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Master's Thesis
Academic Year 2021

Film Real-Time Adjustment Interactive Playback System Based on Audience Decision Model

Keio University
Graduate School of Media Design

Yue Shen

A Master's Thesis
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Master of Media Design

Yue Shen

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Abstract of Master's Thesis of Academic Year 2021

Film Real-Time Adjustment Interactive Playback System Based on Audience Decision Model

Category: Science/engineering

Summary

Horror, war, and crime movies have always been an integral part of the film industry. However, some audiences feel the intensity of the content presented in these genres is often more than they can tolerate. At the same time, others are not satisfied with such intensity. Different audiences show significant differences between "avoidance of stimulus" and "need for stimulus." The mainstream MPA film rating is not a feasible solution to this problem because the audience's viewing preferences cannot be divided simply by age.

In response, the authors propose a new mechanism called "No-warning interactive playback system" as the core contribution of this paper. It is a real-time adjustment playback system based on the audience's physiological signals, such as EDA and heart rate. The core of this system is an algorithmic mechanism based on binary logistic regression, which could predict viewers' decisions with a high probability. Then, the author designed an accessory playback system to play movies with different levels of stimulation and even different storylines for the audience to maintain a smooth viewing experience for all viewers.

Keywords:

data analysis, interactive film, audience experience, physiological signals, human behavior and decision-making

Keio University Graduate School of Media Design

Yue Shen

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Chapter 1
Introduction

The genres of movies are becoming more and more diverse, and each genre has its audience. However, can all audiences enjoy all types of movies? While some specific film genres, such as horror, are increasingly challenging the audience's mental capacity, in effect turning away a portion of the audience. In contrast, other fans of these specific genres are often disappointed that the films do not reach their stimulus expectations.

Audiences have very different needs for these types of films that generate high levels of stress. There should be a considerable consensus that just as ramen restaurants offer noodles of varying hardness (Figure 1.1[1],[2])and soup of varying consistency, the same film should consider the needs of different types of audiences.

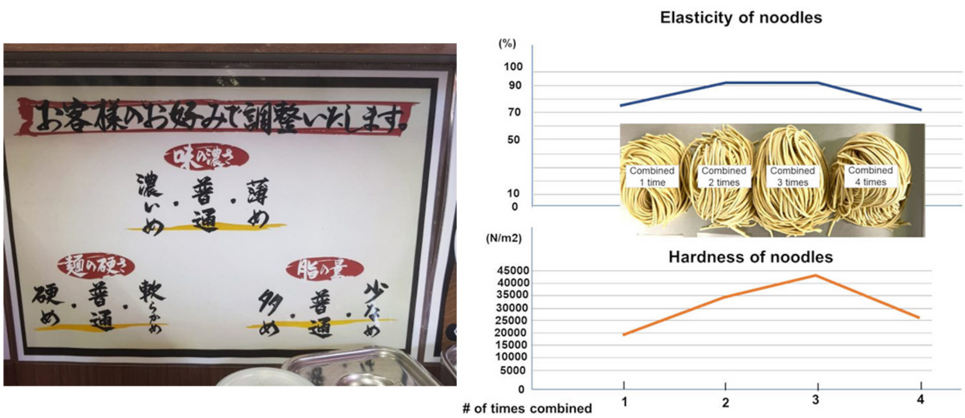


Figure 1.1 Inspired by Japanese ramen[1] [2]

Some of today's current film rating systems simply use 'age' to classify audience types, and there seems to be no other way to classify films that is more based on audience viewing habits.

1.1. Problems of current film rating system

In the author's opinion, the current rating system for films does not solve the enormous difference in the stressful feelings of different audiences towards films. The most common one is the MPA film ratings (Motion Picture Association film rating system), released by the Motion Picture Association of America. The MPA film rating system is based on the content of the film, mainly the assessment of violence, language, substance (mainly drugs), nudity, and sex, and then the rating of whether it is suitable for a specific age group of viewers. Although it is not a mandatory rating system and is not enforced by law, most films are rated according to this system. MPA film ratings classify all films into five categories according to the following rules (some regions may vary)[3].

G – General Audiences All ages admitted. Nothing that would offend parents for viewing by children.

PG – Parental Guidance Suggested Some material may not be suitable for children. Parents urged to give "parental guidance". May contain some material parents might not like for their young children.

PG-13 – Parents Strongly Cautioned Some material may be inappropriate for children under 13. Parents are urged to be cautious. Some material may be inappropriate for pre-teenagers.

R – Restricted Under 17 requires accompanying parent or adult guardian. Contains some adult material. Parents are urged to learn more about the film before taking their young children with them.

NC-17 – Adults Only No One 17 and Under Admitted. Clearly adult. Children are not admitted.

MPA film ratings are very detailed at the film level, assessing five areas: violence, language, substance (mainly drugs), nudity, and sex. However, at the audience level, age is used very simply as the only rating method. It is highly debatable whether this simple, one-sided categorization of audiences by age applies to every film industry area. Many studies have long discussed this controversy, as BA Austin found in his 1980 experiment. He designed statistics and analyses of data on high school students. Results of the experimental manipulation were non-significant (p lager than 0.05). that is, MPAA ratings did not affect the likelihood of viewing the movie and did not elicit a psychological response. (Austin 1980) . The PG Nalkur and PE Jamieson study also point out that while relatively effective in screening for explicit sex, the rating system allows increasingly violent content to enter PG-13 films, thereby increasing teens' exposure to more harmful content. The link between violent media exposure and teen violence should be more sensitive in the current rating system. (Nalkur et al. 2010)

In this paper, the author has analyzed in detail and argued with data that physiological attributes such as age and gender do not significantly impact the viewing habits of audiences. The core of the system proposed by the author is a new mechanism of audience classification, which classifies different types of audience decisions based on their physiological responses. This new mechanism may lead to new mechanisms that can be applied in some more emerging film fields.

As a film lover, you may often encounter this situation: if you are waiting for a movie to start, you will often see a red warning on the big screen, followed by a sentence that usually reads, "this film contains extreme language, violence, strobe lightning and scenes that some viewers might find upsetting" or "the following scenes may be upsetting, violence, strobe lightning and scenes that some viewers might find upsetting" or "the following scenes may be too disturbing for some audiences, viewer discretion is advised." Especially when you see horror films, thrillers, war films, crime films, these specific types of films, this kind of "advice" for the audience is widespread. Sometimes theaters will also advise audiences with cardiovascular and heart disease to carefully select and watch a specific film such as horror films; similar advice can also be seen in the large amusement park extreme rides often (Figure 1.2[4]).

Figure 1.2 Warning everywhere[4]

The name "No-warning system" was inspired by this phenomenon. the author hopes that this system allows all viewers to enjoy a film without scruple rather than see any "warning."

1.2. Different audiences react to stress

"Tension" is a complex emotion and is one of the most primitive and intense human emotions. In watching movies, viewers have more or less experienced a high level of tension, which may come from the uncomfortable horror, violence, gore, a specific type of soundtrack and sound effects, or directly from the plot itself. The genre has a long history of stimulating audiences to generate tension, such as horror films, thrillers, war movies. These films have been developed over many years and have even formed several relatively fixed modes of creating tension. In contrast to the "narrative stimulation" that advances the storyline, there is always a discussion in the film industry about the need for direct "audio-visual stimulation" that stimulates the audio-visual senses of the audience.

Take horror films as an example: research shows that when watching horror films, viewers can often experience two opposing emotions at the same time: fear and pleasure. However, there are huge differences between people on this point. Some viewers feel a rise in fear and a rise in arousal when watching horror clips, while others feel only fear, but not a rise in arousal. These significant differences in psychology have a lot to do with the ability to maintain an appropriate psychological distance from the film: the former group of viewers, faced with the stimulus of great stress, effectively activated their prefrontal lobes and made the judgment that "the current danger is not real"; while the latter group of viewers, due to their strong empathy and stress, affected the effective functioning of the prefrontal The latter part of the audience, because of their strong empathy and stress, mistook the "fake danger" in the movie for the "real danger" in reality. Therefore, we often find that when watching such "high tension" movies, such as horror movies and war movies, some viewers can enjoy themselves even though they feel the tension. In contrast, others cannot bear the pressure and leave their seats or turn off the video, temporarily escaping from the high-pressure environment.(Andrade and Cohen 2007)

Nevertheless, viewers love horror, war, or crime movies or always maintain a strong interest and curiosity in these movies. Different viewers reacted so differently to the same film content made the author very interested in exploring the rationale for this and improving the viewing experience for different viewers.

1.3. Contribution of this paper

The contribution of this paper is to propose a new system called" No-warning interactive playback system". It is a real-time adjustment playback system based on the audience's physiological signals, such as EDA and heart rate. The core of this system is an algorithmic mechanism based on binary logistic regression, which could predict viewers' decisions. Then, an interactive playback system can play movies with different levels of stimulation and even different storylines for the audience to maintain a smooth viewing experience.

The three core concepts of this system are :

- Selectable stimulus
- Interactivity without interface
- Audience's real choice

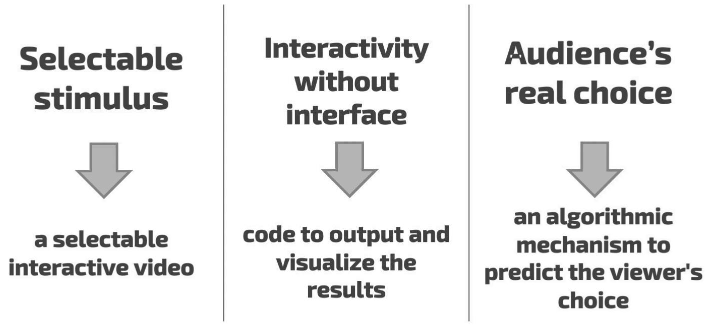


Figure 1.3 Three concepts and corresponding work

In this thesis, the author has done the following three things to realize these three core concepts:

- Made a selectable interactive video
- Wrote code to output and visualize the results
- Create an algorithmic mechanism based on binary logistic regression to predict the viewer's choice (which is the core of this paper)

1.4. Thesis outline

This thesis consists of five chapters.

- In Chapter 1, the background, current limitations, and contributions of this study are discussed.

- Chapter 2 The chapter explores two premise theories: how films increase viewers' stimulation and how viewers interact with films. The study then explores the possibility of viewers making different decisions under different stress and arousal levels and its related research. Finally, the authors examined some previous research, including KMD's thought PhD students. The authors drew inspiration from them and also focused on the differences in their research.

- Chapter 3 describes the design process from conception to finalization of the prototype of this audience-based decision mechanism and the attached playback system, centered on a statistical model analyzed using a binary logistic regression model.

- Chapter 4 analyses the feedback from ten participants who experienced the No-warning system and some of the issues that arose during the experiment. The main contents include user data feedback, user interviews, and a solution about sudden stimulation and Multi-viewing attempt.

- Finally, Chapter 5 analyzes and outlines the current limitations and future development on how to implement the no-warning system in the cinema in the future.

Notes

1 Credits: `https://www.yamatonoodle.com/noodle-master-labs/the-more-pressing-the-harder-the-dough/`

2 Credits: `https://cotoacademy.com/japanese-essentials-ordering-bowl-ramen-japan/`

3 Source: `https://www.amctheatres.com/ratings-information`

4 Credits: `https://www.youtube.com/watch?v=yPlHfLhht3M&ab_channel=IanMorris78/`

Chapter 2
Literature Review

In proposing solutions to improve the moviegoing experience, this study examines two key points:

first, how movies increase the audience's sense of pressure. An accurate understanding of how films enhance the sense of pressure through various technical methods can lead us to do the opposite by reducing the visual and audio sensory stimuli that "spoil the viewing experience."

Second, how the audience interacts with the film; from this perspective, the current development of interactive films can give us great insight into the importance of creating a real-time, realistic interaction without an interactive interface. There have been attempts to improve and innovate interaction methods throughout the history of interactive films.

Then, the study explores the possibility that viewers may make different decisions at different stress and arousal levels and its related research.

Finally, the author researched several previous studies, one of which included KMD's PhD student. The author received inspiration from them and also focused on the differences in their studies. In short, we have some commonalities in terms of interactivity; but we use a completely different approach in terms of the core mechanics.

As a result of a review of the literature and related work, the author derives three leading indicators for improving the moviegoing experience.

2.1. Methods the film creates stress

2.1.1 Visual elements

Each film component can be called a visual element. However, the sense of stress not brought by those ordinary images can often be achieved through some specific means.

The picture

The picture itself is intuitive to pressure the audience, such as horrible monsters, violent and bloody scenes. For example, in the Japanese film "Ju-on: The Grudge," Kayako twisted and moved her body beyond the limits of the average human. The first ten minutes of "Saving Private Ryan" directly represent the Normandy landings, such as the American soldiers being crushed by German heavy machine guns and the bloody beaches covered with corpses and severed limbs. Such images that directly challenge the viewer's sense of perspective can often bring the most vital sense of pressure, especially for those viewers not watching such images.

Closeups

Closeups and partial closeups of characters will make a certain degree of facial distortion, coupled with a certain amount of overhead or elevation shots, to strengthen the image to bring the audience a sense of tension. For example, in the classic horror movie "The Shining" (Figure 2.2[1]), the writer's wife was forced into the room by the crazy writer in a classic scene. Under the closeup, the wife's extreme panic and despair, as well as the writer's extreme madness and distortion, are shown. In the film "Braveheart" at the end, William Wallace's torture screen also used many close-up images of the face, to his body suffered an extreme sense of pain conveyed to the audience.

Figure 2.1 An example shows color correction to deepen the sense of stress in the picture. The top image is the original image, and the bottom image is the author's adjusted higher pressure picture

Figure 2.2 The best example of close-up adding tension: Film 'shining'[1]

Fast switching shots

Fast switching shots can bring a strong sense of impact, fully expressing the urgency of the storyline, the inner tension of the characters. Especially in horror movies, fast switching shots are often accompanied by the sudden appearance of ghosts or gore shots, giving the unsuspecting audience a sudden attack; the sense of tension instantly reached its peak. For example, in the horror movie "The Conjuring, " a ghost nun's sudden appearance in a room full of mirrors is the most defensive point of terror for the audience.

