**Automatically Adjusting Game Difficulty Using A Wearable Device**

By: Robert Jackson

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Faculty Advisor: Professor Dvijesh Shastri

Committee Member: Professor Mitsue Nakamura

Department Chairman: Professor Kenneth Oberhoff

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**Abstract**

Video game designers have always had the difficulty of designing games that are both entertaining and challenging enough to hold player interest. Recent games have also held the trend of having difficulty settings for their games to cater to different playing styles, such as having an easy, medium, and hard difficulty. But with the rise of devices that depend on physical movement and actions of players, such as the Wii controllers made by Nintendo, the study into more physical interactions between player and games has been on the rise. In that vein, there has been some research done in combining player physiological readings with gameplay to see if game difficulty can be dynamically altered in real time based on a person’s readings. Yet, most research approaches are limited to the lab environments either because they used costly sensors such as high resolution thermal cameras, or use contact sensors such as EEG that restrict the players’ movement and leave behind noise that affects the data in such a way that it is only useful for observation.

In this study, we use a wireless electrodermal activity (EDA) sensor, the E4, for monitoring player’s emotional arousals during game play. We hypothesized that when the game difficulty matches the player’s ability, it results in the player’s excitement and engagement in the game. Otherwise too high or too low difficulty levels result in the player’s disassociation from the game. Both emotional states can be quantified via the EDA sensor. Player’s excitement elevates his/her EDA responses and his/her disassociation results into a tonic (or baseline) EDA responses.

E4 is capable of interfacing with Windows, Mac, iOS and Android Operating system devices. This study comprises of various steps: Creating a simple game with easily adjustable difficulty metrics; studying the real time data of the E4 Empatica to identify when stress levels are changing; taking readings from the E4 Empatica from various participants as they are playing the game in different difficulty settings for purpose of analysis and determining whether an algorithm to dynamically alter difficulty settings in a game is viable from this data.

The game was created using the Unity engine and designed to run on a PC running the Windows operating system. The data was collected using an app on an Android phone created by Empatica. The data was read and collected in real time, then uploaded to a server as excel files to be downloaded and analyzed at our convenience. Surveys were used after gameplay sessions to gather demographic information, as well as how much enjoyment they were getting from the play sessions, how stressed they were feeling, and to find out their level of expertise with video games.

We predicted that the device’s real time readings, once analyzed, would provide the information needed to create an algorithm that will dynamically alter the game’s difficulty setting. After analyzing and looking at the data, we found that the EDA data and heart rate were consistent enough to use in analysis, and that EDA seems consistent overall with what was expected to be used to create a dynamically changing algorithm. Heart rate would require much more studies to see if there is a useable trend.

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**Introduction**

Video games have come a long way from the simple 8-bit fascinations created in the late 70’s and 80’s. They’ve become a massive industry that brings in billions in revenue and become so complex that it can take an entire team of artists, musicians, sound technicians and, of course, software developers, years to develop some of the more complex and intricate games. On a social level video games have gone from being played by those more technologically inclined to becoming a staple in many households in America and many other countries. With both the staggering success and growth of the video game industry, it is only natural to start looking at new and revolutionary ways for people to interact with video games to enhance the gaming experience. That is what this project is about. It is an attempt to see if it is viable to create an effective algorithm that allows a game to take a person’s stress and anxiety levels into account during game play and adjust the player experience as a result of those levels.

This paper will be broken up into the following sections. An introduction in which we will define terms used in this paper, then discuss the history of video game interaction, previous studies related to this project, and the device used in this study, the E4 by Empatica. Following the introduction will be a discussion of the research done in this project and the hypothesis. Afterwards the design of the game used in this project with a focus on the difficulty settings and the metrics behind them will be explained. This will be followed by the methodology used in gathering the data for analysis. Following that the data gathered will be analyzed and discussed. A conclusion from the data will then be shown, followed by a discussion regarding potential future studies.

