No significant differences between suspense and control passages were found after the final composition with the bypassed texts ($twords = 1.49$, $pwords = 0.19$, $tsyl = -0.31$, $psyl = 0.76$, $tphr = 1.92$, $pphr = 0.77$).

Table 3
Selected passages for testing the model of the relation between expected outcome and suspense. It includes book title, author (referenced), genre, number of words, number of syllables (*syl.*), number of phrases (*phr.*), INFLESZ Flesch–Szigriszt readability index (*FS*) for Spanish language [76] and Semantria sentiment analysis score (*SS*) [75].

Story	Genre	Words	syl.	phr.	FS	SS
The Spirits' Mountain G. A. Becquer [77, c. III]	Horror	366	746	27	66.30	−0.344
The Ice Princess C. Lackberg [78, c. 2]	Thriller	357	705	22	67.58	−0.229
The Hellbound Heart C. Barker [79, c. 11]	Horror	426	841	43	73.94	−0.157
Shadowfires D. R. Koontz [80, c. 2]	Thriller	355	745	20	58.34	−0.024
Around the World in Eighty Days J. Verne [81, c. III]	Adventure	424	857	18	57.36	+0.125
The Old Man and the Sea E. Hemingway [82]	Lit. fiction	461	856	34	77.60	+0.271
Little Women L. M. Alcott [83, c. 2]	Com. of age	435	856	20	62.49	+0.310
Steppenwolf H. Hesse [84]	Autobiogr.	422	850	20	60.25	+0.373

The PowerPoint™ files were assigned randomly to each participant. Subjects read the texts in a 19'' monitor laptop. The texts were rendered with the font Garamond, 24pt.

Additionally, electromyography (EMG) bodily reactions were monitored. To get emotional responses [85, p. 597], the electrodes were connected in corrugator supercilii as described in [86, p. 106], using surface Ag/AgCl electrodes (24 mm diameter) filled with conductive and adhesive hydrogel.

In order to gather the data, the *MySignals Hardware Developed Platform* set of sensors [87] connected to an *Arduino UNO* [88] was used. The signals were gathered with a sampling frequency of 20 Hz. For each passage/slide, individual response variability was firstly processed to calculate the percentage change scores relative to baseline of the normalized data. The recorded data was high pass filtered with a cutoff frequency at 0.8 Hz for detrending unstable baseline [89, p. 3]. In spite of this, it was impracticable to compare the different participants' facial responses for each passage/slide by simple overlapping because of a) the variability of each participant in reading time; and (b) that facial micro-expressions takes no more than 500 ms [90, p. 181]. This makes micro-expressions' coincidences unlikely. For this reason, we operated with the means of the maximum *corrugator supercilii* variation in each passage/slide data envelope.

To synchronize the reading process with the recording of EMG reactions, a PowerPoint™ macro was developed. It sent a signal to the computer when a slide was passed. This way, the computer tick was registered with each click, allowing its synchronization with the sensor data collected by serial port. After the calibration, the maximum divergences of synchronization were less than 20 ms.

6.3. Method

Participants were individually led to a room, where they were informed about the ethical statement, the fact that anonymized data that was going to be collected, and that voluntarily participating in the study implied the acceptance of these conditions.

After an explanation of the process and the devices, the electrodes were connected to the participant. Following, the participant was required to report how much suspense the participant felt after reading each slide. A 9-point rating scale was used in a paper-and-pencil survey, where it was presented as a pictographic scale based on the SAM model [65].

6.4. Suspense story effect

After the data was processed, two analyses were conducted based on the set of passages: (a) the reported suspense meant to validate the algorithm; and (b) the relation between the EMG physiological reactions and the reported suspense.

6.4.1. Analysis of reported suspense

Comparatively, results show in the variables participant gender (Z = 2.148, $p < 0.05$), book ($\chi^2_7 = 536.22$, $p < 0.000$) and slide (1 to 3, $\chi^2_2 = 15.455$, $p < 0.000$). This behavior is also present when the analysis is centered in suspense passages[3] (*hh*, *ip*, *sh*, *sm*) in participant gender (Z = 3.137, $p < 0.005$), book ($\chi^2_3 = 48.267$, $p < 0.000$) and slide ($\chi^2_2 = 89.318$, $p < 0.000$). The influence of the outcome is significant in these passages ($\chi^2_9 = 54.701$, $p < 0.000$), but the data does not show significant differences between characters' genders (Z = 0.755, $p > 0.4$). Nevertheless, an analysis of neutral passages (*aw*, *lw*, *om*, *st*) only shows differences in participant gender (Z = 1.989, $p < 0.5$), and not significant results were found regarding the effect of the book ($\chi^2_3 = 9.24$, $p < 0.06$) and the slide ($\chi^2_2 = 0.52$, $p > 0.5$).