Light

The film is the art of light; different light can fully mobilize the audience's emotions. For example, in horror movies, the use of dark, dim ambient light, as a way to show the character's weakness and helplessness in this environment and the internal tension and anxiety, also indicates the degree of danger of the environment. The use of different light colors to create high-stress scenes is also widespread, such as red will be heavily associated with violence and gore. In the East Asian culture of horror films, green is often associated with ancient evil forces, zombies, Etc.

2.1.2 Auditory elements

Sound and sound effects in the film, in terms of creating pressure on the audience, such as emphasizing the horror of the gloomy atmosphere to strengthen the violence, often achieve better results than the picture.

Language

The language spoken by the characters in the film, such as the character's scream, a low gasp, or sometimes just a simple line. A notable example of this is the line "I want to play a game" spoken by the creepy masked Jigsaw in the "Saw" series because this line is often accompanied by Bloody violent images, so a simple line can also make the audience pressure multiplied.

Soundtrack

One of the essential roles of a film's soundtrack is always to enhance the atmosphere rendered by the film. In horror thrillers, the soundtrack enhances the pressure on the audience, which can be particularly significant. Horror movie soundtrack will add some dissonant ensemble or make the melody of the ups and downs more intense so that the audience to achieve the effect of fear. The same example of the "Saw" series, when the audience heard the "hello Zepp" soundtrack played, it has been immersed in the film to bring you the feeling of helplessness and despair.

Sound effects

Sound effects are not only to account for the status of objects in the picture; in some films, sound effects are an essential means of enhancing the atmosphere and increasing the immersive experience of the audience. This method is pronounced in war movies. For example, in "Saving Private Ryan," at the beginning of the

Normandy landing, whether it is the sound of German machine guns, the roar of explosions, the helpless cry for help, or even Captain Miller was bombed to ringing in the ears when the analog sound effects. All these sound effects are very successful in rendering the brutality of the battlefield. In the horror film, the particular use of some everyday sound effects can also create a strong sense of tension, such as water drops in a quiet environment, footsteps, metal friction.

2.2. Audience choice

As a relatively new concept, interactivity has been considered for some time as a marketing concept that has been misapplied to no exact product or medium. However, it is an important concept that is implicated in the way we can think. Interactivity promotes a more remarkable ability and interest in audiences to alter and manipulate texts or textual narratives to seek co-participation with the author, thus redefining the traditional author-text-audience relationship. (Naimark 1990) In non-interactive narratives, the audience is often subordinated to the author's decisions. (Mendes Da Silva et al. 2015) is concretely reflected in the author's thesis, where the viewer can only passively accept the stress level set by the film's producer, whether this is too low or too high for this viewer. In contrast, the interactivity of cinema applied to narrative offers a range of possibilities and options and builds up a sequence of events that constitute a story. Thus, the interactivity of film is a way to liberate the viewer from being a simple passive spectator and win the right to choose.

2.3. The evolution of interaction

In fact, in the system proposed in the author's thesis, the audience makes interactive choices similar to those in "interactive films," except that the choices are based on physical evidence such as heart rate or EDA rather than manual choices.

Interactive storytelling has been experimented with in different media. The world's first interactive film, a Czech short called "kinoautomat," appeared at the Montreal World's Fair in 1967. The film's presenter would pause the film at crucial episodes and allow the audience to make choices via red and green buttons.

That was the earliest form of interactive film interaction[2].

Figure 2.3 The world's first interactive film "kinoautomat", showing the earliest form of interactive cinema[2]

In terms of text interaction, in the 1970s, interactive novels or text adventure games, such as the 'Choose Your Own Adventure' series written by American author Edward Packard, were all the rage. The novels set up an identity for the reader, allowing them to make their own choices about the plot and eventually lead to the final ending[3].

Dragon's lair, released by Cinematronics in 1983, is widely regarded as the first interactive movie game in the history of video games to receive widespread attention. The game mode in Dragon's Lair continues to be used today as a prototype for today's QTE (quick time events) games.

In either form, the viewer becomes an active author and co-responsible for the world of images as they participate. As in the earliest interactive films, Kinoautomat, the viewer selects the red or green button at certain times and engages in the process of constant exploration. However, One of the most frequently mentioned negative comments is that the forced and conscious interaction between the film and the audience reduces the audience's sense of being drawn into the narrative.

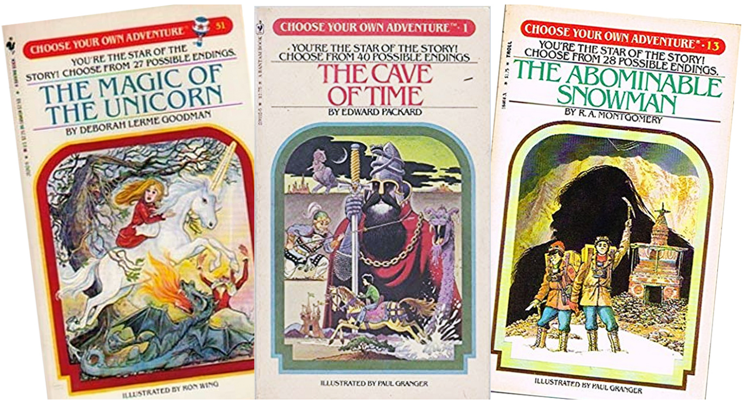


Figure 2.4 Interactive novels 'Choose Your Own Adventure'[3]

In order to reduce this "forced conscious interaction" and increase the immersion and fluidity of the audience, the authors propose the concept of "interaction without a choice interface," which means the actual reaction of the audience determines the direction of the plot. The author's design is based on flu data from the audience's skin activity and heart rate. The data obtained is analyzed by a specific algorithm (including T-test and binary logistic regression model), which is used to predict the audience's next choice. Finally, the system will automatically complete the selection for the audience.

Thus, the audience's physical state directly determines the stimulation level and plot's direction, rather than being distracted by a variety of interactions and options or specifically free up hands to operate. The author hopes this new approach will allow the audience to have a better viewing experience when watching interactive movies.

2.4. Related works

In terms of recognizing the audience's emotions, most of the previous cases have mostly focused on analyzing speech or facial expressions to facilitate the recognition of emotions. (Pantic and Rothkrantz 2003) But the disadvantage of these experiments is that it is convenient to mask facial expressions or simulate a specific tone of voice (Chanel et al. 2007)Therefore, the author believes that by observing the physiological signals of the audience, such as EDA and heart rate, better observation of the audience's stress state can be made.

Previous psychological researchers have studied the emotional expression and perception of stress through a variety of methods. One of them is the particular set of video stimuli developed by KU Leuven (Bartolini, 2011). Using film clips as stimuli to stimulate emotion has many advantages over other methods, including ease of standardization and a high degree of ecological validity. As a result, film clips have been widely used in emotion research.

This study collected and validated a new set of short films for emotion elicitation, and the variables considered were intensity, discreteness, valence, and arousal. In addition, this study is the first to examine a range of film variables that may affect outcomes, such as film genre, clip length, and music level. The results showed that, along with participant variables, these variables significantly and systematically influenced participants' ratings of various emotions.(Bartolini 2011)

It could be stated that the use of video to stimulate and detect the emotions of the audience has proven to be very effective. However, the videos used in this thesis are all videos without a plot, whereas the video used by the author is a complete story.Although the research went in a different direction (this study evaluated emotions, the author's was a decision-making model), the author also gained much inspiration from this study[4].

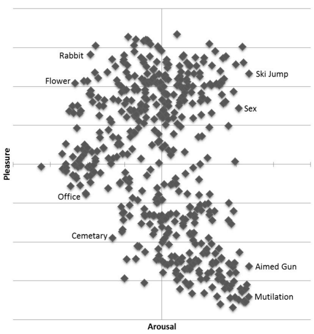


Figure 2.5 Dimensional Distribution of IAPS (Bartolini, 2011)[4]

Also, Mickaël Ménard presented in 2015 an experiment that aims to elicit and recognize emotions by studying physiological data collected from heart rate and skin conductance sensors, mainly to identify the six basic emotions proposed by Ekman and Friesen with 1978: disgust, joy, anger, surprise, disgust, fear, and sadness. (Ménard et al. 2015)

After considering these related researches, the author proposed a method to obtain EDA and heart rate data by using Geist Lab's wristband device. The collected audience data will be analyzed by t-test and binary logistic regression model. Then the audience will be classified into different decision types according to their decision making under pressure.

2.4.1 Seamless Multi-thread films in VR by Mr. Rico Oneris

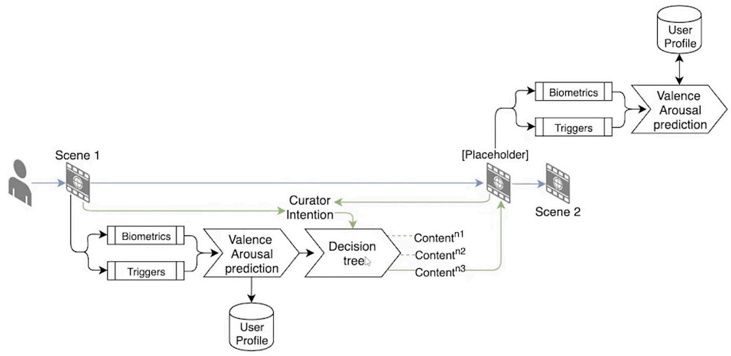


Figure 2.6 The overview of Seamless Multi-thread films by Mr. Rico Oneris[5]

Oneris Daniel Mr. Rico Garcia, a Ph.D. student in KMD, has also proposed a system with similar goals to mine. He proposes "seamless Multi-thread films in VR," a new system for producing VR stories that allow users to interact seamlessly with the content. The research uses subconscious decisions to determine the direction of the story by analyzing the user's attention.(Rico Garcia et al. 2017)

Like the author, Mr. Rico Oneris defines that the moment to make a decision is always a few seconds before the video branches out. We both believe that this allows the system to be preloaded with only the chosen storyline and keep the branching workload as low as possible. In addition, we both agreed that interactive windows and film interruptions primarily break the user's immersion, and Mr. Rico Oneris believes that VR is the most viable way to eliminate them[5].

Here are some of the notable differences between this paper and Mr. Rico Oneris'.

Strategy for storyline branching

Mr. Rico Oneris' strategy for plot branching is to place triggers at specific points in the timeline of a VR movie that will activate or deactivate another storyline depending on whether the user watches them or not. All these processes will happen without the user being aware of them. There will neither be any cues indicating decisions nor any visible signs to let the user know that their story is changing. In other words, Mr. Rico Oneris' research wanted to make the user as unaware of the change in the storyline as possible and that some branching storylines could be skipped.

However, in the author's strategy, the author wanted the audience to feel the change in the stimulation level (especially the enhanced stimulation) to satisfy different kinds of audience, which was evident to the users in the evaluation. Furthermore, the branch that the author has set up is definitely triggered. The trigger is the viewer's physiological signal before the branch occurs, and the viewer must 'choose' between the high or low stimulus content and continue to watch the subsequent content.

Structure of the film

In order to emphasize the seamlessness of this mechanic, Mr. Rico Oneris introduced the concept of the Cycle story, which means that the creator must take into account when writing the script: the starting action required for the user to trigger one or the other branch. The whole chain of logic must be circular, even closed-loop[6].

Although there are different levels of stimulation and storylines in the author's strategy, the narrative strategy is linear, with an overall tree-like branching structure. The author believes that such a structure is relatively more concise and

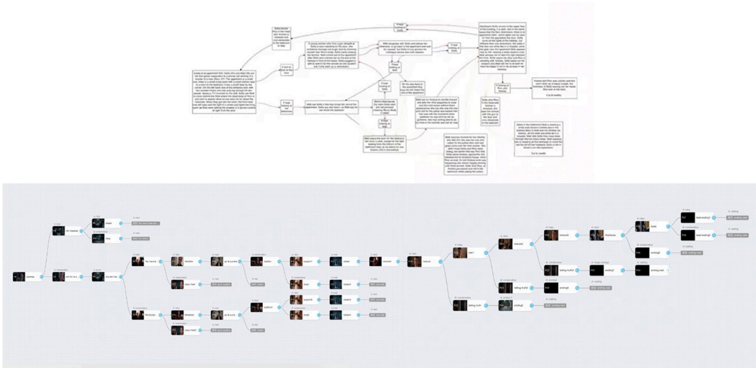


Figure 2.7 The difference between Mr. Rico's cyclic structure (above) and my linear structure (below)[6]

more accessible for the audience to understand, which will be mentioned later in the introduction to the system.

Target user

As Mr. Rico Oneris describes, his research and this mechanism, this agency are for the content creator to create efficient interactive content conveniently. The target user of the author's no-warning system would be the cinema or the content platform, or even the viewers themselves who want to experience the new viewing method. So we are fundamentally different in terms of target users.

The basis of audience selection

This is the most significant difference between our studies.

Mr. Rico Oneris' study proposes a similar 'emotional trigger to the author's, meaning the use of biometrics to determine general emotional state. He grouped these strategies into an agency, allowing this mechanism to help the creator process the audience's physiological data.

Mr. Rico Oneris' research proposes a similar 'emotional trigger to the author's, meaning the use of biometrics to determine the general emotional state. Mr. Rico Oneris uses several methods, mainly eye gaze and facial recognition, and finally, he also tries EEG. He groups these strategies into an agency, allowing this mechanism to help the creator process the viewer's physiological data.

In the author's strategy, the audience's probability of making a risky or conservative choice can be calculated through an algorithmic mechanism. Based on binary logistic regression, this algorithmic mechanism calculates the audience's decision by obtaining physiological signals of the audience, such as EDA and heart rate.

The author will discuss this mechanism in more detail in a later paper.

Summary

The author was very impressed with Mr. Rico Oneris' research, which inspired and referred to the author very much in terms of immersive experiences and real-time engines, and the logic of plot branching. Our research shares some commonalities in parts but takes very different strategies in terms of core mechanics. However, in general, the author agrees with Mr. Rico Oneris' idea that 'the audience is not a puppet, the audience is the final cut .' The author has always believed that the audience is the participant and creator of the story.

2.4.2 'Many Worlds'

'Many worlds' is a short narrative live-action film to provide multiple routes[7]. At two points during the film, decisions are made based on audience bio-signals as to which plot route to take. The use of bio-signals is to allow the audience to remain immersed in the film, rather than manually selecting plot direction. In the end, the researchers were also able to predict which endings the audience found the most' stimulus' through their analysis.(Kirke et al. 2018)

One of the most valuable aspects of 'Many worlds' is that the film was successfully released in several cinemas, and the system was subsequently tested in a real-life setting. However, the researchers also found it challenging to make comparisons between subjects as well, as each person's reaction to the narrative is based on the viewer's personality and life experiences.

