# User Stress Modeling through Galvanic Skin Response


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***Abstract*—The advent of digital era has brought great advances in the quality and accuracy of Bio medical sensors and other physiological devices. Similarly, digital games have also witnessed massive improvements in their scale, mechanics, graphics, and reach, which has led to a fierce debate on their human and societal impact, especially in terms of identifying the correlation, if any, between the gamer and violent transgressors. From a pure technological perspective, it is thus imperative that advances in sensory technologies and machine learning are then utilized to build a model for identifying the stress experienced by the gamer, during any game session. Galvanic Skin Response(GSR), can act as a good indicator of this experienced stress, by measuring the change in skin conductance and skin resistance of the user. However, GSR data, in its raw form, is very much user dependent, often biased, and is difficult to analyze, as it gives a long term measure of the user behavior changes, based on skin precipitation. In this research work, we have collected user's perceived notion of stress along with sensory data from a GSR device, which was then analyzed using various machine learning models, before creating a majority voting based ensemble model for stress modeling. Showing comparable values of accuracy(63.39%) and precision(51.22%), our model was able to substantially increase the class recall rate for identifying stress (27.08%), from the individual approaches (0-8.95%).**



***Index Terms*—Digital Games, Machine Learning, Stress Modeling, Galvanic Skin Response**


## I. Introduction

In the last quarter of a century, technological advancements have hastened human development manifold. While, globalization engineered through the fourth industrial revolution has created deeper connections between the human beings and the machines, it has also raised new moral dilemmas. One of these dilemmas is the impact of digital games (a.k.a video games or computer games), especially the ones focusing on armed conflict resolution on the psychological well-being of individuals. A plethora of research indicates mostly positive and some negative cognitive implications [1]–[3]. However, this representation is completely reversed in the media and general public. The negative cognitive effects of video games indicate an increase in anger and hostility in short term, and in long term leads to aggressive cognition, positive reactivity to violence, tendency to perceive others as hostile, reduced empathy, decreased attention spans, and low cognitive control [4]. The positive effects of video games include quick and accurate attention allocation and spatial visual processing, enhanced mental rotation abilities, improved problem solving, and greater creativity [5]. In human beings, "Stress" is a cognitive phenomena, which according to the cognitive activation theory of stress (CATS) is based upon the stimuli and its perception by the human brain, resulting in a cognitive or physical response. This definition entails four key areas for measuring stress; 1) identifying the stimuli, which however, is the hardest since the same perception of stress is subjective and depends on the experiences of the subject, 2) Identifying this perceived notion of the brain in case the stimuli exists, 3) measuring the arousal state of the human body, where most research is currently focused and 4) explicit feedback from affected subjects [6]. Many physiological sensors can be used to measure the implicit, cognitive and emotional responses of the subject, which when correlated with their explicit responses can help determine their arousal and valence states. Advancements in algorithms and medical devices have led to the development of very compact and useful tools which Leverage the natural responses of the human body in response to external or internal stimuli. These devices can gather not only physiological and emotional human metrics but also cognitional. This has resulted in many state of the art solutions such as emotion recognition through web cams or eye-trackers for measuring explicit human responses and cognition identification through electroencephalography (EEG) and Galvanic Skin Response (GSR) measurement tools. These measurement tools use physiological signals, such as change caused by facial muscles, movement of eyes, electrical activity of the neurons


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in the brain, or the change in skin conductance due to sweating. The signals are then correlated to the external stimuli, in order to measure the emotional or cognitive response [7]–[10]. In this presented research work, we have used a commercially available GSR device along with explicit user feedback to identify and use the relationship between perceived stress and the body's experience, as represented through changes in the GSR. This study only performs an objective analysis of data and does not delve into psycho analysis. The results of this study are empirical in nature and should not be used to form an opinion about the cognitive effects produced by the first person shooter games in general and Counter Strike source by Valve Inc. in particular.

