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Investigating the Influence of Graphical Backgrounds in Violent Video Games on Stress Levels of Competitive Players Using Machine Learning

Abstract: - Violent video games (VVGs) are widely recognized for their potential to increase stress and aggression, particularly among competitive players. This study investigates the effects of different graphical backgrounds in VVGs on the stress levels of competitive players, a topic that has not been thoroughly explored in prior research. Machine learning models are employed to analyze how various background settings influence stress responses in players. Using a dataset of competitive gamers, advanced techniques such as Gradient Boosting for feature selection, Voting and Stacking Classifiers for ensemble modeling, and a Multilayer Perceptron for capturing complex patterns are applied. Significant correlations between background graphics and stress levels are revealed, providing insights into how game design elements may impact player well-being. The results offer a new perspective on the psychological effects of VVGs and propose considerations for game developers in creating less stressful gaming environments for competitive players.

Keywords: Machine Learning, Graphical Backgrounds, Ensemble Modeling, Feature Selection, Player Well-being.

I. INTRODUCTION

According to the research firm DFC Intelligence [1], a company specializing in market research and consulting for the video game sector, approximately 3.1 billion people play violent video games (VVG) yearly. Of those, almost 1.87 billion people play VVG competitively. Many of these players who frequently play VVG are more likely to have higher stress levels than players who do not play as frequently [2]. VVG players can experience higher stress levels due to the immense need to survive in the game [2]. The players are pushed to survive for extended periods in the game to maintain their ranking and level. More competitive players would experience higher stress levels because they have an increased urge to maintain or improve their ranking in the game than non-competitive players. Signs of stress from video gaming in competitive players include increased heart rate, exhaustion, trouble paying attention, withdrawal from people, and increased obsession over winning [3].

Increased stress in competitive VVG players can result in decreased cardiac coherence levels, a difference between heart rates and breath, which can cause immunodeficiency. This causes too much stress in VVG players and can be harmful, increasing stress hormones produced in the players [4]. Sierva [5] from the Human Nutrition Research Center discussed the adverse effects of playing VVG. They discovered that competitive video gaming has negative impact on the mental and physical health of the players. People who play more violent video games tend to be more impatient and aggressive, which increases the stress levels of the players.

Many studies have been conducted to find methods to reduce stress in VVG players, but almost all looked at different exercises or yoga. However, only a few studies have researched the effects of background graphics on stress. Furthermore, only one study, conducted by Brockmyer [6] in the Journal of Experimental Social Psychology,

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looked at the effects of backgrounds of a heavy-action video game and its impact on the stress levels of the players. They demonstrated how the background graphics of an action game resulted in different stress levels. The differing graphics of the action video game caused varying levels of stress in players. Nevertheless, there has been no research on how the differing backgrounds of VVG affect the stress levels of the players.

Machine learning can be instrumental in understanding the correlation between background graphics in violent video games and stress levels by analyzing large datasets of player responses under varying conditions. Classification techniques can help differentiate between stress levels induced by different graphics by identifying patterns and correlations that might not be immediately apparent. By employing diverse classifiers and combining their strengths, models can achieve more accurate predictions of stress levels, ultimately improving the quality and reliability of the insights gained from such analyses.

II. Methods and Methodology

The purpose of the research was to examine the effects of different graphical backgrounds of VVG on the stress levels of competitive players. Initially, a causal-comparative research method studying competitive gamers was conducted. The competitive nature of the players increases peer pressure along with their competitive spirit, which highly increases their stress levels while playing [28]. Competitive players were chosen over the general population of VVG players because research shows that competitive gaming increases mental pressure on the players. In addition, the Journal of Mental Health reports playing video games with other competitive players increases their stress levels due to the competitive nature of the players. Winning against skilled players also builds the players' self-esteem highly. Being at the top of the league makes the player well-acknowledged and popular amongst competitive gamers. Based on the factors mentioned above, competitive gamers provide a likely stressed-out population.

Data Collection

The study compared the stress levels of competitive gamers who played VVG often. Forty-one players chose to participate in the study. The participants were asked to sign consent and disclosure agreements. The principal contacted the parents of the minors to confirm further the parent's permission before participating due to the exposure to violence in the study. The consent agreements were only given to participants with prior experience playing VVG. The results of the different backgrounds of the VVG were measured by distributing the surveys to all the participants. The survey was used to measure the effects of backgrounds because it would accurately show how the participants felt as opposed to outside observation, which could misinterpret the data collected. A combination of tested surveys was used to measure the effects of the different backgrounds accurately.