Fig. 4 shows the increase of suspense along with the slide number in suspenseful passages. The influence of the type of outcome was studied by analyzing the last slide of the narrative excerpts, in which the outcome is introduced. Character gender shows a similar behavior as in the previous analysis ($Z = 1.241$, $p > 0.2$), but, in contrast, results reveal almost no significant differences in participant gender (Z = 1.631, $p > 0.1$) and book ($\chi 2 = 6.846$, $p > 0.07$). However, the type of outcome clearly influences the evaluation $\chi^2_9 = 59.99$, $p < 0.000$). Specifically, the relation between outcome and reported suspense gathered in Section 4 (where terms were evaluated in isolated) is strong ($\rho = 0.809$, $p < 0.005$).

Moreover, the correlation between reported suspense caused by the outcomes in suspense passages predicted by the system and the affective evaluations is also strong ($\rho = 0.748$, $p < 0.05$). Fig. 5 illustrates the last relation. The tendency by gender is included in the graphic, reporting differences between male ($\rho = 0.660$, $p < 0.05$) and female ($\rho = 0.733$, $p < 0.05$) participants', in a similar way than in previous stages.

[3] Again and due to aesthetic reasons, the names of the books will be often represented by acronyms, where *aw* = *Around the World in Eighty Days*, *hh* = *The Hellbound Heart*, *ip* = *The Ice Princess*, *lw* = *Little Women*, *om* = *The Old Man and the Sea*, *sh* = *Shadowfires*, *sm* = *The Spirits' Mountain*, and *st* = *Steppenwolf*.

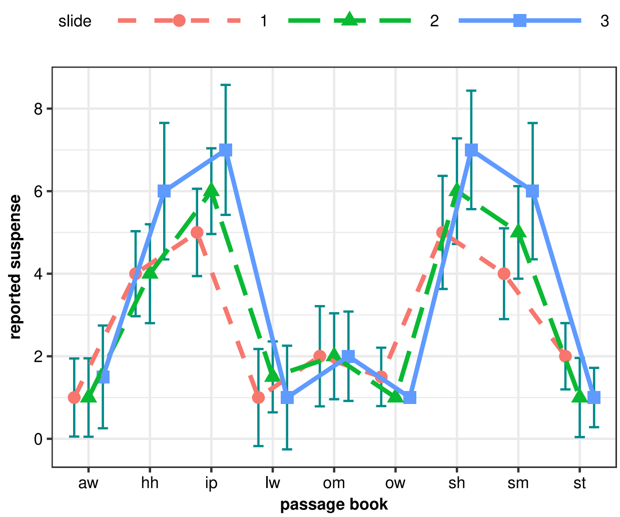

Fig. 4. Medians/standard deviations of reported suspense by passage and slide.

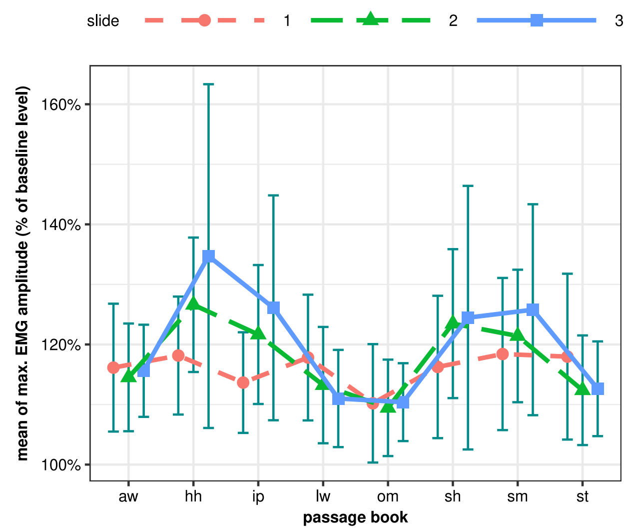

Fig. 6. Medians of last slides' reported suspense contrasting with the model prediction.