The results, however, indicate a good accuracy of the GSR devices, when determining stress experienced by the players. It can therefore be used for improving the user experience (UX) of the digital game by increasing or decreasing stress stimuli [11], [12]. Our methodology is based on three supervised learning algorithms (J48, Naive Bayes, Random Forest, and Decision Trees), along with majority voting to analyze the implicit Skin Conductance Level (SCL) and Skin Resistance Level (SRL) data, along with explicit user feedback. This methodology was applied to determine stress levels experienced by hobbyist gamers, while they played an offline version of Counter Strike source battling against automated players (a.k.a bots).

## II. Related Work

Das et al. [13] analyzed the user's nervous system response to a sudden change in the environmental and physiological system. The authors experiment by presenting the participating users with a short video clip and evaluate their reaction to the scene presented in the video. The collected data is preprocessed to reduce frequency distribution to 5Hz via Welch's Power Spectral Density. The authors considered Welch's power spectral density feature from frequency domain, and six features including mean, median, mode, variance, kurtosis, and skewness from time domain to evaluate the signals. Various Machine Learning (ML) classifiers including Support Vector Machine (SVM), Naïve Bayes, and K Nearest Neighbor (KNN) were used to classify user emotions to happy, sad, natural, or Exited. The SVM classifier classified happy-sad emotion with an accuracy of 78.08% and 100% compared to KNN 78.09%, 97.75% respectively. However, the experiment was performed on only four participants, therefore, the result achieved may differ by toughly analyzing a large set of user's data. A similar study of emotion identification from GSR signal was conducted by Liu et al. [14] The authors d-noised the GSR signals using db5 wavelet function and classified it to happy, sad, angry, fear, and calm classes using SVM with Radial Bias Function (RBF) kernel. The model achieved a training accuracy of 73.57%, and 83.57% by considering 15 features and 30 features respectively. However, the accuracy drastically dropped to 66.67% and 46.67% on test data. [15] conducted a similar study of GSR signal-based emotion recognition by presenting various pictures to the 13 participating users. The gathered signal density was reduced to 5Hz and an imbalanced fuzzy SVM and KNN classifier were used to identify methe emotional class of the user. The emotions considered in the study were limited to surprise, disgust, joy, fear, sadness, anger, and unknown classes. By considering seven features from the frequency domain and 21 features from the time-domain the single-user-model for valence with both SVM and KNN achieved an accuracy of 86.7% and arousal of 80.6%. Goshvarpour et al. [16] presented a short music clip to evaluated its effect on user emotions. A GSR signal was collected while the user was listening to music, and a probabilistic neural network modal was trained to identify user emotion from the GSR signals. The trained model was able to detect a single user as well as multi-user emotions. The single-user model achieved a mean accuracy of 92.52%, 92.58% for Daubechies, and 89.8% for Dicrete Cosine Transform (DCT). Similarly, [17] performed analysis on the GSR signal data to identify user response to a music clips either positive or negatives. The authors categorized data based on type of music clip, aggregate data based on average signal per second, and performed data normalization. Machine learning algorithms SVM with linear kernel, polynomial, radial bias function and with sigmoid function were evaluated and achieved an accuracy of 75.65% with RBF. [18] has performed user emotional evaluation to music videos. The authors have used NB, SVM with polynomial, and J48 algorithms to classify user emotion into surprise, disgust, joy, fear, sadness, anger, and unknown classes. The J48 algorithm surpassed others and classify user emotions with an accuracy of 63%. However, the combination of GSR with EEG significantly improved user emotion detection.

## III. Methodology

The overall methodology for the presented work, as shown in Fig. 1, can be categorized into an offline process for training the model and an online process for detecting stress in the user, while they are interacting with a digital game. The GSR unit is attached on the non-dormant hand, so it does not hinder any movement during the gameplay. Signals produced by this unit provide the implict feedback regarding the stress experienced by the player's body. Additionally explicit feedback in the form of user feedback, based on the think-aloud methodology is also used to acquire the notion of perceived stress by the user. The initial value of explicit feedback is "relaxation", which can be changed by the player announcing when they feel "stress" during the gameplay. This value can then be changed back to "relaxation" by the player announcing so or by the completion of one round. The explicit responses of the player, as shown in Figure 2, show a large bias towards relaxation, since the players spend a lot of time with no activity and therefore do not register any stress.