**Definitions**

1. Video Games, or Games: The two terms will be used interchangeably to refer to digital media created by software developers to entertain and challenge a player.
2. Video Game Player, or Player: These two terms will be used interchangeably to refer to those who play, or interact with video games through various mediums, such as game consoles or PC’s.
3. Video Game Interaction, or Game Interaction: How a video game player controls and affects the ‘world’ within a video game. Usually this interaction is done via input devices called controllers.
4. E4: A wrist device created by Empatica used to gather physiological data from a person wearing the device. More will be discussed in the E4 Empatica section of this paper.
5. Physiological Data: Data obtained from a person’s normal biological workings, such as body temperature, heart rate, nervous reactions, etc…
6. Game Difficulty: Challenges that need to be overcome by a video game player to achieve a reward within a video game.
7. Avatar: The digital representation of the player within a video game.

**A History of Video Game Interaction**

Video games have been around since the 1950’s, but until the late 70’s and early 80’s, they were merely curiosities that were spread from university to university on various systems. What those early games all had in common was either interaction through keyboard, or through another analog device. The Odyssey released a system in 1968 that used a 48-key keyboard with which to interact with its games. In 1977 the Atari is released which used an analog joystick with a button to interact with games. At the same time arcade consoles became popular which required the players to stand and play games while still using joysticks and buttons to interact with the game. [1]

The Nintendo and Sega systems moved away from using joystick and buttons and created controllers that used various kinds of buttons to control the game. They also created ‘guns’ that could point at the game and, using light sensors picked up by the television, figure out where the gun was fired and decide whether a hit was scored. These guns led to very popular games in arcades which used similar technology. While these new methods of interacting with games became the norm, the joystick was not done away with. It was still used as a specialized control for games that had a more arcade feel to them, such as tournament style fighting games. Portable game systems which were miniature consoled with controls built into them also became very popular.

The tradition of using some kind of controller with buttons and or joystick held for several ‘generations’ of game consoles. It wasn’t until the late 90’s and early 2000’s that new forms of interacting with games were created. Controllers began to be designed to vibrate during certain events to enhance the immersion into the game. New technologies in arcades, which eventually were moved to consoles, allowed for more physical interactions with games such as the case with games such as Dance Dance Revolution which had sensors that players would step on to simulate dancing to the commands on the game screen.[2] Similar games with similar controls would be created such as the Rock Band and Guitar Hero games which allowed players to mimic playing various musical instruments (guitar, drums, even singing on a microphones).[3][4] The player’s input would then either match the expected input, earning the players scores, or they would fail and be penalized.

At the same time, social interaction while playing games was growing. With the advent of Massive Multiplayer Online Games, players would begin communicating with each other while playing the same game. On computers, and later on consoles, this created a new way to interact with the game as it allowed both social and game interaction from home. The game could be controlled via keyboard, as could communication with other players. Or with keyboard and a mouse, or a specialized joystick.

Early attempts at virtual reality interaction were also created as some arcades had specialized games where a player would be inside of an arena that captured the player’s motions. They would also wear a headset and wrist devices that would simulate first person environment and the ability to use a weapon to attack.

These would lead to other ways to interact with games. Game makers would design controllers with accelerometers and gyroscopes to sense how the controller was being held or tilted which could then be used to control actions within a game. The Nintendo Wii introduced more physical means of interacting with a game by moving and swinging the Wii-mote around, or standing on a specialized platform to dance and do exercises and many other actions that the Wii system would recognize and apply to the game. [5] Microsoft and Sony both released cameras that could capture a player’s movements and use it in games, as well as other social interactive media. [6][7]

Also with the rise of cell phones and then smart phones, new ways to play games were made. Games on smartphone allow players to interact with games by swiping along the screen or tracing their fingers along the screen.