Firstly, the participants were asked their age and gender to find any correlations the data might indicate. Then the participants were given a preliminary survey to assess their initial stress levels. The survey was adapted from the Perceived Stress Survey [10] developed by Professor Sheldon Cohen, from the College of Psychology of Carnegie Mellon University. This very widely used survey to measure stress for physiological research consisted of answer options on a five-point scale ranging from “very often” to “fairly often” to “sometimes” to “almost never” to “never.” The participants were asked to answer ten questions by evaluating their stress levels. Higher scores in the survey correlated to higher levels of stress.

Secondly, the participants were given a survey to assess their competitiveness in VVG. The survey questions were adapted from the American Competitiveness Survey developed by Walsh [29] from the College of Psychology of Georgia Tech University. Like the stress survey, this survey questions consisted of answer options on a five-point scale, also ranging from “very often” to “fairly often” to “sometimes” to “almost never” to “never.” The participants were asked to answer ten questions evaluating their competitiveness levels. Higher scores corresponded to the more competitive nature of the participants. Only the questions that pertain to games, specifically video games, were chosen. Some of the questions did not pertain to VVG, which could make the data invalid. To restrain any bias or untrustworthy information, the questionnaire was altered to fit the study better.

After taking the two preliminary surveys, the participants were asked to measure their heart rate from a smartwatch. The participants were provided with a smartwatch if they did not have one. A study conducted by Harvard University [30] concluded that smartwatches such as Samsung, Apple, and Fitbit have an accuracy of over 94 percent when measuring heart rate. The smartwatch's heart rate measurement accuracy, along with its availability to the participants, made it a better option compared to the heart rate monitor. The heart rate was used to see how stressed they were before taking the survey. This added to the credibility of stress since it provided more information on stress levels and avoided inaccurate information.

Immediately after taking the heart rate, the participants were asked to watch a video of the first type of background. The participants were asked to watch a video rather than play the game themselves because of the unpopularity of the game. Research done by Weightman [31], the senior lecturer in Games and Visual Effects at Staffordshire University, concluded that watching a video of someone playing a VVG has the same effects on the brain system as playing a VVG yourself. Due to the intense nature of gaming, experienced players who watch videos are more likely to have the same experience as the players because their brain thinks that they are playing the game themselves. The player and the viewers could experience the same emotions and, ultimately, the same stress factors.

The backgrounds that the participants watched were from the violent video game Player's Unknown Battlegrounds (PUBG). The ESRB [7] has rated PUBG for audiences 13 or older. This game was chosen as part of the study because of its unpopularity in the US. It is a VVG developed in South Korea by Krafton, and many American VVG players are unaware of the game in detail. Due to its unpopularity, most participants had no experience playing the game, and it avoided any possible bias to a specific background. It also allowed all the players to have the same experience watching the video because it was the first time all the participants had watched it.

There were three different videos with three different backgrounds that the participants were asked to watch. All the videos were chosen from experienced gamers' videos, which showed the best views of the backgrounds and the best gameplays. The videos were posted by T1 Academy's Lee Sang-hyeok [32], who has participated in the League of Legends World Championships semi-finals three times. These were chosen because of their experience in playing VVG, and since all the videos were from the same people, all the videos had similar playing styles. They are also very well known in the gaming industry, and they have won many gaming tournaments in the past.

In the first video, the backgrounds were more modern and not very crowded. The backgrounds were somewhat colorful, and there were some places for the enemies to hide. In the second video, the backgrounds were desert-like. It had dull colors with almost no space for the opponent players to hide. The backgrounds were not crowded and consisted of little background graphical props. In the last video, the backgrounds had a lot of greenery. It had a lot of bushes and tons of places for the enemies to hide. It was the most colorful background with the most hiding props.