In order to counter this biasedness, we collected the implicit data, in the form of SCL and SRL, readings from the GSR device. These values were then synchronized, by extending the previous perceived explicit feeling of stress. The data pre-processing module, handles this synchronization, which

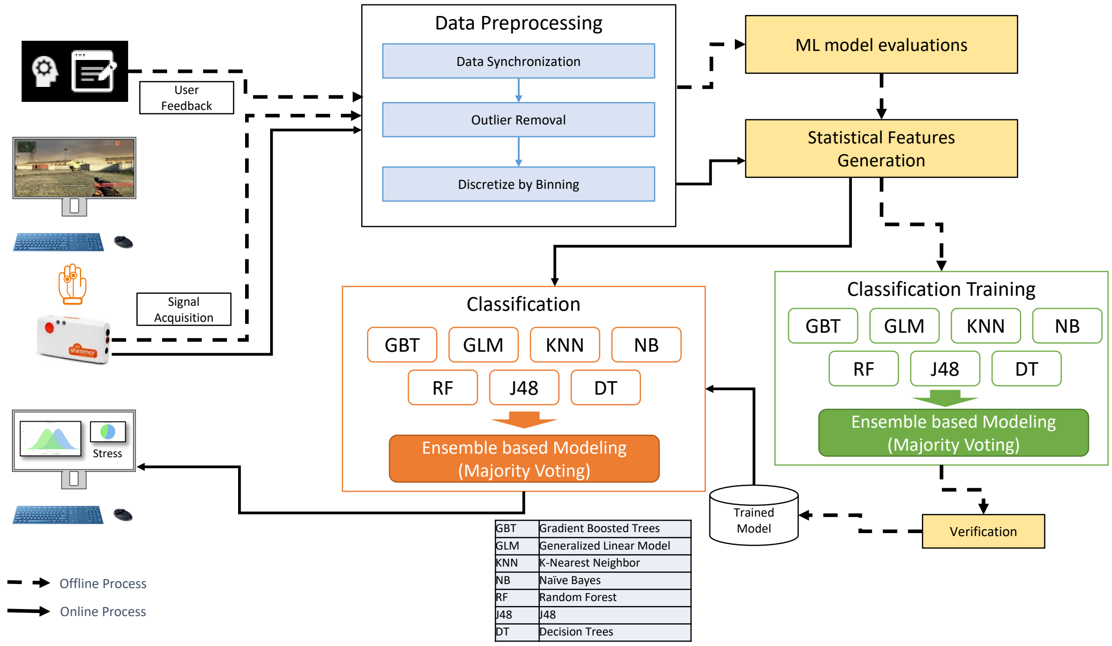



Fig. 1. Training and usage workflow of stress recognition using GSR and explicit user feedback

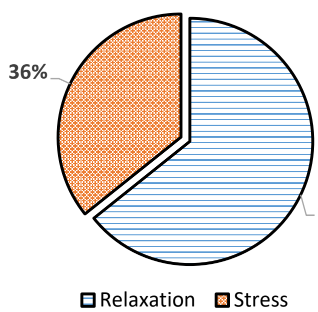



Fig. 2. Data Split according to explicit user responses

is followed by outlier removal, which removes initial and impossible entries from the data. These outlier include initial and final values, which can give sensor readings under 0 or above 100k, especially for SCL, while the sensor is setting up. Afterwards, we discretized the data by creating bins, which enables the data to become more generalized by using average values within bins to correspond to a general trend over some period.

We then applied the Auto Model feature of the Rapid Miner tool to analyze the performance of various machine learning models on this data. The results of these models provided the building blocks for generating new attributes in the data and building an ensemble model with majority voting technique, based on 7 ML algorithms. The data produced, at the end of data pre-processing is still very dense, so we then generate two new statistical features, by using the log of SCL and SRL values, corresponding to each instance of the data. In this way, while we gain new features in the dataset, the general trend of the data is also included. As a result, our next operations for classification can gain additional features with lower value range, which can generalize our results. The classification process uses various machine learning models to classify each instance of the training dataset. This is followed by ensemble based modeling approach which uses majority voting for identifying the correct classification of each instance. This model is then verified and stored for the online process.