This study also suggests a practical solution to alleviate the multiple viewer problem temporarily. A simple pre-survey questionnaire asks people about their film preferences (e.g., do you like horror films?) and then assigns the same results to different viewing groups.

In the film, the viewers influence the film without taking direct action but are passively read by biosensors attached to their bodies as they watch the film. So This project has inspired the author in many ways. But we are still fundamentally different in the core mechanism: the

'Many worlds' has presented an approach to interactive filmmaking that involves the use of arousal detection through multiple biosensors.

the system proposed in this paper, on the other hand, use physiological signals to calculate the viewer's decision making under stress

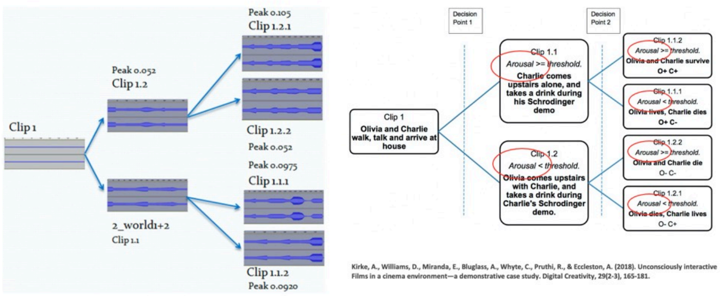


Figure 2.8 The structural hierarchy of 'Many worlds'[7]

2.5. Summary

This study aims to create a new viewing experience that allows the audience to adjust their stress levels. Since we know from the literature review that both visual elements (including visuals, close-ups, quick cuts, light, and shadow) and auditory elements (voiceover, background music, sound effects) play a role in the creation of "non-narrative tension." Then appropriate cuts in these aspects should reduce the sense of stress felt by the audience.

In the interactivity of the movie, the author's goal is to build an interactive method that does not require an interactive window because interactions that require manual manipulation will significantly reduce the immersive experience of the audience. Secondly, the interaction must be real-time and practical because interaction often accompanies the development of the plot. Most importantly, the interaction must be based on the audience's physiological responses, including heart rate and EDA, or other characteristics related to stress and arousal.

The audience's choice determines whether the next step is stimulation or risk avoidance, which is the core of this design. From the review of previous experiments, we can see that different audience types (interest differences, age differences, or gender differences, Etc.) often make different choices under stress and tension, but there are specific patterns to follow.

Therefore, the author proposes a new mechanism called "decision-based audience classification" as the core contribution of this paper. This mechanism analyzes the audience's physical reactions such as EDA and Heart rate through binary logistic regression and classifies the audience into different categories according to their decision types under stress. Furthermore, try to show movies with different stimulation levels and even different storylines for different decision types to maintain a smooth viewing experience for all viewers. To the authors' knowledge, no similar work has been done in the literature before. Other contributions are that, in addition, different audience levels interact with the movie in real-time while viewing it.

In summary, from the literature and related work analysis, these three key points emerge to ensure that viewers achieve the best possible viewing experience.

Notes

1 Credits: `https://movie.douban.com/photos/photo/2565660403/`

2 Credits: `https://michaelnaimark.medium.com/vr-interactivity-59cd87ef9b6c`

3 Credits: `https://retropond.com/choose-your-own-adventure/`

4 Source: Bartolini, Ellen Elizabeth (2011) "Eliciting emotion with film: Development of a stimulus set."

5 Source: Rico Garcia, Oneris Daniel, Benjamin Tag, Naohisa Ohta, and Kazunori Sugiura (2017) "Seamless multithread films in virtual reality," in Proceedings of the Eleventh International Conference on Tangible, Embedded, and Embodied Interaction, pp. 641–646.

6 Source: Rico Garcia, Oneris Daniel, Benjamin Tag, Naohisa Ohta, and Kazunori Sugiura (2017) “Seamless multithread films in virtual reality,” in Proceedings of the Eleventh International Conference on Tangible, Embedded, and Embodied Interaction, pp. 641–646.

7 Source: Kirke, Alexis, Duncan Williams, Eduardo Miranda, Amanda Bluglass, Craig Whyte, Rishi Pruthi, and Andrew Eccleston (2018) “Unconsciously interac- tive Films in a cinema environment—a demonstrative case study,” Digital Creativity, Vol. 29, No. 2-3, pp. 165–181.

Chapter 3
Methodology

3.1. What is No-warning interactive playback system

In this paper, the author propose a new system called" No-warning interactive playback system." It is a real-time adjustment playback system based on the audience's physiological signals, such as EDA and heart rate. The core of this system is an algorithmic mechanism based on binary logistic regression. This mechanism can predict the decisions of viewers with a high probability when they feel stress. Then, an interactive playback system can play movies with different levels of stimulation and even different storylines for the audience to maintain a smooth viewing experience.

Based on this mechanism, an interactive viewing model and its accompanying playback system - No-warning system is proposed:

1 It must contain selectable film content, and they are either weakly stimulating or intensively stimulating, which can be achieved by modifying both visual and auditory elements.

2 This viewing model must be interactive in real-time, including input devices, analysis mechanism, and visualization of analysis results.

3 The audience's physiological response determines the audience's decision, i.e., according to The audience's decision, the audience's physical response is based on the "decision-based audience classification."

3.2. The design process

The solution to the problem and the final proposal of the system was built by using some theories from film and television, combined with the actual viewing experience of the audience, and pursuing an audience-oriented approach. The design process includes six main steps, in which the experiments, data analysis, and code have gone through several iterations before finally reaching the current result.

Observe the phenomenon and investigate Observe the points around movie lovers who are dissatisfied or confused when watching movies, ask, discuss and try to find possible solutions.

User survey Collect the problems of movie lovers through questionnaires and organize them, and confirm the existence of the problems by investigating the playing data of big movie-playing websites.

Literature review The theories of cinematography, studies on interactive movies, and studies on audience decision making were studied, and the elements of these were derived.

Experimental design Collected film footage from the Internet that could be used as an experiment, and re-edited and modified the picture, music, and sound effects, and provided branching plots at crucial plot points (because the experimental material was an interactive movie)

Experiment 30 volunteers were recruited to participate in the experiment, the re-edited material was played for them, and their EDA, heart rate, and other physical signs were recorded through the wristband of the geist lab, and they were asked through a questionnaire to make the option of seeking stimulation or avoiding stimulation.

Statistical calculations T-test and binary logistic regression model calculations were used to determine the correlation between the stress value represented

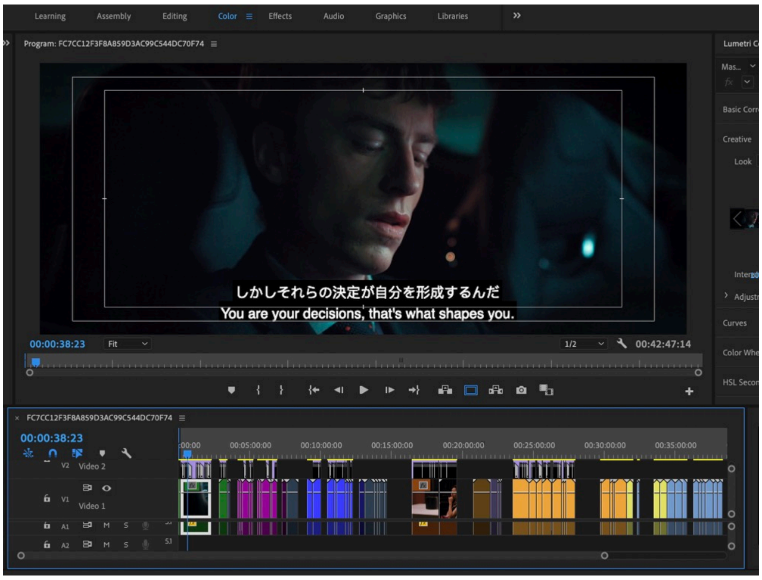


Figure 3.1 Interface for the editing of stress-decision test videos

by heart rate, the arousal value represented by EDA, and the judgment of whether the audience needed stimulation or avoided stimulation. This mechanism is also the theoretical basis and core contribution in this study, from which the system is built.

Code Java, which the author is familiar with, was chosen as the computer language to build the environment and visualize the experimental data.

Final test The completed No-warning system was used to play movies for testers and record feedback. The author built a projection environment closest to a movie theater to ensure the audience's experience and feedback.

3.3. Experiment preparation

3.3.1 Ideation

Based on the literature review, the following three essential requirements were established as the basis for the system design:

Selectable weakened (or stronger) stimulus of the film In order to allow viewers with a low (or high) psychological tolerance threshold to watch the movie more fluently and without hindrance, the stimulus is appropriately weakened while maintaining the fluidity of the film's original storyline.

Interactivity of the movie the system can be more interactive in real-time, including input devices, analysis mechanism, and visualization of analysis results.

The audience's state to determine the audience's choice Which is the core of the system, the selected state should be relatively easy to detect with the EDA and heart rate. The analysis method is T-test and binary logistic regression model.

3.3.2 Film with selectable stimulation

The test videos were all taken from the interactive movie called "late shift." Late Shift is an interactive video game written and directed by a company called Ctrl-Movie. This movie was screened at some international film festivals. The author bought the original game from steam and extracted all 500+ video clips. Furthermore, the author filtered and re-edited them, removing unnecessary options and keeping only the primary storyline.

The software the author used is Adobe Premiere, Audition, and Photoshop. Since there are not many platforms for interactive video creation, and Bilibili's interactive section can show a clear hierarchical structure, the author chose Bilibili as the platform.

Figure 3.2 The softwares the author used

At each key plot point, the viewer can choose a different stress level. There will be two basic storylines that eventually lead to 6 different endings to keep the

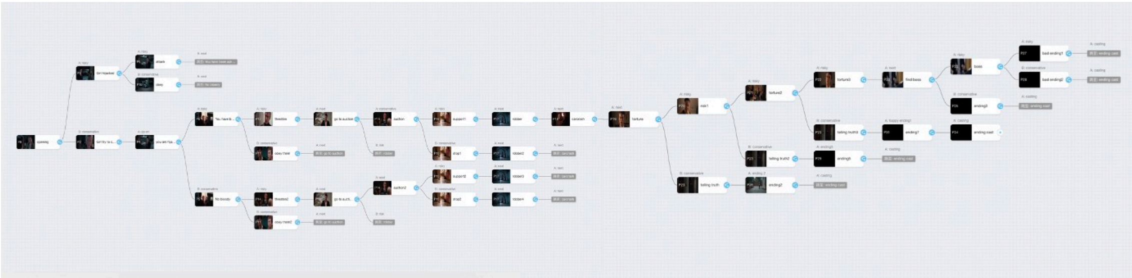


Figure 3.3 Hierarchical structure of the experiment film

story flowing. The material is taken from the film' LATE SHIFT,' but the author has re-edited all to give them different levels of stimulation.

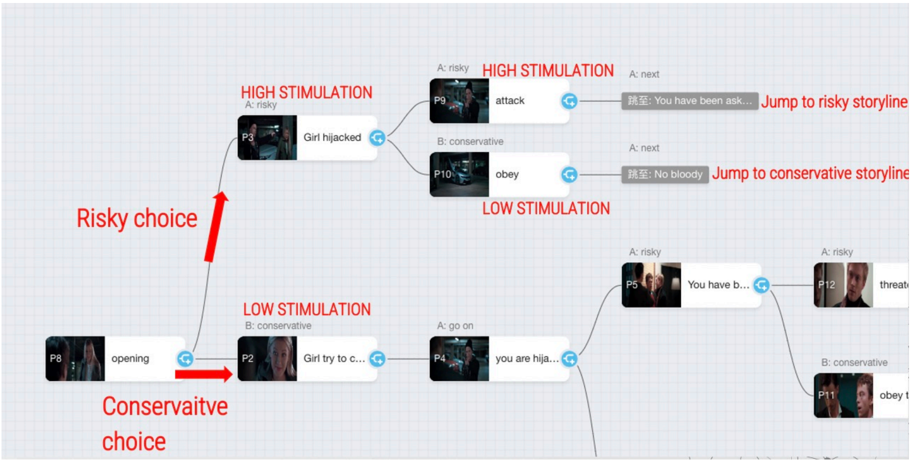


Figure 3.4 At each key plot point, the viewer can choose a different stress level.

3.3.3 Key variables: EDA, heart rate, audience decision-making

EDA Electrical skin activity (EDA) is a property of human skin that indicates changes in the bioelectrical properties of the skin, particularly changes in skin conductance caused by the activity of sweat glands. It is widely considered to be related to mood and stress. EDA is relatively inexpensive and easy to measure, making it one of the most widely used tools for measuring autonomic nervous system responses in psychology and psychotherapy.(Tronstad et al. 2008) One study was conducted by investigating and retrospectively classifying palm sweating. The results were that stress and exercise had the most significant effect on the increase of palm-sweating compared to the relaxed state.(Krogstad et al. 2006) In addition to this, EDA is widely used in psychology, communication research, and medicine to assess emotional arousal. EDA has been a method used to measure audience arousal during media exposure since researchers in the social sciences and psychology became aware of the potential use of psychophysiological measures.EDA is not subject to many other limitations, such as varying degrees of cognitive accessibility, subjective interpretation, or social desirability. However, when researchers use EDA to measure the arousal potential of movie content, two significant limitations must be taken into account: first, the audience's familiarity with the content, if it is familiar, the arousal level will be significantly reduced, and second, other personal characteristics will also moderate the audience's response to content stimuli, such as psychological tolerance for stress. (Leiner et al. 2012)

For these reasons, in this paper, EDA still plays a crucial role in testing audience arousal and stress levels and the relevance of audience decision-making (risk-averse or risk-averse).