The participants were asked to take their heart rate before and after watching each video to ensure any changes in the heart rate from the previous videos were accounted for. The participants filled out another survey after they watched the videos. The questions were adapted from Witmer's [21] study on the effects of backgrounds on arcade games. The survey consisted of questions about how stressed or anxious they felt and their thoughts on which background they liked the most. The questions consisted of answer options on a five-point scale, also ranging from "very often" to "fairly often" to "sometimes" to "almost- never" to "never." There were a few questions about the backgrounds and the gameplay. If the participants answered the background questions correctly, five points were added to the total stress score compared to 0 if they answered it incorrectly. According to Witmer [21], getting background questions correctly correlated to higher stress scores because it indicates that the participants were more focused on the background than the gameplay. This would increase the stress levels of the players because the participants will be more stressed due to their inability to locate the enemies. Similarly, five points were added if they answered the gameplay questions incorrectly, compared to 0 points if they answered correctly. Getting gameplay questions correctly correlated to lower stress scores because it indicates that the participants were more focused on the gameplay than the background and were able to locate the enemies much more quickly. It showed that the background had little impact on the players. However, if more background-related questions were correct, it corresponded to less concentration on the gameplay and higher stress levels. The combination of these three surveys provided the most detailed and practical data set.

Lastly, for the analysis of the collected data, preliminary stress scores and heart rates were compared to the stress scores and the heart rates after watching the videos. The trends related to competitiveness and stress levels were also analyzed to determine if the graphical backgrounds had an impact on the stress levels of the competitive players. These factors are further analyzed to determine if they are statistically significant.

A. Data Preprocessing

The data collected was converted to a csv file and the essential preprocessing tasks were conducted. The first step is handling missing values using the SimpleImputer, which fills any missing data using the most frequent value in each column. Next, categorical variables like 'Gender' are encoded using LabelEncoder to convert them into numerical values, making them suitable for machine learning models. The target variable 'Y' is similarly encoded to prepare it for classification tasks. After encoding, the dataset is split into features (X) and target (y), and all features are numeric to avoid errors during model training.

To address class imbalance in the dataset, which could lead to biased predictions, the SMOTEENN technique is applied. SMOTE (Synthetic Minority Over-sampling Technique) combined with ENN (Edited Nearest Neighbors) generates synthetic samples to balance the class distribution and removes noisy samples, enhancing model robustness. The code also employs polynomial feature generation to capture potential interactions between features, thereby increasing the complexity and richness of the input space. After generating these features, they are standardized using StandardScaler ensure that all features contribute equally to the model training process. Finally, the dataset is split into training and testing sets, ensuring the model can be evaluated on unseen data to estimate its generalization performance.

B. Model

i. *Gradient Boosting Classifier for Feature Selection*: The Gradient Boosting Classifier is employed for feature selection by using the SelectFromModel method. This approach leverages the importance of features as determined by the Gradient Boosting model, which is an ensemble of decision trees built sequentially to minimize errors. The model selects the most significant features, reducing the dimensionality of the data while retaining the most informative attributes. This step is crucial as it improves model performance by eliminating irrelevant or redundant features, leading to better generalization on unseen data.

ii. *Voting Classifier with Hyperparameter Tuning:* A Voting Classifier is utilized, combining the strengths of Logistic Regression, Random Forest, and Support Vector Classifier (SVC). Hyperparameter tuning is performed for Random Forest and SVC using GridSearchCV to identify the best parameter combinations, enhancing the model’s performance. The Voting Classifier aggregates predictions from the individual models, either by majority voting (hard voting) or by averaging probabilities (soft voting). This ensemble technique often results in better predictive performance compared to individual models, as it reduces the variance and biases inherent in single classifiers.

iii. *Stacking Classifier*: Stacking is an advanced ensemble technique where multiple base models are trained, and their predictions are used as inputs to a meta-model, which makes the final prediction. In this case, the base models include Logistic Regression, Random Forest, SVC, and K-Nearest Neighbors (KNN), with Logistic Regression serving as the meta-model. The Stacking Classifier aims to leverage the strengths of each base model, improving overall accuracy. By using cross-validation, the Stacking Classifier helps prevent overfitting and enhances the robustness of the final model.

iv. *Multilayer Perceptron (MLP):* The MLP is a type of neural network that consists of multiple layers of neurons, typically used for capturing complex patterns in data. Here, an MLP with two hidden layers, each containing 50 neurons, is trained. The MLP's ability to model non-linear relationships makes it suitable for classification tasks where the decision boundaries are not linearly separable. The MLP is particularly powerful in scenarios with large amounts of data and features, as it can automatically learn intricate feature interactions.

v. *Random Forest with Recursive Feature Elimination (RFE*): Recursive Feature Elimination (RFE) is a feature selection technique that iteratively removes the least important features, using a Random Forest as the estimator to rank features. The RFE method systematically reduces the feature set to a specified number of features, optimizing model performance by focusing on the most relevant attributes. After feature selection, a Random Forest classifier is trained on the reduced feature set, leading to a more interpretable model with potentially higher accuracy due to the exclusion of noisy features.

vi. *Voting Classifier (Repeated):* This iteration of the Voting Classifier is similar to the previous one but emphasizes the use of the soft voting method, where the probability estimates from Logistic Regression, Random Forest, and SVC are averaged to make the final prediction. Soft voting can be particularly beneficial when individual classifiers output probability scores, as it can provide a more nuanced and accurate final prediction compared to hard voting. This method is especially useful when dealing with imbalanced datasets or when classifiers exhibit complementary strengths.