And as of this study, Sony is releasing the Playstation VR system, a system that allows playing games while wearing a VR headset to simulate being immersed into the game, and interact with the game using the Playstation Move controllers. [8]

In addition to the mechanisms used to interact with a game, the way the player tries to overcome the games challenges have evolved over the years as well. When games first began to be developed the player was expected to play the game based on how the developer created the challenges for the game. In most circumstances, a game would get progressively harder as the player played the game until either the game ended or the player was defeated. With time, developers began to implement optional difficulty settings that would adjust how hard a game was and would get based on a player’s assumed skill level. These settings were traditionally marked as easy, medium, and difficult with some developers adding extra settings for varying degree of challenges. Several of the more modern games have also begun to implement dynamically changing difficulties that are based off various metrics in the game. For instance, the game series known as Elder Scrolls has been known to alter the encounters a player has within the game based off the strength, or level, of the avatar the player is controlling.

As it can be seen, games have been shifting from traditional control of games through devices without much movement on the part of the player, to more physical engagement with games and immersion into games. And, as the interaction with games have been changing, so have means of providing an engaging experience for the players. But they are not without limitations, as will be seen in the discussion on studies involving games.

**Prior Studies**

Scientific research and development in game development is a relatively new field with studies varying from how to interact with games to how games affect players physically and psychologically. Studies that are applicable and related to this study include research done in dynamically altering difficulties, as well as studies that try and use a person’s physiological data to influence games.

We begin by looking at Hunicke’s study where he theorizes that players will “feel cheated if game difficulty is altered.”[9] In his study he creates a dynamic system that allows the game to alter itself based on previous player performance, making the game easier if the player is doing poorly, or harder if he is doing well. In his study he found that the players didn’t really notice the actual adjustments in the game and in fact believed aspects of the game had been adjusted that had not in fact been changed. He also found that expert players enjoyed the adjusted game play more than novice players did, and that to novice players the game was difficult regardless of adjustment and expert players just took the changes in stride. The takeaway from this study is that players don’t tend to notice the dynamic changes made in the game, and that to adjust difficulty it is necessary to focus on quantitative aspects of the game that can easily be adjusted. In his game, the difficulty changes were the health and attack capability of the enemy and the amount of resources available to the player. Sampayo-Vargas et. al.’s study focused on whether using dynamically changing difficulty in games meant for education would help a student’s learning, and whether they would notice the change in difficulty. The important aspects of this study that are relevant are that the researchers found that the students did not notice when the game adaptively changed to their skills. Furthermore, the difficulty changes were kept simple. The more questions the student successfully answered, the more difficult the questions they were given. And vice versa, the less questions they answered, the easier the questions they received.[10] Hawkins’ et. al.’s study focuses on testing the different approaches by players when playing a dynamically altering setting. They don’t discuss whether the players noticed the change in difficulty, but manage to show that difficulty changes can remain simple and still have an impact in player performance. In their study they merely changed the speed of targets appearing in their game and changed how often meaningful versus distracting targets appeared. [12]

What these studies on dynamically changing games have in common is that the dynamic changes of the game are based on an algorithm that takes player performance into account. The challenge versus reward dynamic has been changed from the traditional formula of rewarding a player for overcoming challenges with rewarding a player from overcoming challenges, then increasing those challenges. This doesn’t consider whether a player enjoys the increase in challenge, or whether the increase in challenge is sufficient to keep the player engaged.

With this, we delve into a couple of studies that look into a potential connection between game play and a person’s physiology. A study conducted by Lin and Hu showed that stress levels as recorded through Galvanic Skin Response (GSR), Blood Volume Pulse (BVP) and heart rate (HR) are in fact affected while playing a game.[12] Yun et. al. takes it a step further and uses physiological data to adjust game difficulty. They use a stress cam to monitor a player as they are playing and, taking that data, attempt to modify the difficulty. They are successful in being able to dynamically adjust the video game settings from thermal readings gained from the supraorbital region of the face.[13] This shows that physiological readings can be used to adjust difficulty settings successfully.