Heart Rate Heart rate is the number of heartbeats per minute. Heart rate variability (HRV) is the fluctuation of the time interval between successive heartbeats (1). Heart rate (HR) and its variability (HRV) are thought to be the result of autonomic nervous system (ANS) activity. There is consensus on the persistent variability of heart rate during periods of mental stress. Daily stress and anxiety are generally highly correlated with high heart rate and low heart rate variability (HRV).(Brosschot et al. 2007)

stress causes sympathetic activation and parasympathetic withdrawal and significantly reduces variability, and chaotic behavior of stress causes sympathetic activation and parasympathetic withdrawal and significantly reduces variability and chaotic behavior of HRV.(Castaldo et al. 2015)

In a healthy human heart, the average HR at rest is 75 bpm. (Shaffer and Ginsberg 2017) higher resting HRV is associated with flexible adaptability and cognitive processing, which is highly conducive to emotional regulation in the face of stress. In contrast, lower resting HRV is associated with impaired cognitive reflection to emotional stimuli, meaning that viewers with lower resting HRV tend to react poorly and resist when confronted with high stressful images (Park and Thayer 2014)

In summary, an increase in heart rate accompanied by a decrease in HRV has been shown to reflect fear and stress. Therefore, for the above research considerations, both HR and HRV will be considered in this author's paper to assess the current stress level and the relevance test for viewer choice (risk aversion or demand risk-taking).

Audience decision-making Decision-making refers to the 'ability of humans and other animals to choose between competing courses of action based on their relative value of consequences. (Balleine 2007) Whereas stress and decision making are intricately linked, the impact of stress on decision quality is of particular interest, and stress may influence how we make everyday decisions and life-changing choices.

People tend to make different choices under stressful conditions than under stress-free conditions. Porcelli and Delgado (2009) found that compared to participants in stress-free conditions, participants under stress made more conservative decisions on trials in gain-domain trials, but made more conservative decisions on trials in loss-domain trials domain made more risky decisions in trials. (Porcelli and Delgado 2009) Youssef (2012) found that stressed participants made fewer utilitarian judgments in dilemmas than participants who were not stressed, meaning that intuition had an increased weight for decision making.(Youssef et al. 2012)This is the reason why the author chose to classify the stress test films into "low-stress films," "medium stress films," and "high-stress films" after the deterrent.

Likewise, the effect of stress on decision-making was also somewhat evident in terms of gender differences. Both stress and gender influence risk-taking tendencies independently, but the two factors may also interact to influence risk-related decisions. According to natural selection, stress leads to different biobehavioral responses to stress in males (fight-or-flight) and females (tend-and-befriend). So

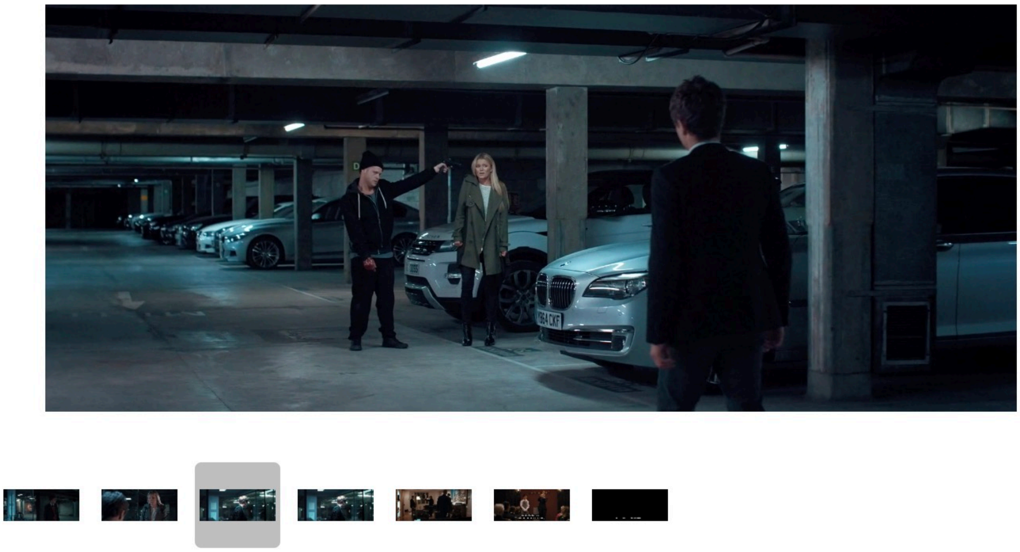


Figure 3.5 Six stress-decision test videos

it tends to show that males choose to take more significant risks under stress, and conversely, females behave more conservatively under stress. (Lighthall et al. 2009)

In this thesis, when the audience sees those images that will cause them great stress, what kind of decision they will make, whether to avoid the risk to reduce the stimulation, or choose the risk to seek the stimulation. Of course, this depends on the viewers' psychological tolerance for stressful images and sometimes on the different decision-making habits of each viewer. Therefore, in this study, we used several sets of emotional dilemmas, either high or low, from the interactive film "Late Shift," each providing a riskier and safer decision choice. In addition, the author used various methods to increase stress in each film segment, such as scary background music and sound effects, or to reduce stress, such as by mosaicking the gory images.

In the subsequent data analysis, the dependent variable 0 is conservative (stimulus avoidance) and 1 is risk- taking (need for stimulus)

We hypothesized that high stress would lead to more safety-seeking decisions. In comparison, low stress would lead to more risk-seeking decisions because the

Figure 3.6 An example of reducing the gore level by using mosaics. In the original picture, the bones of the injured man's arm were broken and poked out of the skin, thus being described by many viewers as excessively gory

stress would largely influence decision-making's cognitive process. The other two factors, individual viewers' psychological tolerance for stressful images (examined by EDA and heart rate), and already the difference in decision making between males and females, will also be taken into account in this film study.

3.4. Experimental approach

In this experiment, the author took six key episodes from the movie ¡late shift¿ and presented the audience with six dilemmas, each followed by a risky and conservative choice. In addition to the correlation between risky and conservative, some of these options also have emotional or moral dilemmas such as altruism or self-interest, high gain or low gain, and valuing responsibility or neglecting responsibility. When viewing the film, the audience's tension may come from these dilemmas, such as forcing the characters to ignore their responsibilities through the temptation of money or forcing them to obey through the threat of intimidation or even threatening their lives. In addition, the author also deliberately added BGM to two segments of the film to enhance the sense of tension.

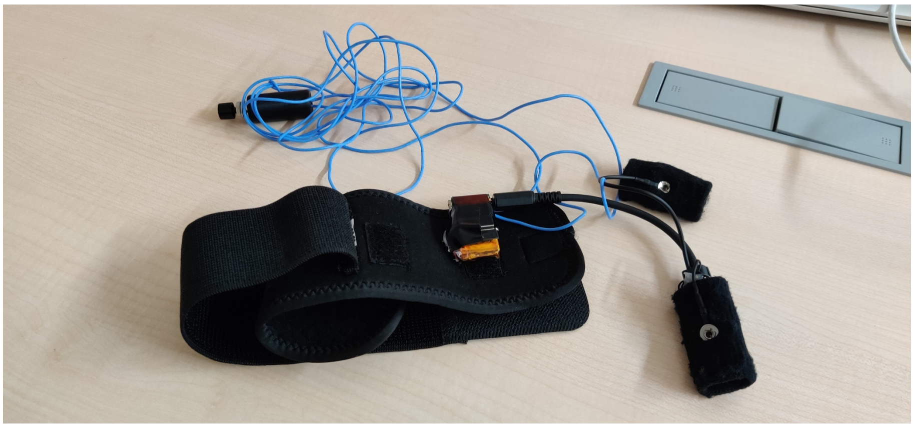


Figure 3.7 Wristband from Geist lab

Data During the viewing process, the author will use the geist lab's wristband to monitor the physical signs, including EDA and heart rate, and import them to the laptop to store in CSV data format for later data analysis.

Decision making At the same time, the author also for after watching each segment of the film, in order to get the most realistic response from the audience, the audience was also asked to make a choice (i.e., risky or conservative decision) within 10 seconds as soon as possible, because often, in reality, there is no longer time to consider making decisions. For statistical purposes, the questionnaire was divided into one for men and one for females, although the content was the same.

video material Why choose the film "late shift" because its theme is more in line with reality. The choice made by the audience is more from the actual consideration. In entertainment films, role-playing is often done out of personal interest, emphasizing the novelty of the plot experience. The audience will consider the personal choice in the "game environment" rather than the personal choice, in reality, so the pressure is often not so intense. In movies that simulate real-life issues, the role-players tend to (more or less) consider their situation in the "game environment" concerning their situation in reality, so their choices are often significant so that the audience can feel the absolute pressure. In addition, as one of the few interactive films to have been released in theaters, "late shift" has a good reputation in the interactive film industry and is very representative and experimental. It also has six different storylines, some of which are very adventurous, and some are relatively conservative. All of these conditions are well suited for the testing purposes of this thesis.

Language To minimize the reduction of immersion brought about by linguistic inconvenience, which further affects the incomplete perception of stress, the author set subtitles for all films in two language versions, Japanese English bilingual subtitles, and Chinese English bilingual subtitles.

We hypothesized that stress plays a tremendous but predictable influence on decision-making and that performance tends to be very different across mental capacity and gender. Because according to Lighthall's experiment in 2009, we hypothesized that women would make more conservative choices in high-stress situations and more risky choices in low-stress situations, while men would make risky choices in high and low-stress situations.(Lighthall et al. 2009)

3.5. Categorizing the results of the questionnaire

Data were gradually collected from April 2020, with 15 women and 14 men eventually participating in the experiment (the number is continuously increasing). The author re-edited six clips from the interactive film "Late Shift," and the six clips had different stress levels. The author also wanted to understand the level of stress and tension that the audience could feel when watching different films and verify whether the author's previous settings (such as mosaics, BGM, and sound effects) were practical. Therefore, the author set up questions for each film in the questionnaire: choice responses ranging from (1) "relax" to (10) "stress."

Finally, at the end of each video, the audience was asked to give the corresponding conservative and risky options. In the subsequent data collection, "0" represented the conservative (stimulus avoidance) option, while "1" represented the risky (stimulus seeking) option. The questionnaire also included demographic variables, including age and gender, as potentially influencing viewers' decisions.

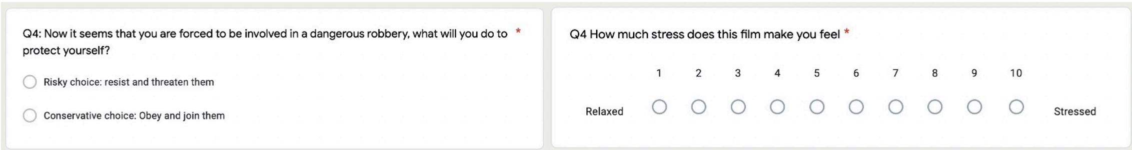


Figure 3.8 After watching the video, the audience was asked two questions. Above is an example of Q4

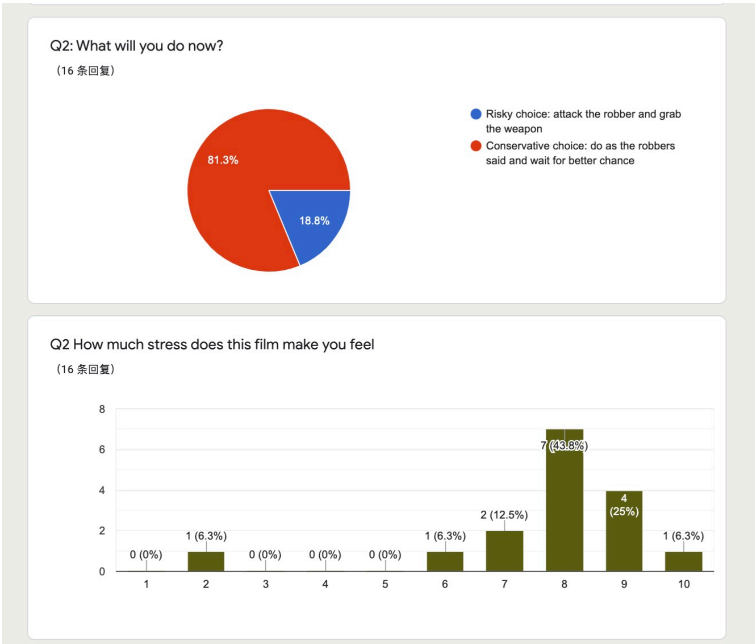


Figure 3.9 Results of the questionnaire for female viewers (Q2)

Finally, the author summarized the questionnaire feedback and data of all the viewers. The six films were ranked according to the stress level of audience feedback and the monitored heart rate, and the results are as follows.

Question 6 The stress level from audience feedback was 8.82/10, with an average audience bpm of 95. Contains elements are explicit torture scenes, physical torture, and verbal threats. Roughly corresponds to the MPA film ratings of NC-17 or R.

Question 2 The stress level from audience feedback was 8.15/10, with an average audience bpm of 92. Elements included: verbal threats, gunfire, increased BGM (in post-test interviews, a large proportion of participants said they remembered the BGM well.) Roughly corresponds to the R in MPA film ratings.

Question 4 The stress level from audience feedback was 7.23/10, with an average audience bpm of 90. Elements included: 2 seconds of gore: flesh and bone exposed (direct representation of the injury). It was roughly corresponding to the MPA film ratings of R.

Question 3 The stress level from audience feedback was 5.9/10, with an average audience bpm of 87. Elements included: verbal threat. Roughly corresponds to a PG-13 in MPA film ratings.

Question 5 The stress level from audience feedback was 4.1/1, with an average bpm of 81. Elements included: foul language, moral dilemma choice, and environmental threat. Roughly corresponds to a PG-13 in MPA film ratings.

Question 1 The stress level from audience feedback was 2.1/10, and the average bpm of the audience was 81. Elements included: foul language, moral dilemma choice. Roughly corresponds to PG in MPA film ratings.

According to the stress level, we divided the six questions into three categories: questions 6, 2 and 4 were classified as "high stress segments", questions 3 and 5 were classified as "medium stress segments", and question 1 was classified as "low stress segment ". Before the data analysis was done, according to the author's observation in the experiment: when the audience encountered a low-stress segment, they often chose to take risks (seeking stimuli); when they encountered a medium-stress segment, the audience often made a more hesitant choice, which would involve the logic of the story, personal interest, and even the good feeling of the actors and many other aspects. When viewers encounter high stress clips, viewers tend to make quick choices, but the way they make decisions often varies greatly from viewer to viewer. However, these are just speculations, and the specific audience decision analysis needs to be given by the data analysis afterwards.

3.6. Experimental data analysis: T-test

T-test and binary logistic regression model were chosen for the data analysis, and the software used was SPSS version 28.0.