The online process collects only the GSR signals from the user. It skips the synchronization process, and moves to outlier removal, followed by discretization of data by binning. Statistical features in the form of log values for the SCL and SRL signals are added in this data. Then using the trained model and the ensemble modeling based on the 7 selected ML algorithms (Gradient Boosted Trees, Generalized Linear Model, K-Nearest Neighbor, Naive Bayes, Random Forest, J48, Decision Trees) each instance is classified as corresponding to "stress" or "relaxation". This is used to provide the UX expert or game developer with a temporal graph of identified stress.

## IV. Experimental Setup

The experimental setup for collecting stress data is based on player's interaction with bots, inside a popular first person shooter game, Counter Strike Source [19]. This game was first released in November 2004 and has been developed and published by Valve Corporation. The game, features two opposing teams and several game modes, towards achieving a traditionally positive (such as rescue hostages or prevent bombing of important locations) or negative(planting and exploding a bomb in a pre-marked location or preventing hostage rescue) goals. The game has several maps, where the objectives are preset, with a built-in artificial intelligence (AI),

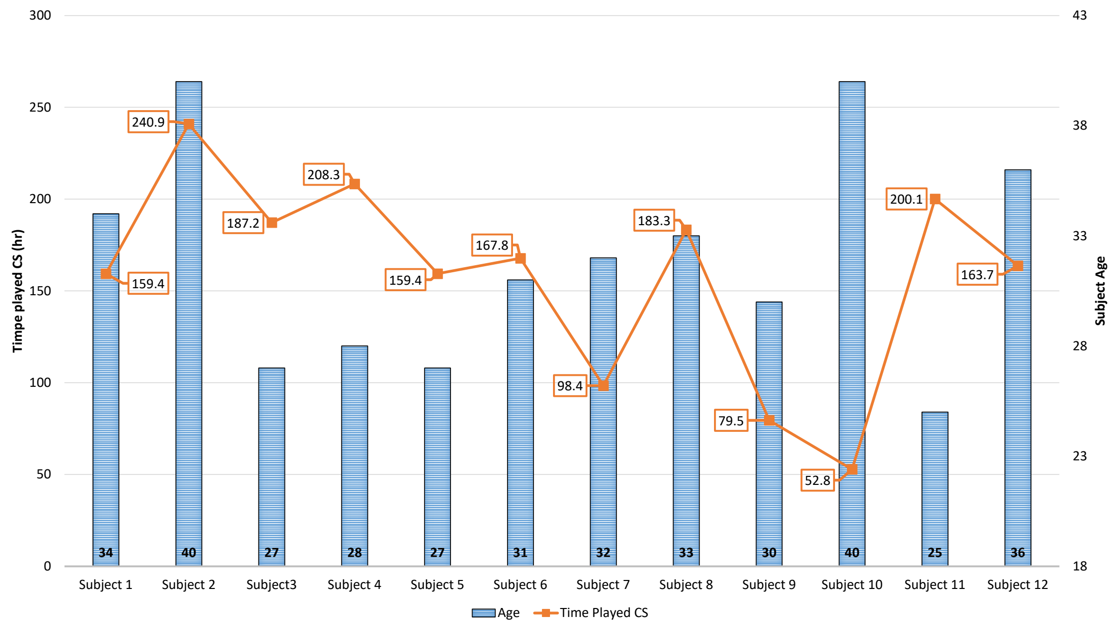



Fig. 3. Player's age and previous familiarity with the game

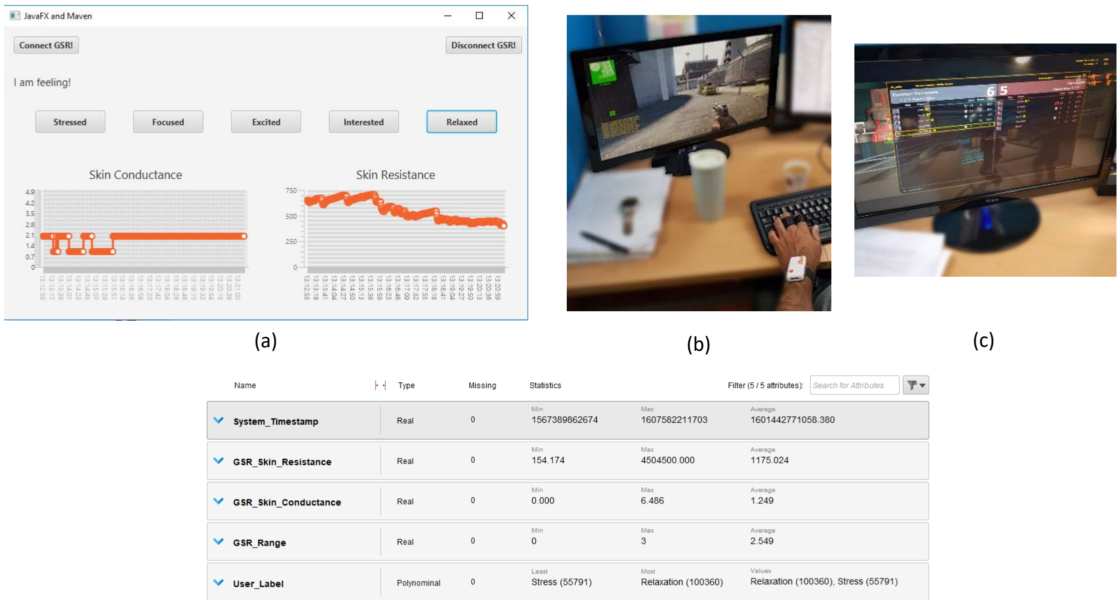
for controlling the various actions performed by the bots. The bots have four levels of difficulties, ranging from very easy, normal, hard, and expert bots. For our experiments we have used the Expert bots, which provide the most challenge by responding quickly to the player challenges and not giving any leeway to the player. In this way, the player would experience stress most often, providing us with useful data. The experiment was run for 15 rounds, with each round spanning a maximum time of 2.5 minutes.