While it has been shown to be possible to adjust games using physiological readings, studies in this vein have had severe limitations. In the case of Yun et. al.’s study, it is dependent that the user sit in front of a stress cam and be limited in movement to obtain the data needed to adjust the difficulty. Furthermore, the device used is not economically viable. In Lin and Hu’s study, contact sensors were used that are effective while a player is staying still but introduce noise into the data when a person begins moving, thus potentially altering the data needed to determine difficulty settings.

**E4 Empatica Wristband**

The E4 Wristband, by Empatica, is a device that was designed to measure stress levels and anxiety using various readings. [14] This device was created not only for any who wished to purchase and use it, but also for researchers wanting to delve into studies on stress and anxiety. They support this research by providing a web site, Empatica Connect, and various mobile apps that allow a user to monitor the device from their smartphone and, once the test is concluded, uploads the data in the form of various excel spreadsheets to Empatica Connect. From there researchers can share their data with others and download it for their use. Furthermore, to make the data accurate, Empatica has created a set of algorithms that uses an accelerometer to monitor body movement and, using this data, filters out noise that normally affects physiological data gathered by worn devices.

The data provided by the E4 in excel format is as follows:

* Accelerometer in the X, Y and Z axis
* Blood Volume Pulse (BVP)
* Interbeat Interval(IBI)
* Heart Rate(HR)
* Electrodermal Data (EDA)
* Temperature in Celsius

The BVP is derived from photoplethysmography (PPG) Sensor on the Empatica. Using the BVP, both HR And IBI can be derived. It’s added by Empatica that data estimated from running or physical activity is not suitable and that it is only useable for resting heart-rate during everyday scenarios. [14] This does limit the use of the wristband to games that involve sitting and not actively jumping and moving around. An optical thermometer gathers temperature, electrodermal activity sensor gathers EDA, and a 3-axis accelerometer gathers the 3-axis accelerometer data.

On average the sensors would pick up data thirty-two times per second, with BVP being he exception at sixty-four data points a second. But how often the data was recorded was depended on the data type. Temperature was recorded an average of once a second, BVP recorded all of its signals. From BVP, it would derive IBI an average of once every three seconds and HR an average of once a second. EDA was recorded an average of four times a second, and accelerometer data was recorded once every thirty-two seconds.

This is the data that will be looked at to see if an effective dynamic difficulty algorithm can be created. To gather data, as part of this project, a simple game will be developed with very simple game metrics, as described next.

**Research Question**

The question this projects seeks to answer is thus: Will the data obtained by the E4 Wristband be suitable for creating an algorithm that will allow a game to dynamically alter its difficulty during gameplay?

**Hypothesis**

Given prior research and proof that gameplay does affect a person’s physiology, I believe that it is possible that at least one set of data obtained by the E4 will be suitable for the creation of an algorithm. By suitable I will further add that the data will consistently show increases and decreases in arousal levels between an easy and harder difficulty. Furthermore, I believe that there will be a correlation between how much the player is enjoying the game and the increase in arousal levels.

**Game Development**

Before the data from the E4 can be obtained, a game must be chosen with which to obtain the data. For the first part of this project a simple game will be developed for testing purposes. What follows is a discussion on the game design and the difficulty metrics of the game.

**Design**

Due to time restraints, the game had to be one that could be put together in at most a month’s time, but still be enjoyable to play and meet the needs of this project. To that end a simple game that is a throwback to the old Atari games of the 1980’s, combined with a tower defense design idea from a board game called Villains’ Assault resulted in the overall idea behind the design. I like to call it Galaga meets Tower Defense. The game was designed using the Unity Physics engine and packaged to run on a Windows Operating system.