The experiment focused on detecting how and with what weight EDA and HR influence the audience's decision-making. Firstly, we proposed three main hypotheses, and the subsequent data analysis focused on testing these three hypotheses. (1) the higher the stress level given to viewers by the film and the lower the arousal level, the higher the probability that viewers will make conservative decisions (avoidance stimuli) and the lower the probability that they will make risky decisions (demand stimuli). (2) The film gives the audience a high level of stress and a high level of arousal, and the higher the odds that the audience will make a risky decision (demand stimulus) and the lower the odds that they will make a conservative decision (avoidance stimulus). (3) With insufficient stress levels (regardless of arousal level), viewers are more likely to make risky decisions.

A brief explanation of the variables:

The dependent variable 0 is conservative (stimulus avoidance) and 1 is risk-taking (stimulus seeking)

EDA is the highest value minus the lowest value in the 20-30 seconds before the viewer makes a decision, indicating an increase

The author obtained the following information by using the wristband device and questionnaire from Geist Lab. Taking the EDA of a test subject as an example, the following figure shows the results.

BPM is the mean value of BPM in the 20-30 seconds before the viewer makes a decision

High and medium stress differentiated by the results of the viewer ’ s questionnaire (how stressed you are after watching this video)

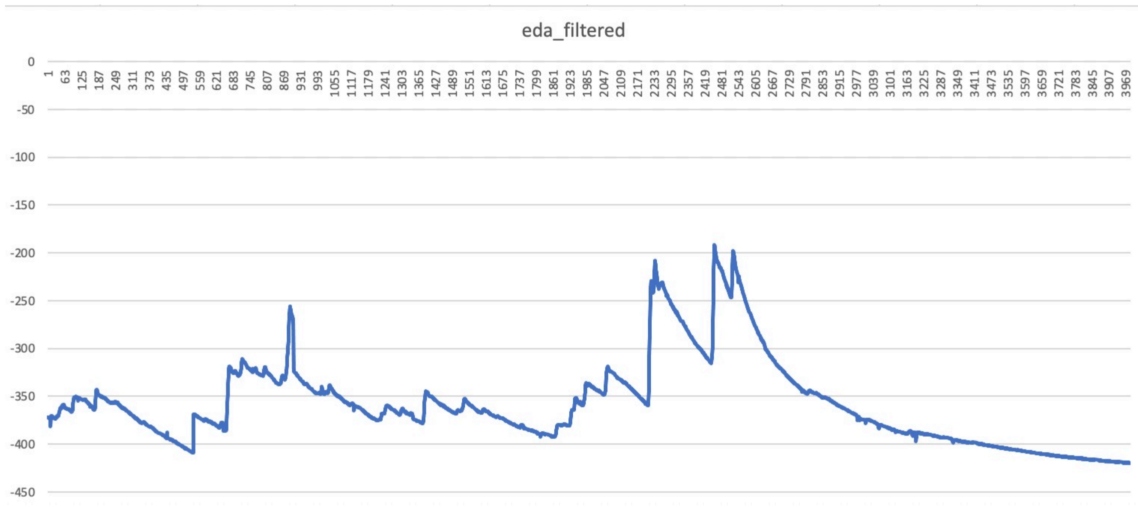


Figure 3.10 EDA curve for one test subject

T-test is a type of inferential statistic used to determine a significant difference between the means of two groups, which may be related to certain features. If the values of the proportional terms in the test statistic are known, then the test statistic will follow a normal distribution when the t-test is most often applied. In this paper, the author mainly used the t-test to test whether there is a significant effect relationship between the three independent variables of EDA, BPM (i.e., heart rate), gender, and the dependent variables 0 and 1 (conservative and risk-taking), respectively.

Binary logistic regression is a method that we use to fit a regression model when the response variable is binary. In this experiment, we will figure out how much the values of EDA and In this experiment, we will find out how much the values of EDA and BPM affect 0 (conservative/stimulus avoidance) and 1 (risky/stimulus seeking) respectively, and what is the weight of each effect.

Regression methods have become an essential part of any data analysis today, focusing on describing the relationship between a response variable and one or more explanatory variables. In general, the outcome variable is discrete, with two or more possible values. Over the past two decades, the logistic regression model has become one of the standard analytical methods in many fields for this situation.

According to one of the fundamental theories of logistic regression, the most significant difference between the logistic regression model and a linear regression model is that its outcome variable is binary, (Hosmer Jr et al. 2013) Moreover, the two outcome variables that the author wants to derive are exactly "risky (need more stimulation)" or "conservative (avid stimulation). " Therefore, in this paper, the author uses logistic regression as the core data analysis method. The main reasons why logistic regression is suitable for the author's paper are as follows.

Firstly, the dependent variable is a binary variable, i.e., whether to choose conservatism (stimulus avoidance) or risk-taking (stimulus seeking). Secondly, there is at least one independent variable. Finally, there is no covariance between the independent variables, which in this study include the continuous variables EDA and BPM and the categorical variable - gender.

The author's sample size was not large, and the number of variables was relatively large. So that before conducting the binary logistic regression analysis, the author first examined the relationship between all independent and dependent variables using the T-test, expecting to filter out some independent variables that might be meaningless or have minimal effects. So the author first did a line-by-line T-test with SPSS for each independent variable to test its significance, and the results are shown in the following figure.

3.6.1 EDA T-test

These are the results of the independent samples t-test for EDA at three pressure levels (the judgment interval for EDA is bounded by the three median high pressure 81.20, medium pressure 84.05, and low pressure 72.76 for EDA).

As seen the three graphs above, EDA has a p-value of less than 0.001 in the high-stress video, which shows a highly significant effect on viewer decision-making. p-value=0.002 for EDA in the medium stress video is also a highly significant effect. However, in low-stress content, EDA did not have a significant effect on viewer decision-making.

HIGH_EDA_1	HIGH_EDA_2	HIGH_EDA_VALUBLE		MID_EDA_1	MID_EDA_2	MID_EDA_VALUBLE
-363.41	-294.28	69.13		-387.34	-305.98	81.36
-358.39	-282.94	75.45		-446.02	-367.54	78.48
-310.94	-233.3	77.64		-430.99	-352.25	78.74
-359.22	-281.99	77.23		-364.19	-282.53	81.66
-409.86	-340.31	69.55		-423.11	-346.97	76.14
-406.25	-326.85	79.4		-327.5	-253.94	73.56
-344.91	-275.58	69.33		-350.85	-263.29	87.56
-369.3	-294.63	74.67		-443.12	-367.72	75.4
-367.64	-284.54	83.1		-376.31	-304.25	72.06
-414.34	-320.54	93.8		-437.83	-358.87	78.96
-406.22	-314.88	91.34		-376.9	-294.76	82.14
-341.85	-262.46	79.39		-409.51	-328.41	81.1
-369.71	-271.18	98.53		-351.3	-279.35	71.95
-339.58	-261.48	78.1		-317.19	-231.36	85.83
-310.48	-216.82	93.66		-368.08	-284.63	83.45
-307.52	-217.88	89.64		-351.59	-274.86	76.73
-306.97	-234.63	72.34		-408.97	-334.63	74.34
-378.18	-293.95	84.23		-407.38	-327.63	79.75
-435.19	-342.89	92.3		-331.24	-247.91	83.33
-363.25	-281.6	81.65		-427.72	-352.42	75.3
-341.66	-267.28	74.38		-411.27	-326.62	84.65
-371.94	-285.57	86.37		-428.85	-350.43	78.42
-368.48	-287.13	81.35		-379.78	-292.84	86.94
-363.54	-284.99	78.55		-374.06	-297.23	76.83
-430.01	-329.81	100.2		-324.63	-241.06	83.57
-347.97	-271.64	76.33		-351.95	-275.94	76.01
-385.05	-291.83	93.22		-368.98	-288.16	80.82

Figure 3.11 A part of the raw data of EDA and BPM

Independent Samples Test

		t-test for Equality of Means		
			Significance	
		df	One-Sided p	Two-Sided p
High_NUMchoice	Equal variances assumed	29	<.001	<.001
	Equal variances not assumed	25.133	<.001	<.001

		t-test for Equality of Means		
		Significance		
		One-Sided p	Two-Sided p	Mean Difference
Mid_NUMChoice	Equal variances assumed	.002	.004	.492
	Equal variances not assumed	.002	.004	.492

		t-test for Equality of Means		
		Significance		
		One-Sided p	Two-Sided p	Mean Difference
Low_NUMChoice	Equal variances assumed	.094	.188	.150
	Equal variances not assumed	.041	.083	.150

Figure 3.12 Significance results of EDA

3.6.2 BPM T-test

These are the independent samples t-test of BPM at three pressure levels (the judgment interval of BPM is bounded by three medians, high pressure 92.41, medium pressure 83.32, and low pressure 76.66).

Independent Samples Test

		t-test for Equality of Means		
			Significance	
		df	One-Sided p	Two-Sided p
High_NUMchoice	Equal variances assumed	29	.058	.115
	Equal variances not assumed	28.560	.058	.116

		t-test for Equality of Means		
		Significance		
		One-Sided p	Two-Sided p	Mean Difference
Mid_NUMChoice	Equal variances assumed	.002	.004	-.492
	Equal variances not assumed	.002	.004	-.492

		t-test for Equality of Means		
		Significance		
		One-Sided p	Two-Sided p	Mean Difference
Low_NUMChoice	Equal variances assumed	.299	.598	.058
	Equal variances not assumed	.297	.595	.058

Figure 3.13 Significance results of BPM

As seen from the above three t-test results, the p-value of BPM in the high-pressure video is less than 0.058, which is close to 0.05, so it can be considered as a relatively significant effect. P-value=0.002 for BPM in the medium pressure video, which indicates a very significant effect. However, in low-stress content, BPM, like EDA, did not significantly affect viewer decision-making.

3.6.3 Gender T-test

What is more difficult to weigh is the gender factor, which can be deduced from the significance P-value in the graph above. (1) The p-value of gender for high

Independent Samples Test

		t-test for Equality of Means		
			Significance	
		df	One-Sided p	Two-Sided p
High_NUMchoice	Equal variances assumed	28	.014	.028
	Equal variances not assumed	27.886	.014	.028
Mid_NUMChoice	Equal variances assumed	28	.136	.271
	Equal variances not assumed	27.603	.136	.271
Low_NUMChoice	Equal variances assumed	28	.500	1.000
	Equal variances not assumed	28.000	.500	1.000

Figure 3.14 Significance results of gender

stress is 0.014, which is smaller than our threshold of 0.05, so it can be considered a more significant effect. Thus, there is indeed some difference in the decision-making of different genders when watching high-stress videos. 2) The p-values of gender for moderate stress and low-stress situations are 0.136 and 0.5, respectively, which are much larger than 0.05, concluding that there is no significant difference. Therefore, there is no significant difference in decision-making between genders when watching videos under moderate stress or low stress.

Although when performing a one-way analysis of variability, the p-value requirement is generally relaxed to about 0.1-0.15 to avoid missing some important factors. So, in this case, 0.136 under moderate stress can be considered as a difference. Furthermore, some independent variables are not statistically significant but are considered closely related in clinical or practice settings are generally taken into account. Given the results of some previous experiments, both stress and gender influence the propensity to take risks independently. These two factors may also simultaneously influence risk-related decisions, sometimes manifesting as men choosing to take more significant risks after stress. Conversely, women are more conservative after stress.(Lighthall et al. 2009) It is also clear from the MEAN values in the figure below that the probability of men choosing 1 (i.e., risky decision) is greater than that of women, except in low-stress videos where the decision is consistent, either in medium or high-stress videos.

Group Statistics

	Gender	N	Mean	Std. Deviation	Std. Error Mean
High_NUMchoice	female	15	.27	.458	.118
	male	15	.67	.488	.126
Mid_NUMChoice	female	15	.53	.516	.133
	male	15	.73	.458	.118
Low_NUMChoice	female	15	.93	.258	.067
	male	15	.93	.258	.067

Figure 3.15 Mean values of male decision making and female decision making under three types of stress

Therefore, because of the above two reasons and the initial intention to explore the influence of gender on decision-making, the author finally decided to include the gender factor in the logistic regression analysis afterward.

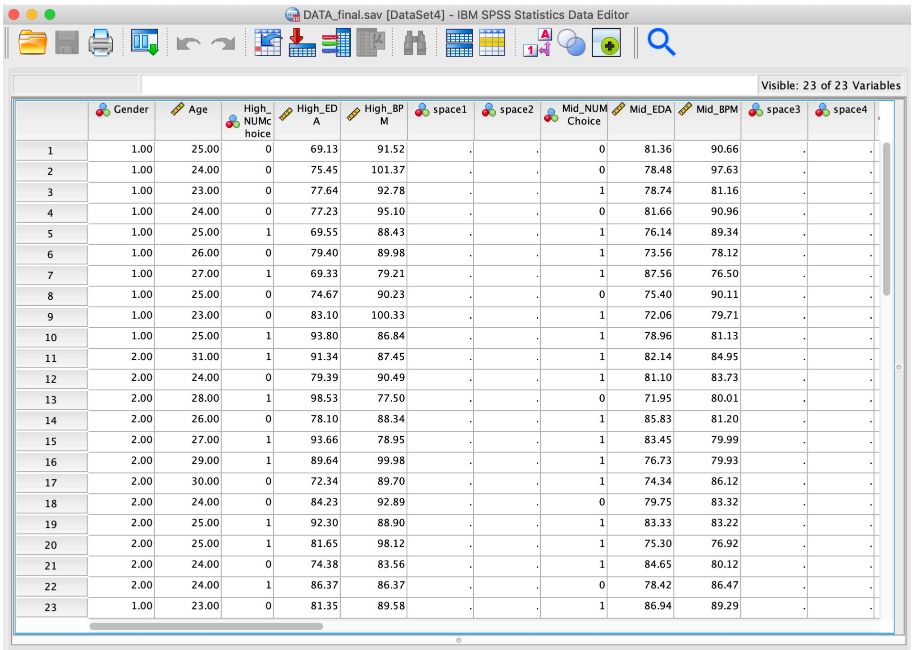
3.6.4 Other independent variables

In addition, after several rounds of t-test, the author found that the age factor had no significant influence on the decision making under any stress level. So finally, the independent variables included in the logistic regression model were EDA, BPM, and gender. The EDA had the most significant effect on viewers watching high-stress content, and the BPM had the most significant effect on viewers watching moderate stress content. The gender variable is unknown at this time, and the current hypothesis is that there is some difference in decision-making between genders under high stress. However, the exact difference needs to wait for the binary logistic regression test results before confirming.