In the classification task, multiple models were strategically employed through ensemble techniques like Voting and Stacking, alongside individual models like the Multilayer Perceptron (MLP) and Random Forest with Recursive Feature Elimination (RFE). Ensemble methods, such as the Voting and Stacking Classifiers, combine the predictions of various models—Logistic Regression, Random Forest, Support Vector Classifier (SVC), and K-Nearest Neighbors (KNN)—to create a more robust and accurate final model. This approach leverages the strengths of different algorithms, each of which might excel in capturing different patterns or relationships within the data. By aggregating the outputs of these diverse models, ensemble methods reduce the risk of overfitting and increase generalization to unseen data. Each model captures different patterns and nuances within the data, which might not be fully recognized by a single classifier. By combining these models, such as through ensemble methods like Voting or Stacking, the overall predictive performance is enhanced. This approach reduces the likelihood of misclassifying instances from any of the three classes, providing more reliable and generalized predictions across all categories. It also helps in dealing with class imbalance or complex decision boundaries that might exist within the dataset, ultimately leading to a more comprehensive understanding and classification of the data.

III. Results and Discussion

To evaluate the effects of backgrounds on stress levels, the average stress of the participants for each background was compared. Many of the previous studies compared the average stress scores for each background to understand the effects of each of the backgrounds on stress. The average stress level of the participants was 19.4 before watching the videos. These scores indicated that the participants had moderate stress levels before participating in the study. The average competitiveness of the participants was 31.7, with all players having a competitive score of over 25. A score over 25 indicates that the participants are either competitive or very competitive. 20 participants scored over 35, suggesting that they were very competitive compared to the 21 competitive participants.

To measure the gamers' stress levels after watching the videos, participants answered a ten-question survey designed by Witmer [21]. The average stress score of the participants after watching the videos and the average heart rate changes were calculated to exclude any invalidity of the data.

The analysis showed that bright crowded backgrounds had the highest rate of change of heart rates of 4.43 compared to 0.13 for the modern and partially crowded background and -2.23 for the bland desert-like scenes. This finding suggests that the bland desert-like backgrounds decreased the stress levels of the players. Similarly, 88.6 percent of the participants answered the gameplay questions correctly for the deserted background, compared to 60 percent for the modern background and 22.8 percent for the bright, crowded background. These results were considered statistically significant ($p=0.004$). A p-value less than or equal to 0.05 was considered statistically significant.

After watching the modern background video, 61% of the very competitive group and 83% of the competitive group experienced decreased stress. These results were considered statistically significant ($p=0.005$). For the deserted background video, 93% of the very competitive group and 84% of the competitive group experienced decreased stress. These results were considered statistically significant ($p=0.0028$). Lastly, after watching the crowded greenery background video, 7% of the participants in the very competitive group and 11% in the competitive group experienced decreased stress. These results were considered statistically significant ($p=-0.0042$).

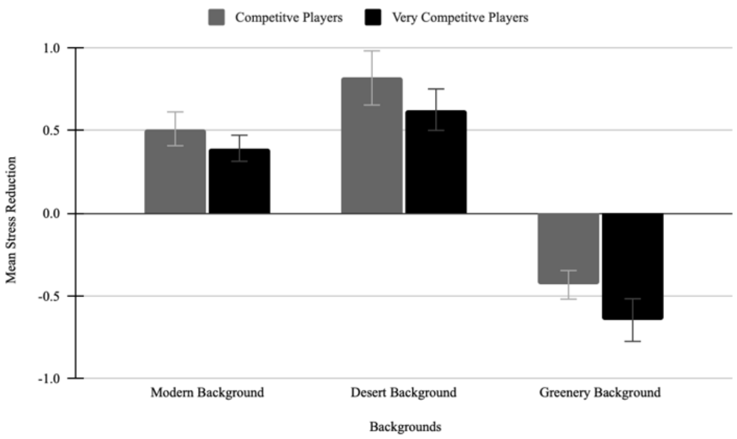

Fig.1 Average decline in stress

Fig.1. shows the average decline in stress experienced after watching each video by each group, competitive or very competitive. Decreased stress is shown as positive values, and increased stress is shown as negative.