The mechanics of the game are simple. The player moves left and right on an arc protecting a wall behind them. Enemies begin to appear on random points in an arc heading towards the wall. The player then moves to intercept and defeat the goblins. If the player is fast enough, the enemy will be destroyed. If not, the player may take damage and the goblin may get past them to damage the wall. The game ends when either the player dies or the wall is destroyed. As players continue to kill goblins, a score is kept with a player garnering ten points for each goblin destroyed. This provides a form of incentive to try and beat their previous score, similar games in the 80’s such as Space Invaders or Pac-Man. A diagram of the basic game design can be seen in **appendix B**.

**Difficulty Metrics**

As is pointed out in Aponte et. al.’s study, “difficulty scaling is a central task of good game design.” [15] The difficulty is what provides the player the challenge and engagement that keeps them engaged and playing the game. It is overcoming these challenges and getting rewarded that makes playing a game worthwhile.

In the older 1980’s game, as stated previously, such a reward was getting a high score before being defeated. Games such as Space Invaders, Pac-Man, Galaga, and several others had no ending to the game and no objective other than to survive and see if you could eventually beat the highest scorer, or at the very least defeat your previous score. And that is the reward system we are going for in this game. The game, for the purposes of this project, is designed to eventually overwhelm and defeat you. The challenge is in trying to score as high as you possibly can before that inevitable defeat.

The challenges included in the game to make obtaining a high score and surviving difficult were based on several simple metrics. Goblin speed, how often goblins appeared, and the frequency of certain types of goblins appearing over the other. The speed of the goblin was based using a common formula used in the Unity engine to calculate the speed at which an object moves. All that one needs to provide is a decimal value. The higher the value, the faster the object moves. In this case the goblins began at a value of 1.0 and their speed would increase along with the value. How often goblins appear is based off a formula involving time within Unity. After x amounts of seconds have passed, where x is a decimal value, a new goblin will appear. In the case of this algorithm though, we could have multiple goblins appear at once at a predetermined time, allowing us to create an algorithm that could create entire swarms of goblins should we choose to. And finally, a simple algorithm based off modulo and percentages was created to handle how often one of two types of goblins would spawn. Depending on the difficulty setting, either the charging goblin would have a much greater chance of appearing, or the club-wielding goblin would.

For testing purposes two difficulty settings have been set up; an easy mode and a hard mode. The easy mode difficulty starts off very slow. This gives the player a chance to get used to the controls and how to defeat the goblins. As the players successfully defeat more goblins, the game slowly increases in difficulty. The easy difficulty setting never gets as difficult as the hard difficulty setting, and could potentially be played the entire play session without any deaths. The goblins’ speed ranges from a value of one to three at their fastest, the most goblins that ever appear at once is one, and the algorithm used to decide which goblin appears ensures that the club wielding goblin rarely appears at the beginning, then appears as often as the goblin charger.

The hard difficulty starts off at a more difficult level than the easy difficulty ever achieves. It is designed to eventually overwhelm the player after three minutes of play time, thus ensuring the player dies at least three times in one play session, though the average player died many more times than that. This was designed to see if we could identify spikes in stress levels in the data obtained. Ideally there would be at least three instances in which stress levels and anxiety would rise as the difficulty leads the player to an unwinnable situation. The speed of the goblin ranges from a value of one to four, with speed incrementing at a higher pace. The game starts off by having goblins appear consecutively immediately after each other and eventually has groups of two goblins appearing at once. And, finally, the club wielding goblin appears more often and then becomes the predominant enemy.

It is a combination of the simple design and the eventually overwhelming difficulty that we are hoping will illicit enough of a response in stress and anxiety levels while playing that we will be able to look at the data collected and see if there is a means of using that data to develop a dynamically changing difficulty algorithm.