The dataset was collected from 12 players, who all had some familiarity with the game, registering between 50-250 hours of previous gameplay experience. The median age for the players is 31.5. An overview of the player characteristics related to this study can be seen in Figure 3.

This data collection process utilized a custom built application shown in Figure 4 (a). This application can connect, via bluetooth, with the Shimmer3 GSR+ [20], placed on the player's off-hand with connections to the index and second finger, as shown in Figure 4 (b), which produces a large amount of data, however for our experiments, we collected only 4 variable, including "System_Timestamp", calibrated "GSR_Skin_Resistance", calibrated "GSR_Skin_Conductance", "GSR_Range" (which provides numeric value defining the desired gsr range with 0 corresponding to 10kOhm - 56kOhm, 1 corresponding to 56kOhm - 220kOhm, 2 to 220kOhm - 680kOhm, 3 to the range 680kOhm - 4.7MOhm and 4 to Auto Range). An additionaly 5th variable was collected from user feedback which is initialized as relaxation and then changed when the observer clicks on the stress labeled button on the user interface. When, again, the observer clicks on the relaxation button, the user feedback for all corresponding values is set as relaxation. These events are generated when the player calls out his perceived cognition state as being in stress or relaxed. A screen shot of the in-game score sheet between the two teams is shown in Figure 4 (c), with a statistical view of the 156,151 recorded GSR instances shown in Figure 4 (d).