Another controversial point is the viewer's decision when watching a low-stress video. After the author's analysis, it was found that neither EDA nor BPM, gender any of the independent variables could significantly affect the dependent variable (i.e., 0 or 1 decision) when watching the low-stress video. If we look at viewer behavior specifically, when watching the first video (low-stress video from viewer feedback with a stress level of 2.1/10 and an average viewer bpm of 81), most viewers' choices were RISKY, regardless of their EDA, BPM, or gender. The author speculates that because they need more stimulation to excite and stress them out. So for such statistically insignificant cases, the author decided not to include the data when viewers watched low-stress videos in the binary logistic regression analysis.

3.7. Experimental data analysis: Binary logistic regression

After completing the initial variable screening, the author used SPSS as the software for logistic regression analysis. It can efficiently calculate and produce analysis graphs and is one of the standard software used in academia to do logistic regression.



	Gender	Age	High_NUMchoice	High_EDA	High_BPM	space1	space2	Mid_NUMChoice	Mid_EDA	Mid_BPM	space3	space4
1	1.00	25.00	0	69.13	91.52	.	.	0	81.36	90.66	.	.
2	1.00	24.00	0	75.45	101.37	.	.	0	78.48	97.63	.	.
3	1.00	23.00	0	77.64	92.78	.	.	1	78.74	81.16	.	.
4	1.00	24.00	0	77.23	95.10	.	.	0	81.66	90.96	.	.
5	1.00	25.00	1	69.55	88.43	.	.	1	76.14	89.34	.	.
6	1.00	26.00	0	79.40	89.98	.	.	1	73.56	78.12	.	.
7	1.00	27.00	1	69.33	79.21	.	.	1	87.56	76.50	.	.
8	1.00	25.00	0	74.67	90.23	.	.	0	75.40	90.11	.	.
9	1.00	23.00	0	83.10	100.33	.	.	1	72.06	79.71	.	.
10	1.00	25.00	1	93.80	86.84	.	.	1	78.96	81.13	.	.
11	2.00	31.00	1	91.34	87.45	.	.	1	82.14	84.95	.	.
12	2.00	24.00	0	79.39	90.49	.	.	1	81.10	83.73	.	.
13	2.00	28.00	1	98.53	77.50	.	.	0	71.95	80.01	.	.
14	2.00	26.00	0	78.10	88.34	.	.	1	85.83	81.20	.	.
15	2.00	27.00	1	93.66	78.95	.	.	1	83.45	79.99	.	.
16	2.00	29.00	1	89.64	99.98	.	.	1	76.73	79.93	.	.
17	2.00	30.00	0	72.34	89.70	.	.	1	74.34	86.12	.	.
18	2.00	24.00	0	84.23	92.89	.	.	0	79.75	83.32	.	.
19	2.00	25.00	1	92.30	88.90	.	.	1	83.33	83.22	.	.
20	2.00	25.00	1	81.65	98.12	.	.	1	75.30	76.92	.	.
21	2.00	24.00	0	74.38	83.56	.	.	1	84.65	80.12	.	.
22	2.00	24.00	1	86.37	86.37	.	.	0	78.42	86.47	.	.
23	1.00	23.00	0	81.35	89.58	.	.	1	86.94	89.29	.	.

Figure 3.16 Input data to construct binary logistic regression model in SPSS

Before interpreting the results of the analysis, a few critical outcome data are briefly described.

”B” is the regression coefficient: the parameter in the regression equation that indicates the magnitude of the effect of the independent variable x on the dependent variable y. A more significant regression coefficient indicates a greater effect of x on y. A positive regression coefficient indicates that y increases as x increases, and a negative regression coefficient indicate that y decreases as x increases. The equation can be written based on the regression coefficients.

”Sig” value is the statistical P-value, which indicates whether the independent variable is statistically significant to the dependent variable, if the P-value is 0.01¡P¡0.05, the difference is significant, if P¡0.01, the difference is highly significant. On the other hand, p¿0.1 means the difference is not significant, and the corresponding statistical data should be regarded as invalid and excluded.

”EXP(B)” The OR value of the corresponding variable ”EXP(B)” (also called dominance ratio, the ratio of values) is the rate of change in the probability of occurrence of an event for each 1-unit change in the independent variable, with other variables held constant. The OR value ¿ 1, the greater the influence of the independent variable on the probability of the event (risk factor), OR = 1, the independent variable does not influence the event’s occurrence, OR ¡ 1. The smaller the influence of the independent variable on the probability of the event (protective factor)

3.7.1 High-stress analysis

From this classification table, we can see that if we use this binary logistic regression model to predict the audience’s decision, the probability of correctness is 87.1 percent. In other words, this model can predict the decision pattern of the 30 audience members in this experiment with a high probability. Moreover, if the sample size is large enough, the audience’s decision pattern prediction can be generalized.

From the p-values in omnibus tests of model coefficients, it can be seen that among the variables included for consideration (i.e., EDA, BPM, gender), at least one variable has a statistically significant OR value that represents that the whole model is statistically significant.

Classification Table[a]

Observed			Predicted: High_NUMchoice conservative	Predicted: High_NUMchoice risky	Percentage Correct
Step 1	High_NUMchoice	conservative	16	0	100.0
		risky	4	11	73.3
	Overall Percentage				87.1

a. The cut value is .500

Figure 3.17 High-stress classification table

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	19.712	3	<.001
	Block	19.712	3	<.001
	Model	19.712	3	<.001

Figure 3.18 High-stress omnibus tests of model coefficients

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.424	8	.817

Figure 3.19 High-stress Hosmer and Lemeshow test

The Hosmer and Lemeshow test examined the goodness of fit of the model. Since the p-value of 0.817 greater than 0.05, it was concluded that the information in the current data was sufficiently extracted, and the model fit was relatively good.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	High_EDA	.228	.090	6.336	1	.012	1.256
	High_BPM	-.206	.100	4.287	1	.038	.814
	Gender(1)	-.101	1.083	.009	1	.926	.904
	Constant	-.048	8.379	.000	1	.995	.953

Variables in the Equation

		95% C.I.for EXP(B)	
		Lower	Upper
Step 1[a]	High_EDA	1.052	1.499
	High_BPM	.669	.989
	Gender(1)	.108	7.548
	Constant		

a. Variable(s) entered on step 1: High_EDA, High_BPM, Gender.

Figure 3.20 High-stress Variables in the equation

This most crucial table shows the effect of each independent variable on the dependent variable in the high-stress film. In the first line, High-EDA has a p-value of 0.012, indicating a significant effect between EDA, which represents arousal, and viewers making a "1" decision. Moreover, with each unit increase in EDA, the probability of viewers making a risky decision increases by a factor of 1.256 (95 percent fluctuation between 1.052 and 1.499). In the second line, the p-value of High-BPM, 0.038, also indicates a significant effect between BPM, which represents stress, and viewers making a "1" decision. However, unlike EDA, there is a negative effect of BPM, i.e., for each unit increase in BPM, the audience is 0.814 times more likely to make a risky decision (95 percent fluctuation between 0.669 and 0.989). In the third row, gender has a p-value of 0.926, which is much larger than the predetermined value of 0.05, i.e., it shows that there is no significant effect of gender on viewers' making "1" decisions. Hence, the data analyzed in this row are also not statistically significant.

To summarize the above conclusions, in watching high-stress films, the higher the EDA of the audience, the more likely to make risky decisions. The lower the

BPM is, the more likely they to make risky decisions. Moreover, the probability of viewers making risky decisions can be calculated by the EXP(B) values of both.

3.7.2 Middle-stress analysis

Classification Table[a]

			Predicted		
			Mid_NUMChoice		Percentage Correct
Observed			conservative	risky	
Step 1	Mid_NUMChoice	conservative	7	3	70.0
		risky	2	19	90.5
	Overall Percentage				83.9

a. The cut value is .500

Figure 3.21 Middle-stress classification table

From this classification table, we can see that if we use this binary logistic regression model to predict the audience's decision, the probability of correctness is 83.9 percent.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	17.501	3	<.001
	Block	17.501	3	<.001
	Model	17.501	3	<.001

Figure 3.22 Middle-stress omnibus tests of model coefficients

The p-value of the combined test of model coefficients shows that among the variables included in the consideration (i.e., EDA, BPM, and gender), the OR of at least one variable is statistically significant and also represents a statistically significant model as a whole.

The Hosmer and Lemeshow test examined the goodness of fit of the model. Since the p-value of 0.481 was more significant than 0.05, it was concluded that the information in the current data had been sufficiently extracted, and the model fit was relatively good.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.527	8	.481

Figure 3.23 Middle-stress Hosmer and Lemeshow test

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Mid_EDA	.266	.158	2.822	1	.093	1.305
	Mid_BPM	-.513	.184	7.744	1	.005	.599
	Gender(1)	1.781	1.297	1.884	1	.170	5.934
	Constant	22.432	13.768	2.655	1	.103	5.524E+9

Variables in the Equation

		95% C.I.for EXP(B)	
		Lower	Upper
Step 1[a]	Mid_EDA	.957	1.780
	Mid_BPM	.417	.859
	Gender(1)	.467	75.462
	Constant		

a. Variable(s) entered on step 1: Mid_EDA, Mid_BPM, Gender.

Figure 3.24 Middle-stress Variables in the equation

In the first line, the p-value of 0.093 for Mid-EDA is slightly larger than 0.05, indicating an effect but not a significant one between EDA and viewers making "1" decision. On the other hand, its EXP(B) value is somewhat informative, i.e., for each unit of elevated EDA, the probability of viewers making a risk increases by a factor of 1.305. In the second line, the p-value 0.005 for Mid-BPM also indicates a very significant effect between BPM, which represents stress, and viewers making "1" decision, and both are negative as in the case of high-stress films. That is, for every unit increase in BPM, viewers are 0.599 times less likely to make risky decisions (with 95 percent fluctuations between 0.417 and 0.859).

In the third line, the p-value of 0.17 for gender, which is much larger than the predicted value of 0.05, indicates that there is no significant effect of gender on the audience's decision to make "1", so the data in this line of analysis are once again not statistically significant.

To summarize the above findings, the lower the BPM, the more likely it is to make a risky decision in watching a moderately stressful movie, and the specific probability of occurrence can be calculated by the EXP(B) value. In contrast, the higher the viewer's EDA, the more likely they may make risky decisions. However, its affectivity is not very significant, and the specific probability of occurrence calculated by the EXP(B) value is inaccurate. Therefore, it is not used in this paper.

3.8. The resulting formula and output interface

So based on the data obtained from binary logistic regression and logistic regression formula[1], we can come up with this formula.

With this formula, we can predict which decision they will make with high probability by knowing the audience's EDA and BPM. For example, if a viewer's EDA is 78.57 and BPM is 77.33, the probability of this viewer making a risky decision is 84.79 percent. So we already have The mechanism to predict the audience's choice and output or visualize the result.

Based on this formula, the author wrote a program on the java platform. The function of this code is to take the EDA and BPM data collected by wristband and calculate them in real-time using the formula and visualize the result immediately,

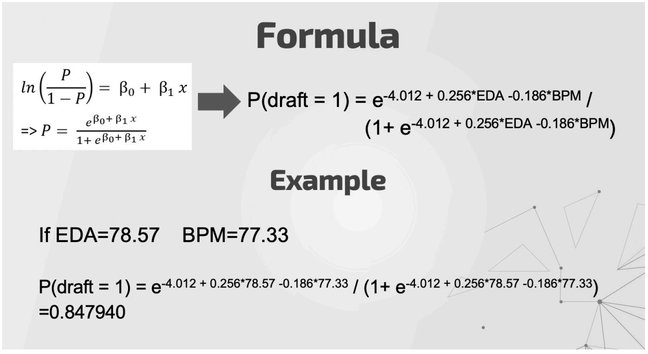


Figure 3.25 Formula and Example

especially outputting the decision possibilities.

Figure 3.27 is the output interface. "edafiltered" line is the real-time EDA value; the "StatusEDA" line is the EDA change value in 25 seconds, the "BPM" line is the mean value in 25 seconds. Moreover, the "decisionMaking" line is the probability of the audience making a risky decision.

localTime	edaFiltered	statusEDA	bpm	decisionMaking
2021/06/14 10:30:20	-337.46	43.82	93.32	0.0% H
2021/06/14 10:30:18	-336.36	43.82	94.06	0.0% H
2021/06/14 10:30:17	-334.22	43.82	94.14	0.0% H
2021/06/14 10:30:16	-332.25	43.82	94.16	0.0% H
2021/06/14 10:30:15	-329.69	43.82	94.0	0.0% H
2021/06/14 10:30:14	-323.92	52.88	93.7	0.04% H
2021/06/14 10:30:13	-319.65	53.07	93.33	0.04% H
2021/06/14 10:30:12	-322.91	63.13	93.46	0.54% H
2021/06/14 10:30:11	-329.83	64.01	93.35	0.69% H
2021/06/14 10:30:10	-331.44	64.01	93.3	0.7% H
2021/06/14 10:30:09	-328.62	75.5	93.17	11.91% H
2021/06/14 10:30:08	-325.28	75.5	93.14	12.02% H
2021/06/14 10:30:07	-320.14	75.5	93.05	12.12% H
2021/06/14 10:30:06	-312.47	75.5	93.0	12.23% H
2021/06/14 10:30:05	-325.9	99.75	92.81	98.63% H
2021/06/14 10:30:04	-331.85	83.24	92.78	51.22% H
2021/06/14 10:30:03	-334.78	81.87	92.68	43.02% H
2021/06/14 10:30:02	-341.67	74.99	92.75	11.4% H
2021/06/14 10:30:01	-340.88	74.25	92.76	9.61% H
2021/06/14 10:30:00	-343.28	74.12	93.11	8.7% H

Figure 3.26 Output interface

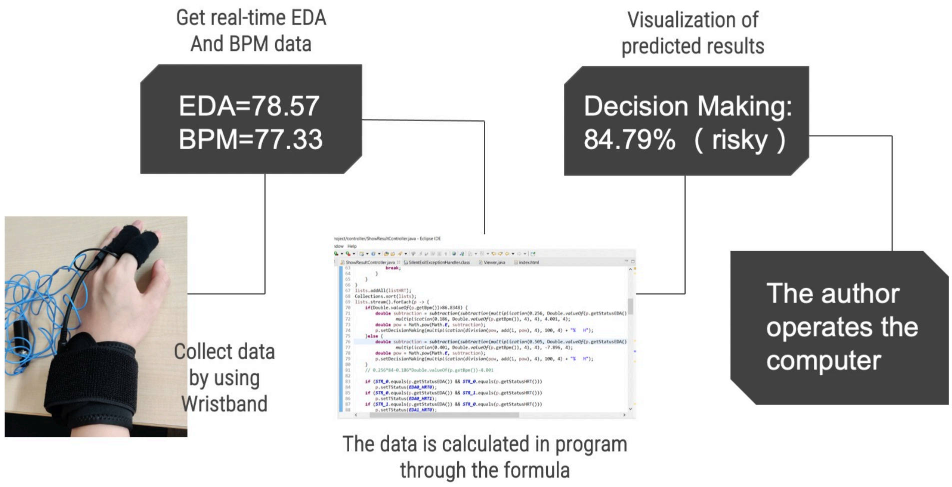


Figure 3.27 The whole process about how the system works

3.9. Summary

In summary, the final analysis of this binary logistic regression model resulted in the finding that gender was not a very important predictor in most cases. However, it is also clear that the data from this study support our previous hypothesis that both EDA and heart rate are closely related to audience decision-making. Even after controlling for several other variables (including age and gender), these are still two significant predictors of the outcome variable. Thus, we have a solid foundation to assume that by counting and analyzing EDA and BPM in real-time, we can make general predictions about the user's next decision and infer the probability of making a risky decision.