**Methods**

The methods for collecting the data were a simple formula derived from previous studies. The subject would rest for ten minutes while listening to relaxing music. This would lessen or eliminate any previous stress they may be experiencing and would help develop a baseline for their physiological data. After the ten-minute rest, they would play the Easy difficulty for ten minutes. This would allow the player to not only get used to the controls and the gameplay, but it would allow us to ensure that the data is being gathered without any problems with the device or the game. After the first play session, the players would be given a survey to partially fill. A copy of the survey is available in the appendices, but this allowed us to get an idea as to the subject’s expertise level of play, whether they enjoyed the play sessions, their thoughts on the gameplay, and whether they felt any active stress while playing the game. We end up using their expertise and enjoyment levels to see if there is any correlation between that information and the data we gathered. While the players are filling out the survey I downloaded the first set of data to ensure it was captured correctly and prepare the device for the next session. In the next session, the player would once again rest while listening to relaxing music for ten minutes to try and relieve the stress from the previous session and once again determine a baseline for their physiological data. The subjects would then play the game in the harder difficulty for ten minutes, followed by their filling out the last part of the survey.

To summarize, each subject would rest listening to relaxing music for ten minutes, play the easy difficulty for ten minutes, fill out part of a survey, rest for ten minutes while listening to relaxing music, play the hard difficulty for ten minutes, then fill out the rest of the survey. A copy of this survey can be found in **appendix A.**

**Data Analysis and Discussion**

Once the data was collected and visualized, it was clear to see that there was some data that could not be used for the development of an algorithm. That data will be discussed first before discussing the data that has potential.

First, we discuss the IBI data. This data was not only the most irregular of all of the data sets, it was also the most unreliable. In the case of two subjects, the IBI data was only recorded while they were resting, and was not recorded while they played the game. For the other subjects, the IBI data recorded constantly while they rested, but only produced sporadic data while they were playing the game. Thus, this data could not be used for the purposes of creating a game altering algorithm. Samples of this data can be found in the appendices.

Then follows the BVP data. While it did provide the most data points out of all the data sources, it was also very irregular. The only pattern that was viewed between the two data points is that the numbers oscillated much more between the data’s lower and upper values while the subject was playing the game, and that the minimum and maximum values between which the data oscillated were less while the player was playing the difficult setting. Samples of this data can be seen in the appendices.

The temperature data was easy to read and shows gradual rises and falls in temperature. What it lacked was consistency. Some players’ temperatures would rise as they played the game and fall as they relaxed, which is what we imagined should happen. But others would have temperatures that rose while relaxing and fell while they played the game, or rose and fell sporadically with no rhyme or reason. The reason for this is because the device measures skin temperature, not internal temperature. As such when the person perspires their skin gets cooler. This is a good thing for EDA data because it allows for significantly better readings and helps show engagement.

This brings us to EDA, HR and accelerometer data which provided consistent and potentially useable data. I will discuss each one in turn.

**EDA**

The electrodermal data, or EDA, provided the most consistent data of the data sets. First I would like to look at the overall trend between easy mode and hard difficulty.

The first graph, Easy Vs. Hard EDA Trends, shows the trend between easy difficulty and hard difficulty. As can be seen, the average subject showed a rise between the two, with a couple of exceptions. While the changes doesn’t seem that much, keep in mind that EDA changes in increments of .01, so what looks like a small change is actually significant. The red line shows the average from all nine subjects, while the green line shows the average when removing the extreme outlier (Subject 9). Overall it does show that an increase can be seen between the two difficulty settings.

Looking at the second graph, EDA Slopes, this shows the slopes of each subject at each phase, rest 1, easy mode, rest 2, hard mode. Again, with a couple of exceptions, this shows the trend that EDA is higher when the subject is engaged in the game than when resting, which is what is expected. One of the other trends that is noticed is that the EDA of the second rest phase tends to be higher than the EDA of the first rest phase, but still lower than either phases where the subject is playing the game. The red line depicts the average slopes from all the subjects, while the green line depicts the average slopes without the extreme data given by subject 9.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| P-Value Comparisons | Rest 1 | Easy Mode | Rest 2 | Hard Mode |
| Rest 1 |  |  |  |  |
| Easy Mode | 0.284057581 |  |  |  |
| Rest 2 | 0.402387048 | 0.34603664 |  |  |
| Hard Mode | 0.107128008 | 0.10712801 | 0.192583931 |  |