## V. Results

The objective of this research work was to obtain high performance in determining stress as a function of experienced and perceived user responses. However, as can be seen in Table I and compared to the data split according to Figure 2, these models perform no better than a random process, which identifies each reading as relaxation. Five models, including NB, Fast Linear Margin (FLM), Deep Learning (DL), Decision Trees (DT), and Random Forest (RF), show 0 precision and recall for the stress class and 100% recall for relaxation class. For other models, such as Gerneralized Linear Model (GLM), Logistic Regression (LR), Gradient Boosted Trees (GBT), and Support Vector Machine (SVM) the recall and precision rates are only relatively better. However, all these models show good performance when identifying the precision and recall of relaxation. In order to balance these results, we created the majority voting based ensemble model presented above, which shows slightly better accuracy at 63.39%, when compared to the other models. The precision rates for stress are however lower at 51.22%, from SMV at 52.51% and the highest value of 52.76% for LR. However, the recall rate for stress show a substantial increase to 27.08% from the other models showing between 2.15% for GBT and 8.95% for SVM. However, this increase comes at the cost of reduced recall rates for identifying the negative stress (relaxation) class, at 84.8%; a drop of more than 10% from its nearest neighbour, SVM.



(d)

Fig. 4. Data acquisition process with (a) custom application to collect GSR signals and record user feedback, (b) gameplay setup with GSR device, (c) a view of in-game score sheet, (d) statistical view of recorded data

TABLE I
PERFORMANCE COMPARISON OF VARIOUS ML ALGORITHMS AND MAJORITY VOTING BASED ENSEMBLE MODEL

| Model | Accuracy | Precision (Stress) | Precision (Relaxation) | Recall (Stress) | Recall (Relaxation) |
|---|---|---|---|---|---|
| Naïve Bayes (NB) | 63 | 0 | 62.99 | 0 | 100 |
| Generalized Linear Model (GLM) | 63.1 | 50.76 | 63.4 | 3.75 | 97.86 |
| Logistic Regression (LR) | 63.1 | **52.76** | 63.25 | 2.24 | 98.82 |
| Fast Large Margin (FLM) | 63 | 0 | 62.99 | 0 | 100 |
| Deep Learning (DL) | 63 | 0 | 62.99 | 0 | 100 |
| Decision Tree (DT) | 63 | 0 | 62.99 | 0 | 100 |
| Random Forest (RF) | 63 | 0 | 62.99 | 0 | 100 |
| Gradient Boosted Trees (GBT) | 62.9 | 48.8 | 63.15 | 2.15 | 98.67 |
| Support Vector Machine (SVM) | 63.3 | 52.21 | 64 | 8.95 | 95.18 |
| Majority Voting Ensemble Model | **63.39** | 51.22 | **66.36** | **27.08** | 84.8 |

## VI. CONCLUSION

The main objective of this study is to assess the impact of game playing and in turn to detect the elevated levels of stress through GSR signals. In this regard, Shimmer device is used to measure skin conductivity for measuring the stress level of a user. Moreover, this study also contributes to the relevant dataset collection based on the game playing of a number of users. A set of machine learning algorithms are used to construct an ensemble model for final decision modeling i.e. user status = stress, relaxation. It is empirically demonstrated that the result of the ensemble technique based on majority voting is consistently better than that of the individual models. Results of this study are consistent with the reported results on ensemble modeling. This study can be extended in a number of directions such as more relevant data can be gathered to comprehensively assess stress detection in game playing, deep learning models can also be included in the experimentation provided the dataset is comprehensive enough, and enhance data modalities to include other physiological sensors such as eye-tracking and EEG, etc.

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## References

[1] Muhannad Quwaider, Abdullah Alabed, and Rehab Duwairi. The impact of video games on the players behaviors: A survey. *Procedia Computer Science*, 151(2018):575–582, 2019.

[2] Simone Kühn, Dimitrij Tycho Kugler, Katharina Schmalen, Markus Weichenberger, Charlotte Witt, and Jürgen Gallinat. Does playing violent video games cause aggression? A longitudinal intervention study. *Molecular Psychiatry*, 24(8):1220–1234, 2019.