However, it has to be admitted that the generalizability of these results is limited. Due to the epidemic, finding enough participants for the experiment was a difficult task. Because all participants had to come to our building and use our equipment for data acquisition, we could only recruit a minimum sample size of 30 to derive statistical analysis results this time. If we could get a more extensive and more diverse data sample, we might derive more precise results and more valid influences. Although we included gender and age in this logistic regression analysis (other identity factors such as occupation and nationality were already expected), personality traits and interest traits were not measured in this survey. It is unknown whether these factors are predictive. Although theoretical flaws exist, our previous most crucial hypothesis is largely confirmed: EDA and heart rate are closely related to viewers' decisions.

Notes

1 https://www.dotnetlovers.com/article/225/logistic-regression-explained

Chapter 4
Evalutaion

In the previous chapters, the concept and design process of No-warning system was described. Moreover, by testing the first experiment, we can already see that the No-warning system can infer with high probability the decisions of three different types of viewers to play content for them with different levels of stress.

Of course, there are several limitations of the previous experiment that can be discussed. First of all, most of the subjects in this experiment were school students (most of them were KMD students), with similar age and educational backgrounds, and might have some similarities in their stressful feelings and decision-making styles about the movie. In addition, after these people learned about the subject of the study, some social desirability bias would arise, such as they would try to choose the option that seemed more righteous, even if their inner feelings were the opposite. Of course, the conditions of the experiment also played a fundamental role in influencing the audience; for example, the subjects would have different physiological indices at different times of the day, and the subjects' EDA and BPM before and after meals were also very different.

So further evaluation is still needed to assess whether the finalized system will be more effective in improving the audience's viewing experience. The goal is to adjust the evaluation values for EDA and HR to more accurately determine the arousal and stress state of the audience to produce more accurate results to predict the audience's choice.

Therefore, before the test, we need to conduct the audience's EDA and heart rate under normal conditions and then conduct a pretest to determine the audience's ability to tolerate high-stress content. Recording their EDA and heart rate and entering them into the EDA and heart rate were recorded and entered into a binary logistic regression model to determine which decision type they belonged to. The author then plays the full interactive movie "late shift" for him, but certainly, all the choices are made automatically, and the logic follows the mechanism proposed by the author.

The final test aims to collect first-hand user feedback to understand the general perception of No-warning system.

Figure 4.1 A female participant(conservative audience) in the experiment, The author is operating for her.

4.1. Scenario design

The conceptualization process followed the idea of providing a better movie-going experience for movie lovers. In order to consolidate this idea and refine the system based on the actual needs and feedback from the audience, target characters, scenarios, and user cases were created.

Target Persona The target audience of No-warning system is movie lovers. Movie lovers are often willing to try different types of movies, even if they know in advance that the movie is not the type of movie they like and are used to. In author estimation, the target audience of X-System is likely to be a larger proportion of female viewers. Some studies have shown that there are gender differences in how different types of people approach media violence: men tend to show more interest than women, while women are more likely to show disgust and rejection. Moreover, when it comes to the treatment of horrific content, women tend to remain in the sense of fear and stress for longer than men.(Sparks and Sparks 2000)(Sapolsky et al. 2003). Therefore, the author speculates that some female viewers may have a lower psychological tolerance and acceptance of violent, bloody, and horrific content than male viewers.

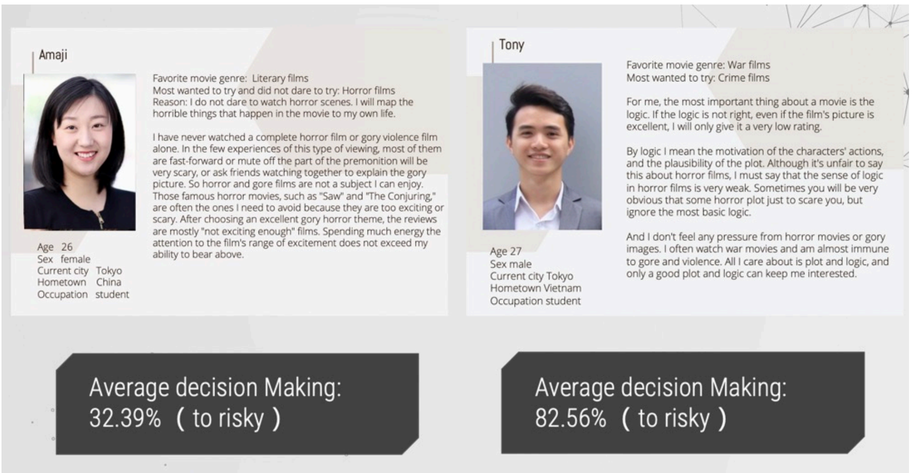


Figure 4.2 Profile of two participants

Scenario Recently, a new Japanese horror movie was released, and Amaji wanted to try it. However, people around her repeatedly advised her not to try it if she was not mentally strong enough or if she did not have the experience of watching horror movies often. However, a friend recommended to Amaji a newly launched movie viewing system, X. No-warning system will automatically switch the pressure level for the audience according to their physical state while watching the movie to watch the film smoothly.

Amaji took the advice, decided to try the No-warning system, tested on her decision-making level, and was classified as a "conservative viewer" by the system. The system promised to adjust the film's intensity for her so that she could watch the entire film smoothly.

Amaji put on the bracelet responsible for monitoring her physical signs and fearfully turned on the computer to start watching the horror movie. Amaji felt that she was gradually able to accept the intensity and better integrate it into the plot without realizing it.

For the first time in her life, Amaji successfully watched a horror movie alone. She feels that this is a good start; she has already started to make a list of classic horror films that she had always wanted to see but was afraid to. Amaji feels that this first experience of horror films could not have been possible without the kind assistance of the No-warning system.

4.2. Questionnaire

In order to gain a deeper understanding of participants' feelings about the system, the author set up a questionnaire for the testers.

Questionnaire:

- Do you feel any disconnection between film sequences?
- Can you feel that the system is playing you content that enhances (or weakens) the stimulus?
- Do you think the system made the judgment you wanted?
- Did the system improve your viewing experience?

As shown in the Figure 4.3, 62.5 percent of viewers felt that they could feel enhanced or weaken stimulation of the video. 37.5 percent of viewers felt sometimes. This result was significant to the author and very much in line with expectations. Because the author wanted the audience to feel the change in stimulation, this result shows that the previous different stimulation level settings were affected.

Moreover, most of the viewers felt that the system's decisions were following their ideas. Basically, in a limited number of cases, the system has done well to enhance the audience's viewing experience.

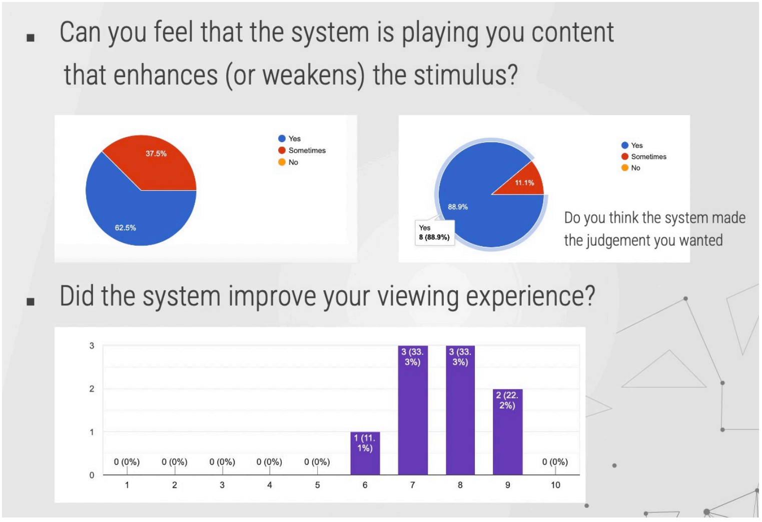


Figure 4.3 Results of questionnaire

4.3. Cases and interviews

A male tester, Tony, took a simple pretest before the test, and the result was that he had a high tolerance threshold for high-stress images and was judged to be an "risky audience." So the author raised the BPM and EDA values in the code accordingly, which means that the male tester could only be judged as high stress and high arousal by the system if he was given higher BPM and EDA. Not surprisingly, the system chose "risky" for the male tester at the beginning of the determination, and the system also played more stimulating content for him.

Let us look at the feedback from the male tester (the risky viewer)

Question: Did the viewing process feel smooth? Did you maintain a high level of interest the whole time?

Answer: Yes, the viewing process was very smooth. One interesting thing is that whenever I felt that the show was getting boring, the system seemed to "know" what I was interested in and played it for me. I could clearly notice that the pace of the episode was becoming faster, the background music became more intense, and even the color hue of the images changed.

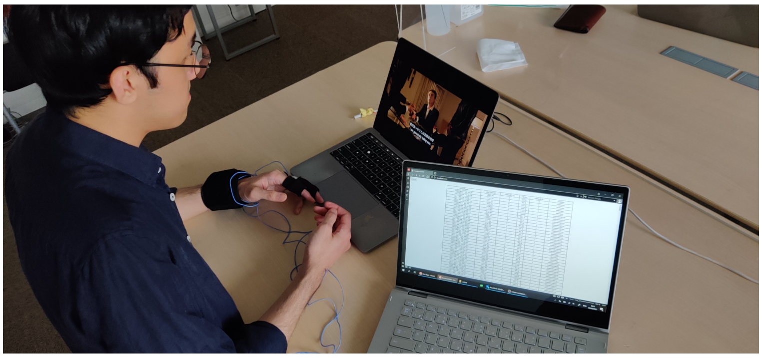


Figure 4.4 A male participant in the experiment (risky audience)

A female tester, Amaji, also took a simple stress pretest before taking the test, and the author played a film clip with a certain amount of horror, violence, and gore and recorded the changes in EDA and HR. The results showed that the female viewer had a relatively low tolerance threshold for high stress and was judged by SPSS as a "conservative viewer."

So the author set the EDA and BPM at 78 and 90, which means that this female tester was judged to be high stress and high arousal by the system after being given a relatively modest boost in EDA and HR. As expected before starting the experiment, the female viewer immediately entered the high stress and high arousal state after the movie started. The system automatically switched to "low stimulation mode" for her to play. In the end, the female viewer remained in a relatively stable state of stress throughout the entire viewing process. Next, let's look at the feedback from the female tester (a conservative viewer).

Question: Does the viewing process feel smooth? Do you get the kind of images that put so much pressure on you that you can't continue watching?

Answer: Yes, the viewing process was very smooth. The images that used to put too much pressure on me did not appear today. I noticed the reduction in volume, the mosaic of gore. Whenever I felt pressure, the film seemed to automatically switch to an acceptable version for me, so the viewing process was smooth.

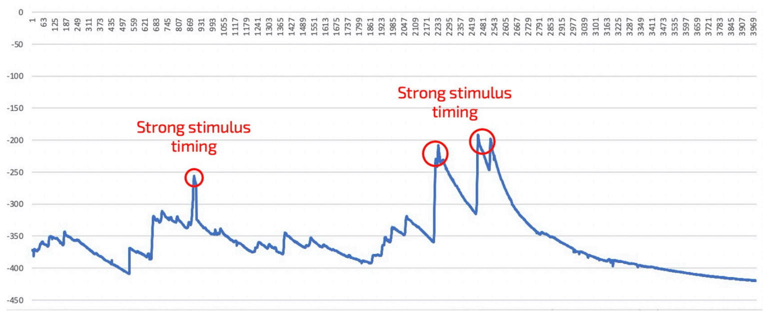


Figure 4.5 Choose a high stimulus timing for the plot branch

4.4. A solution about sudden stimulation

Some viewers have reported that they are often startled by sudden horrific and gory images while watching the film. Correspondingly, there is a sudden spike in the EDA and BPM curves.

As the physiological signals of 25-30 seconds before the viewer makes a decision are now used, this range is not necessarily accurate. However, for the sake of standardization of the statistics, the author has chosen this range. Nevertheless, this time range should be flexible and does not have to be restricted to the 25-30 seconds before the decision, but can also be the first and last 5 seconds of a strong stimulus.

So when choosing the branching points, the author tries to choose them near the strong stimulus content and avoids flat areas. As a result, explicit EDA and BPM changes are easier to observe, easier to calculate, and allow the audience's reaction to the strong stimulus to determine the next decision directly.

4.5. Multi-viewing attempt

Multiple viewers are a constant problem with interactive content. In the 'many worlds' study mentioned in the literature review, the researchers encountered the same problem and came up with a practical solution: a simple pre-set questionnaire asking people about their preferences for films (e.g., do you like horror films?). And then splitting viewers with the same preferences into a group for testing. (Kirke et al. 2018)

For the author, this is the most effective solution, but the author has improved it slightly: use the first few minutes of the film to do some tests and give a bias to the physiological data of each viewer. Thus, this makes the film's beginning reasonably substantial, so the author has re-edited the beginning of the film to measure the obvious EDA and BOM fluctuations.