The final diagram, the P-value comparisons, shows the P-values between the various sets of data. The data in red shows that there is potential of receiving the same results between hard mode and rest 1 and hard mode and easy mode. The hard mode and easy mode potentials is what is important here. If there is a good potential that the EDA of a subject will be higher between the easy difficulties and harder difficulties of a game, then there is a good potential to create an algorithm that will adjust the game settings based on this. It would take more testing with more samples to confirm this.

This graph shows average changes in EDA based on enjoyment level. When it came to enjoyment, 6 subjects enjoyed the harder difficulty more than the easy difficulty, and it shows. The increase in EDA is noticeably higher between easy and hard difficulty which shows a correlation between enjoyment and arousal levels.

**Heart Rate**

Thus, we move on to discuss heart rate, which did not follow the expected trends. Overall, most of the players had a slower heart rate when playing the difficulty setting over the easy setting. I can only speculate that as the subjects were accustomed to the game that it didn’t increase heart rate as much as when they were first getting used to the game play.

The first graph, Easy Vs. Hard HR Trends, shows this deviation from the EDA data. Many of the subjects either had a slower heart rate when playing the hard over the easy difficulty, or the increase was minimal. The red line shows the overall average change and as can be seen while there is an increase, it is very minimal.

The second graph, HR Slopes, also shows the odd trend that the heart rate during the hard difficulty is lower than in easy difficulty. And, as shown in the previous graph, the red line is the trend of the average slopes and, again, there is an overall increase through the phases of data collection, but it is very minute.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| P Value Comparison | Rest 1 | Easy | Rest 2 | Hard |
| Rest1 |  |  |  |  |
| Easy | 0.455322237 |  |  |  |
| Rest2 | 0.246098555 | 0.28587 |  |  |
| Hard | 0.272711721 | 0.299027 | 0.217006 |  |

More discouraging is the P value comparison of the data sets. It seems that the p-values do not predict that the same trends will be seen in future testing. This could be encouraging in saying that with more testing I might find the trend that a harder difficulty means an increased heart rate, or that there is no trend and it varies from person to person.

With heart rate, as with EDA, I did look at the values in reference to expertise and enjoyment levels. Those graphs are once again in the appendices, but there doesn’t seem to be a pattern. Both the most novice of players and expert of players had a lower heart rate during the difficult setting over the easy setting, but those with average or above average video game experience had a higher heart rate when playing the difficulty setting over the easy setting. I would have thought that the more experienced players would collectively have the lower heart rates overall and the least experienced would have a higher heart rate on difficulty, but this isn’t shown in the data.

Enjoyment levels also didn’t seem to be a factor as the players who enjoyed the game on a scale of 3 and 4 out of 4 had a mix range of lower to higher heart rates during the hard difficulty. The three who rated the game on a scale of 2 out of 4, two had a higher heart rate on hard than on easy, but one had a higher heart rate on easy than on hard, so again no discernable pattern could be found.

**Accelerometer**

I looked at the accelerometer data to see if there was a correlation between the movements of the player and the data. Using a formula to calculate energy use, I could determine that overall for most players there was little to no energy used while playing the game. This suggests that most of the changes in data were cognitive versus physical, which would explain the results in the EDA data. The formula can be found in the appendices.

The first graph, Easy Vs. Hard Energy Use, shows that there is very little energy used overall throughout the two play sessions. In fact, the red line shows that on average energy use was reduced between the easy play session and the hard play session. I can only assume that this means the subjects got used to the controls and required less movements to manipulate the avatar on the game screen.