6.4.2. Analysis of electromyography (EMG) responses

An ANOVA was conducted in order to determine whether the subjects' EMG responses were influenced by passage, slide, gender and type of outcome.

The analysis reveals a significant effect ($F_{112,671} = 1.292$, $p < 0.05$) for passage ($F_{7,671} = 10.05$, $p < 0.000$), slide ($F_{2,671} = 4.858$, $p < 0.005$), and type of outcome ($F_{9,671} = 3.83$, $p < 0.000$). However, participant gender ($F_{1,767} = 0.39$, $p > 0.7$) and character gender ($F_{1,383} = 2.57$, $p > 0.1$) do not report any significant influence. Fig. 6 shows the influence of passage and slide, presenting a spider-like graph similar (though flattened) to Fig. 4. A more comprehensive analysis focusing in the last slide of the suspenseful narrative excerpts (in which the outcome is introduced) reveals a weak to moderate correlation between the EMG responses and the reported suspense ($r = 0.352$, $p < 0.000$), and between the EMG responses and our model ($r = 0.358$, $p < 0.000$), which may support the validity of the predictive model.

7. Discussion

This section discusses some aspects and design decisions, following the same order in which these have been introduced in the paper.

Firstly, the information source for the preliminary collection of outcomes comes exclusively from films. Even though there are web rankings for thriller and horror books, we considered that the outcome identification process would have been much slower and tedious for the participants if they were required to read books instead of watching movies. Since the plot itself is what receives the focus, we argue that the final set of terms would be sufficiently similar whether it was gathered from films, books or any other medium. Actually, the model was tested using excerpts of written novels, giving similar results. Also, human revisions and the subsequent classification of outcomes present a risk of bias which may lead to underestimate certain stimuli. However, our intention is not to carry out a complete study of every possible outcome in suspense plots, but to gather a sufficiently extensive, common and representative list that covers the most of suspense outcomes to compute the predictive model.

Secondly, the generative algorithm is simple but effective for this contribution, and the underlying structure of chromosomes covers the different impacts of a variety of suspense features. Nevertheless, the implementation has not been optimized for performing with an extensive set of terms and clusters. A study

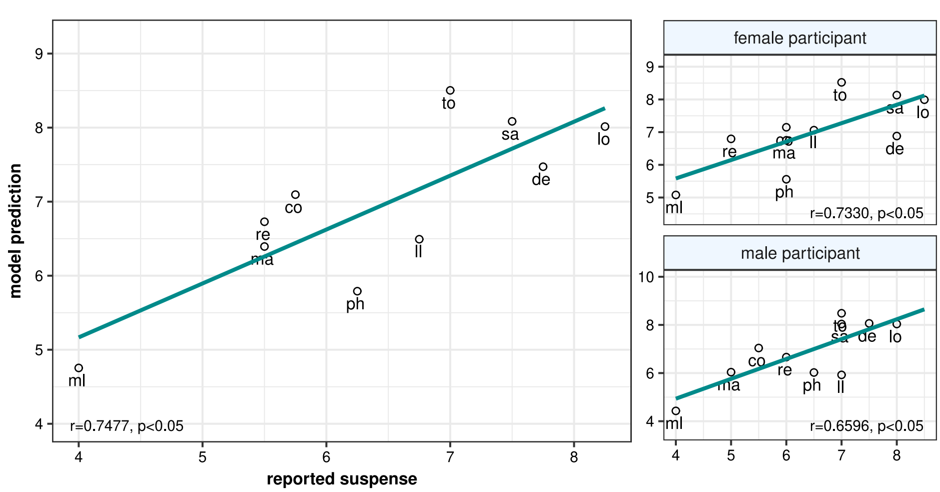

Fig. 5. Correlation between reported suspense for the last slides and the return value of the predictive model.

of optimal alternatives in comparison with the current SGA strategy must be carried out before its use in real cases of automatic suspense generation. This topic will be addressed in future contributions.