This system's strength is that it can predict audience decisions with a high probability. This advantage also facilitates the sorting of audiences, so this pre-emptive process can sort audiences into 'risk-taking' and 'conservative' audiences, as shown in Figure 4.2.

By grouping similar viewers, the probability of making different decisions is not entirely avoided, but it is significantly reduced.

Chapter 5
Conclusion

5.1. Discussion

With the rapid development of film, more and more film technology improves the audience's viewing experience, such as IMAX, surrounding Dolby audio. The movie's content is also becoming more and more diversified, giving rise to a certain type of movie correspondingly for a specific group of viewers, such as horror movies for horror movie lovers. Nevertheless, some movies keep part of the audience out of the viewing threshold because of horror or violence, gore elements.

In this case, the author investigated the challenge of playing film content appropriate for the audience based on their physical reactions. The No-Warning system was proposed to achieve this goal, an interactive movie playback system containing three main goals of selectable movie pressure stimulation, movie interactivity, and judging viewers' choices by their physical states.

No-Warning system can obtain the viewer's EDA and heart rate to know the current state of stress and arousal and determine whether the viewer wants to "avoid stimulation" or "need stimulation" and play the movie content for the viewer accordingly. With this system, viewers can watch a whole movie in a relatively smooth stress state, whether they are "conservative viewers" who do not need intense stimulation or "risky viewers" who need constant stimulation.

This system constructed by the author, and a classification mechanism based on viewer decision making was evaluated several times in different settings. The purpose of the evaluation was to determine if the system could maintain the viewer's stress level and improve the viewer's viewing experience. According to the feedback received, the system proved to be a helpful tool to improve the viewing experience. However, the limitations of the current design and the insights from the final evaluation leave a substantial amount of room for future improvement and development, and the following author describes in detail the current limitations and goals for future improvement.

5.2. Limitations

From the results and analysis of several experimental evaluations, some limitations about the functionality of the No-warning system have been more possibilities to be observed.

More judgment criteria One of the No-warning features is the ability to obtain the user's physical indicators in real-time. However, due to the limitations of the equipment and audience comfort considerations, we can currently only use the geist lab's wristband as a tool to obtain the user's physical signs. The indicators that can be obtained are only a few indicators, including EDA and HR, and it must be admitted that there are still some inaccuracies in the data obtained.

More diverse data can yield a more detailed portrait of the audience, which allows the system to determine the behavior of users more accurately. For example, the author once considered pupil monitoring equipment to obtain the audience's pupil diameter and blink statistics. However, for the audience's comfort, especially for the audience wearing glasses, the author finally chose to give up the pupil detection equipment. Although perhaps in the future, smart glasses, pupil monitors, and other products become more and more lightweight, pupil detection must be a crucial potential development direction.

System integration When the code section judges the audience's state, it will display the predicted audience choice on the screen, and then the author will press the selected button by mouse click. In anticipation of future systemic improvements, the author's operation will be replaced by a computer program (a function that is not technically very difficult to implement due to the author's limited programming skills alone).

It can be inferred that another significant prospect of this system is to integrate with the current relatively mature video playback software (such as QuickTime, VLC media player) specifically for interactive movies, and is to balance the use of theaters and individual users. This new viewing system and new viewing mode may bring a considerable change to the current "majority-minority" interactive movie theater playback mode.

5.3. Future works

5.3.1 Better solutions for multiple audiences

As mentioned before, the possibility of viewer-to-viewer interaction emerged during the user testing process, and this aspect is bound to be considered in future system improvements. The No-warning system is much more fun and social to watch if more than two viewers participate. From the results of previous experiments, it is evident that different decision types, such as "risk-taking" and "conservative" viewers, make very diverse decisions when faced with high levels of stress. So when two or more audience members disagree, how does the system decide whose choice to continue the screening? Although the current questionnaire plus grouping solution solves part of the problem, the author expects a better solution to emerge.

5.3.2 Implementation into theatres

At present, in theaters with interactive films, the principle of "majority rule" is generally adopted, such as preparing a button for each audience or installing an app on the cell phone in advance. Whenever there is an interactive choice, the majority choice is often followed. This approach is not appropriate because the No-warning system is equivalent to customizing a film according to each viewer's unique needs. This customization is one of the core values of the No-warning system. So, for now, more possibilities need to be investigated for interactions between two or more viewers, especially those with different decision-making categories.

As the system is envisaged to be used in cinemas or as an interactive film platform in the future, field research is also important. The author intends to visit the cinemas in Tokyo where interactive films can be shown to investigate the limitations and feasibility of using the no-warning system. In addition, the use of interactive video platforms, such as Netflix or Bilibili, is also in the plans.

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Appendices

A. Coding processing

Configuration File for Detecting Failures

```
package GraduationProject.controller;

import java.io.BufferedReader;
import java.io.FileInputStream;
import java.io.InputStreamReader;
import java.math.BigDecimal;
import java.math.MathContext;
import java.text.NumberFormat;
import java.text.SimpleDateFormat;
import java.util.ArrayList;
import java.util.Collections;
import java.util.LinkedList;
import java.util.List;
import java.util.Optional;
import java.util.OptionalDouble;
import java.util.Queue;

import org.springframework.stereotype.Controller;
import org.springframework.ui.Model;
import org.springframework.web.bind.annotation.RequestMapping;

import GraduationProject.entity.Viewer;

@Controller
public class ShowResultController<E> {
```

```
// localhost:8080/
// file path
final static String PATH_EDA = "C:\\Users\\sendl\\Desktop\\Sy\\final3_98-F4-AB-09-00-C0
final static String PATH_HRT = "C:\\Users\\sendl\\Desktop\\Sy\\final3_98-F4-AB-09-00-C0
// EDA HRT threshold value
final static Double THRESHOLD_EDA = 20.91;
final static Double THRESHOLD_HRT = 70.01;
// results
final static String EDA0_HRT0 = "none";
final static String EDA0_HRT1 = "nervous";
final static String EDA1_HRT0 = "rishy";
final static String EDA1_HRT1 = "conservative";
// EDA time range
final static int GROUP = 25;

final static String STR_0 = "0";
final static String STR_1 = "1";
final static SimpleDateFormat SDF = new SimpleDateFormat("yyyy/MM/dd hh:mm:ss");

@RequestMapping(value = "/index")
public String logout() {
return "index";
}

@RequestMapping("/local")
public String localRefresh(Model model) {
List<Viewer> lists = new ArrayList<>();
List<Viewer> listEDA = getLists(PATH_EDA, 0, 4, THRESHOLD_EDA, Boolean.TRUE);
List<Viewer> listHRT = getLists(PATH_HRT, 0, 4, THRESHOLD_HRT, Boolean.FALSE);
for (Viewer eda_data : listEDA) {
for (Viewer hrt_data : listHRT) {
if (eda_data.getLocalTime().equals(hrt_data.getLocalTime())) {
eda_data.setBpm(hrt_data.getBpm());
eda_data.setStatusHRT(hrt_data.getStatusHRT());
listHRT.remove(hrt_data);
```

```
lists.add(eda_data);
break;
}
}
}
lists.addAll(listHRT);
Collections.sort(lists);
lists.stream().forEach(p -> {
if(Double.valueOf(p.getBpm())>86.8348) {
double subtraction = subtraction(subtraction(multiplication(0.256, Double.valueOf(p.get
multiplication(0.186, Double.valueOf(p.getBpm()), 4), 4), 4.001, 4);
double pow = Math.pow(Math.E, subtraction);
p.setDecisionMaking(multiplication(division(pow, add(1, pow), 4), 100, 4) + "%   H");
}else {
double subtraction = subtraction(subtraction(multiplication(0.505, Double.valueOf(p.get
multiplication(0.401, Double.valueOf(p.getBpm()), 4), 4), -7.896, 4);
double pow = Math.pow(Math.E, subtraction);
p.setDecisionMaking(multiplication(division(pow, add(1, pow), 4), 100, 4) + "%   M");
}
// 0.256*84-0.186*Double.valueOf(p.getBpm())-4.001

if (STR_0.equals(p.getStatusEDA()) && STR_0.equals(p.getStatusHRT()))
p.setTStatus(EDA0_HRT0);
if (STR_0.equals(p.getStatusEDA()) && STR_1.equals(p.getStatusHRT()))
p.setTStatus(EDA0_HRT1);
if (STR_1.equals(p.getStatusEDA()) && STR_0.equals(p.getStatusHRT()))
p.setTStatus(EDA1_HRT0);
if (STR_1.equals(p.getStatusEDA()) && STR_1.equals(p.getStatusHRT()))
p.setTStatus(EDA1_HRT1);
});

model.addAttribute("viewers", lists);
return "index::table_refresh";
}

private List<Viewer> getLists(String filePath, int dateIdx, int valInx, Double d, boole
```

```
List<Viewer> lists = new ArrayList<>();
try (BufferedReader reader = new BufferedReader(
new InputStreamReader(new FileInputStream(filePath), "utf-8"));) {
// title
System.out.println(reader.readLine());
//take first line localTime and edaFiltered
String[] split = reader.readLine().split(",");
String timeString = SDF.format(Long.valueOf(split[dateIdx]));
Double edaFiltered = Double.valueOf(split[valInx]);
// edaFiltered for 1
int count = 1;
Double average = 0.00;
// from second start cycling
String line = null;
Queue<List<Double>> queue = new LinkedList<List<Double>>();
List<Double> edaFilteredList = new ArrayList<Double>();
edaFilteredList.add(edaFiltered);
while ((line = reader.readLine()) != null) {
String item[] = line.split(",");
if (timeString.equals(SDF.format(Long.valueOf(item[dateIdx])))) {
// if (f) {
if (edaFilteredList.isEmpty()) {
edaFilteredList.add(edaFiltered);
}
edaFilteredList.add(Double.valueOf(item[valInx]));
// }
edaFiltered += Double.valueOf(item[valInx]);
count++;
} else {
BigDecimal b = new BigDecimal(edaFiltered / count);
double _avg = b.setScale(2, BigDecimal.ROUND_HALF_UP).doubleValue();
if (f) {
String statusEDA = STR_0;
queue.offer(edaFilteredList);
edaFilteredList = new ArrayList<Double>();
if (queue.size() == GROUP) {
```

```
List<Double> dList = new ArrayList<Double>();
queue.stream().forEach(q -> {
dList.addAll(q);
});
queue.poll();
Collections.sort(dList);
// statusEDA=dList.get(dList.size()-1)-dList.get(0)>=d?STR_1:STR_0;
statusEDA = subtraction(dList.get(dList.size() - 1), dList.get(0), 4) + "";
}
lists.add(new Viewer(timeString, String.valueOf(_avg), statusEDA, null, null, null));
} else {
if (edaFilteredList.isEmpty()) {
edaFilteredList.add(edaFiltered);
}
queue.offer(edaFilteredList);
edaFilteredList = new ArrayList<Double>();
if (queue.size() == GROUP) {
List<Double> dList = new ArrayList<Double>();
queue.stream().forEach(q -> {
dList.addAll(q);
});
queue.poll();
// Collections.sort(dList);
// division = division(dList.stream().reduce(Double::sum).get(), dList.size(), 4);
average = dList.stream().mapToDouble(Double::doubleValue).average().getAsDouble();

}

lists.add(new Viewer(timeString, null, null, String.valueOf(new BigDecimal(average).set
null));
}
timeString = SDF.format(Long.valueOf(item[dateIdx]));
edaFiltered = Double.valueOf(item[valInx]);
count = 1;
}
}
```

```
} catch (Exception e) {
e.printStackTrace();
}
return lists;
}

public double add(double a, double b) {
BigDecimal b1 = new BigDecimal(a);
BigDecimal b2 = new BigDecimal(b);
return b1.add(b2).doubleValue();
}

public static double subtraction(double a, double b, int setPrecision) {
BigDecimal b1 = new BigDecimal(a);
BigDecimal b2 = new BigDecimal(b);
return b1.subtract(b2, new MathContext(setPrecision)).doubleValue();
}

public static double multiplication(double a, double b, int setPrecision) {
BigDecimal b1 = new BigDecimal(a);
BigDecimal b2 = new BigDecimal(b);
return b1.multiply(b2, new MathContext(setPrecision)).doubleValue();
}

public static double division(double a, double b, int accurate) {
if (accurate < 0) {
throw new RuntimeException("1");
}
BigDecimal b1 = new BigDecimal(a);
BigDecimal b2 = new BigDecimal(b);
return b1.divide(b2, accurate, BigDecimal.ROUND_HALF_UP).doubleValue();
}

}

package GraduationProject.entity;
```

```
public class Viewer implements Comparable<Viewer>{
private String localTime;
private String edaFiltered;
private String statusEDA;
private String bpm;
private String statusHRT;
private String tStatus;
private String decisionMaking;

public Viewer() {
super();
}

public Viewer(String localTime, String edaFiltered, String statusEDA, String bpm, Strin
String tStatus) {
super();
this.localTime = localTime;
this.edaFiltered = edaFiltered;
this.statusEDA = statusEDA;
this.bpm = bpm;
this.statusHRT = statusHRT;
this.tStatus = tStatus;
}

public String gettStatus() {
return tStatus;
}

public void settStatus(String tStatus) {
this.tStatus = tStatus;
}

public String getDecisionMaking() {
return decisionMaking;
}
```

```
public void setDecisionMaking(String decisionMaking) {
this.decisionMaking = decisionMaking;
}

public String getLocalTime() {
return localTime;
}

public void setLocalTime(String localTime) {
this.localTime = localTime;
}

public String getEdaFiltered() {
return edaFiltered;
}

public void setEdaFiltered(String edaFiltered) {
this.edaFiltered = edaFiltered;
}

public String getStatusEDA() {
return statusEDA;
}

public void setStatusEDA(String statusEDA) {
this.statusEDA = statusEDA;
}

public String getBpm() {
return bpm;
}

public void setBpm(String bpm) {
this.bpm = bpm;
}
```

```
public String getStatusHRT() {
return statusHRT;
}

public void setStatusHRT(String statusHRT) {
this.statusHRT = statusHRT;
}

public String getTStatus() {
return tStatus;
}

public void setTStatus(String tStatus) {
this.tStatus = tStatus;
}

@Override
public int compareTo(Viewer o) {
// TODO Auto-generated method stub
return o.getLocalTime().compareTo(this.getLocalTime());
}
}
```