The second graph, energy use slopes, shows there is very little change in energy over time. In fact, your average slope ranged between -.001 and .001 values. With little change in energy between the different sessions (play and rest) this helps show that energy was hardly used throughout the course of the sessions. This further suggests that the majority in change in physiological response was mostly cognitive rather than physical.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| P-Values | Rest1 | Easy | Rest2 | Hard |
| Rest1 |  |  |  |  |
| Easy | 0.116526 |  |  |  |
| Rest2 | 0.055735 | 0.142394 |  |  |
| Hard | 0.014964 | 0.229605 | 0.093941 |  |

The P-value comparison chart shows that overall there is a good chance that this data would be repeated in future studies. The Rest2 versus Easy mode and the Hard versus Easy may have slightly different data, but I am fairly confident that the use of energy over several more studies would not change in this kind of study.

As per the prior studies, energy use was looked at based on expertise and enjoyment. The graphs for these are in the appendices but overall neither enjoyment level nor expertise had any bearing in energy use. The average subject used very little energy during game play sessions overall.

**Challenges**

One of the greatest challenges in this study was designing the difficulty metrics for the game. I tried to ensure that the difficult mode was significantly harder than the easy mode to see a great difference. After reading the surveys though, while the players did state they felt more challenged in the hard difficulty, they didn’t feel like the difficulty was too great of a stressor for them.

In addition, changing the scope of the project was a bit of a challenge. At first it was thought that the dynamic changing algorithm could be created during this project. But after seeing how radically different the data was overall, it was altered to data collection just to see if the algorithm could be collected. Now that the data samples have been narrowed down to EDA and potentially heart rate, perhaps an algorithm can be put together.

Furthermore, designing the game itself was a bit of a challenge. The graphics and animation were created by myself and I had to learn modelling and animation over the summer to be able to create the models and animate them for the game.

**Conclusion**

The conclusion of this project is that yes, an algorithm that will dynamically alter the difficulty settings of a game using a person’s physiological responses is possible. According to the data gathered in this project, EDA is the greatest contender to be used in the creation of this algorithm, with HR being a second potential after more samples have been obtained.

While there seems to be some correlation between enjoyment and experience level and the data, there isn’t enough to say that it will greatly alter any potential algorithm that might be created.

**Future Works**

This study is far from over and there is much more that can be done before creating a physiologically based algorithm using a wearable device. This would include-

* Designing the game to have a more challenging difficulty setting and adding a third setting, medium, to run more tests with. This will allow for another data set under different circumstances to see if it changes the data earned.
* Running more tests to narrow down the data values needed with EDA to create the algorithm and, potentially, see if there is an identifiable use for HR in the creation of said algorithm.
* Creating the potential algorithm and testing it to see if it succeeds as intended.

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**Appendices**

**Appendix A: Survey**

Name:

Gender:

Male

Female

N/A

Other

Age:

18 - 25

25 - 35

35 - 45

45 & Older

N/A

Preferred Genre:

Action

Adventure

FPS

RPG

Puzzle

Other

Strategy

Sports

Fantasy

How often do you play video games?

Often

Whenever I Can

Not Often

Not At All

How times did you play in the last 7 days?

1-3

4-6

Every Day

Not At All

How did you feel about Session 1 and its difficulty?

How did you feel about Session 2 and its difficulty?

How did you feel about Session 3 and its difficulty?

How much did you enjoy:

Session 1:

Not At All

Enjoyed A Little

Enjoyed A Lot

Enjoyed

Session 2:

Not At All

Enjoyed A Little

Enjoyed A Lot

Enjoyed

Session 3:

Not At All

Enjoyed A Little

Enjoyed A Lot

Enjoyed

What trial did you enjoy the most? Why?

How was your stress level during session 1?

High

Not Noticeable

Low

Moderate

How did the stress affect your enjoyment of the game?

How was your stress level during session 2?

High

Not Noticeable

Low

Moderate

How did the stress affect your enjoyment of the game?

Comments/Suggestions overall?

**Appendix B: Game Design**

**Goblin Assault:**