[3] Hamed Aliyari, Hedayat Sahraei, Mohammad Reza Daliri, Behrouz Minaei-Bidgoli, Masoomeh Kazemi, Hassan Agaei, Mohammad Sahraei, Seyed Mohammad Ali Seyed Hosseini, Mohammad Mehdi Hadipour, Mohammad Mohammadi, and Zahra Dehghanimohammadabadi. Research Paper: The beneficial or harmful effects of computer game stress on cognitive functions of players. *Basic and Clinical Neuroscience*, 9(3):177–186, 2018.

[4] Sara Prot, Katelyn A. McDonald, Craig A. Anderson, and Douglas A. Gentile. Video Games:. Good, Bad, or Other? *Pediatric Clinics of North America*, 59(3):647–658, 2012.

[5] Isabela Granic, Adam Lobel, and Rutger C.M.E. Engels. The benefits of playing video games. *American Psychologist*, 69(1):66–78, 2014.

[6] Holger Ursin and Hege R. Eriksen. The cognitive activation theory of stress. *Psychoneuroendocrinology*, 29(5):567–592, 2004.

[7] Danni Peng-Li, Raymond C. K. Chan, Derek V. Byrne, and Qian Janice Wang. The Effects of Ethnically Congruent Music on Eye Movements and Food Choice—A Cross-Cultural Comparison between Danish and Chinese Consumers. *Foods*, 9(8):1109, 2020.

[8] R. Laureanti, M. Bilucaglia, M. Zito, R. Circi, A. Fici, F. Rivetti, R. Valesi, C. Oldrini, L. T. Mainardi, and V. Russo. Emotion assessment using Machine Learning and low-cost wearable devices. *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 576–579, 2020.

[9] John Gero and Julie Milovanovic. A framework for studying design thinking through measuring designers' minds, bodies and brains. *Design Science*, 6:1–44, 2020.

[10] Gamze Ural, Firat Kaçar, and Sinan Canan. Wavelet phase coherence estimation of EEG signals for neuromarketing studies. *NeuroQuantology*, 17(2):112–120, 2019.

[11] Johannes Steinrücke, Bernard P. Veldkamp, and Ton de Jong. Determining the effect of stress on analytical skills performance in digital decision games towards an unobtrusive measure of experienced stress in gameplay scenarios. *Computers in Human Behavior*, 99(November 2018):144–155, 2019.

[12] Anne M. Porter and Paula Goolkasian. Video games and stress: How stress appraisals and game content affect cardiovascular and emotion outcomes. *Frontiers in Psychology*, 10(APR):1–13, 2019.

[13] Priyanka Das, Anwesha Khasnobish, and D. N. Tibarewala. Emotion recognition employing ECG and GSR signals as markers of ANS. *Conference on Advances in Signal Processing, CASP 2016*, pages 37–42, 2016.

[14] Mingyang Liu, Di Fan, Xiaohan Zhang, and Xiaopeng Gong. Human Emotion Recognition Based on Galvanic Skin Response Signal Feature Selection and SVM. *Proceedings - 2016 International Conference on Smart City and Systems Engineering, ICSCSE 2016*, pages 157–160, 2017.

[15] Goran Udovičić, Jurica Derek, Mladen Russo, and Marjan Sikora. Wearable emotion recognition system based on gsr and ppg signals. In *Proceedings of the 2nd International Workshop on Multimedia for Personal Health and Health Care*, pages 53–59, 2017.

[16] Atefeh Goshvarpour, Ataollah Abbasi, and Ateke Goshvarpour. An accurate emotion recognition system using ECG and GSR signals and matching pursuit method. *Biomedical Journal*, 40(6):355–368, 2017.

[17] Djoko Budiyanto Setyohadi, Sri Kusrohmaniah, Sebastian Bagya Gunawan, Pranowo, and Anton Satria Prabuwono. Galvanic skin response data classification for emotion detection. *International Journal of Electrical and Computer Engineering*, 8(5):4004–4014, 2018.

[18] Daniela Girardi, Filippo Lanubile, and Nicole Novielli. Emotion detection using noninvasive low cost sensors. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*, pages 125–130. IEEE, 2017.

[19] Valve. Counter-strike: Source on steam, 2020.

[20] Shimmer. Shimmer3 gsr+ unit, 2020.