Regarding the accuracy of the tests, the survey shows that the system seems to adequately predict suspense from the outcomes. However, the EMG reactions reported a correlation relatively low. By itself, EMG accuracy assessment is not straightforward because of the waveform variability, background noise, electrodes' precision, and each subjects' individual ergonomics and facial reactions. Moreover, the study was conducted with a flexible, portable EMG device that could not perform with a maximum level of accuracy. Additionally, while the first question about reported suspense (stage *SA*) was introduced using just a list of terms, the last stage (stage *OM)* was conducted using the context of narrative passages from which it may be inferred collateral emotions (such as empathy, sadness, or surprise) that may also generate physiological reactions and, consequently, add noise into the measure. A more advanced instrument as well as working with other physiological reactions could improve the robustness [91–93]. In any case, both Figs. 4 and 6 show similar emotional responses for passage/slide, according to the model prediction.

8. Conclusions

This paper presents a predictive model of the effect of outcomes on the perception of suspense in narratives. The results indicate a clear correlation between the predicted emotional intensity evoked by the outcome and the perceived suspense, both in terms of the reported values and EMG reactions.

The model is provided as a resource for choosing the best outcome based on its emotional impact in computational storytelling. In this way, the quantitative measure of the effects of a suspenseful outcome would allow to balance out the evoked suspense according to the fear of victimization that the audience feels for the characters' expected fate. This makes it possible to automatically generate situations that evoke a greater emotional response by increasing the hazard of the outcome. It also allows to evoke and measure the emotional effect of diminishing this hazard, for instance for the purpose of adapting suspenseful scenes to a more impressionable audience while maintaining the overall plot.

Setting a specific value of desired suspense as the goal of the generative process would allow the system to compute the best outcome of the scene among the potential candidates, as proposed by the computational model and showed in the introduced experiment.

The process of modifying a scene, however, is more complex than simply stating a different outcome. On the one hand, the audience must know or interpret, from a preliminary information provided (which is limited to the functioning of the story generation system), what potential outcome to expect. On the other hand, changes in the staging and resolution of the scene will often be required from the new outcome. Even though these changes may be considered minor in outcomes with similar practical implications, most plots will presumably require modifications to ensure consistency and continuity. To achieve this, the story generator system must consider the relationships between the potential outcomes and the causal pathways leading and following them.

Indeed, semantically, the events represented by such states must be consistent with the proposed outcomes. This consistency must also be ensured by the elements introduced, according to their roles in the scene. Outside the scope of this contribution, maintaining semantic consistency is a complex issue [94–97]. It not only involves the events of the story-line, but also the emotional effects evoked by all the elements and features in the plot.

Accordingly, the structure of the evolutionary algorithm introduced in this paper has been designed to be used beyond outcome generation: Even though the outcome is a clear factor for evoking suspense, the selection of the optimal outcome is limited by other factors affecting the story consistency, due to the fact that not all outcomes are feasible depending on the particularities of the plot [21,98]. In this sense, the outcome may not be prioritized with respect to other features like empathy [99,100], proximity [101,102], or environment features [68,103] (also influencing how the readers feel). As previously introduced, a study of the accuracy and performance of the algorithm concerning these other clusters will be addressed in future contributions.

Ethical statement

All the experiments reported on this paper were carried out in accordance with the recommendations of national and international ethics guidelines, *Código Deontológico del Psicólogo* and American Psychological Association. The study did not present any invasive procedure, and it did not carry any risk to the participants' mental or physical health, thus not requiring ethics approval according to the Spanish law BOE 14/2007 and the ethical guidelines of authors' institutions. All subjects participated voluntarily and gave written informed consent in accordance with the Declaration of Helsinki. They were free to leave the experiment at any time. There was no compensation for participating in the evaluations.

CRediT authorship contribution statement

Pablo Delatorre: Conceptualization, Methodology, Software, Resources, Investigation, Formal analysis, Visualization, Writing - original draft, Supervision. **Carlos León:** Conceptualization, Methodology, Resources, Writing - original draft, Writing - review & editing. **Alberto G. Salguero:** Conceptualization, Methodology, Investigation, Resources, Writing - review & editing. **Alan Tapscott:** Conceptualization, Methodology, Resources, Writing - review & editing.

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.

Acknowledgments

This work has been supported by the Andalusian Government under the University of Cadiz programme for Researching and Innovation in Education (SOL-201500054211-TRA); by the CANTOR project (PID2019-108927RB-I00) funded by the Spanish Ministry of Science and Innovation; by the project FEI INVITAR-IA (FEI-EU-17-23) of the University Complutense of Madrid; and by the ComunicArteproject (PR2005-174/01) by BBVA Foundation Grants Scientic Research Groups 2017.

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