All three videos had statistically significant results, and the average stress reduction was highest in the deserted backgrounds for both the competitive and very competitive groups, suggesting that bland, least crowded backgrounds are the most beneficial in lowering the stress levels of the competitive VVG players. Most players answered the gameplay questions correctly for the deserted backgrounds. Similarly, it was the only background where the heart rates of the players decreased, strongly suggesting that the desert backgrounds resulted in the least stress for the competitive VVG players. One possible reason for blander backgrounds to be more effective in reducing stress is that they allow players to see the enemies better. Since they can see the enemies better, they can better attack the enemies since the opponents have no place to hide. However, if the background is more crowded and brighter, the enemies can merge into the background and be harder to locate. As can be seen in Figure 1, the more crowder and brighter the backgrounds were, the higher the stress levels of the players. These findings support that blander backgrounds were more effective in reducing stress, which is also supported by Witmer's [21] study. These observed patterns in stress reduction and background complexity are mirrored in the effectiveness of the classification models used to predict player performance across these backgrounds. For instance, the Stacking Classifier, as shown in Table I, demonstrated robust performance with 96% accuracy, effectively leveraging the combined strengths of multiple base models. While slightly less accurate than the Voting Classifier, it still provided consistent and high-quality predictions, making it a strong choice for complex classification tasks. This model's performance underscores its ability to handle the nuanced effects of different backgrounds on stress levels, further validating the insights gained from the stress analysis.

Table I: Performance metrics of the stacking classifier for different graphical backgrounds in violent video games. Precision, recall, and F1-score values are reported for each background class—Modern, Desert, and Bright—along with the overall accuracy of the classifier.

	Precision	**Recall**	**F1-Score**
Modern	0.96	0.95	0.96
Desert	0.97	0.97	0.96
Bright	0.96	0.95	0.97
Accuracy	**0.96**		

The MLP (Table. II) achieved 91% accuracy, showing its capability to model non-linear relationships. However, it had slightly lower precision, recall, and F1-scores compared to the ensemble methods, indicating some challenges in distinguishing between the classes as effectively.

Table II: Performance metrics of the MLP classifier for different graphical backgrounds in violent video games.

	Precision	**Recall**	**F1-Score**
Modern	0.93	0.93	0.92

Desert	0.92	0.93	0.90
Bright	0.92	0.91	0.91
Accuracy	**0.91**		

The RFE (Table. III) achieved 90% accuracy, focusing on the most relevant features through RFE. While it provided solid predictions, its performance was slightly lower than the MLP and ensemble models, suggesting that it may not capture all nuances in the data as effectively as the more advanced methods.

Table III: Performance metrics of the RFE classifier for different graphical backgrounds in violent video games.

	Precision	**Recall**	**F1-Score**
Modern	0.90	0.90	0.92
Desert	0.92	0.90	0.90
Bright	0.91	0.91	0.91
Accuracy	**0.90**		

The Voting Classifier (Table. IV) outperformed all other models with 97% accuracy, indicating its strength in aggregating predictions from Logistic Regression, Random Forest, and SVC. It achieved high precision, recall, and F1-scores across all three classes, making it the most reliable for accurately classifying player performance across different backgrounds.

Table IV: Performance metrics of the voting classifier for different graphical backgrounds in violent video games.

	Precision	**Recall**	**F1-Score**
Modern	0.97	0.96	0.96
Desert	0.97	0.97	0.96
Bright	0.98	0.98	0.97
Accuracy	**0.97**		

The results of the classification models demonstrate the effectiveness of ensemble methods, such as the Voting and Stacking Classifiers, compared to individual models like the MLP and Random Forest with Recursive Feature Elimination (RFE). The Voting Classifier achieved the highest accuracy at 97%, with consistently high precision, recall, and F1-scores across all three classes—Modern, Desert, and Bright. This indicates that the Voting Classifier was able to accurately predict the correct class for almost all instances, making it the most reliable model among those tested. The Stacking Classifier also performed well, with 96% accuracy, but slightly lower performance metrics compared to the Voting Classifier.

The MLP and Random Forest with RFE models, while still performing admirably, showed lower accuracy rates of 91% and 90%, respectively. These models were slightly less effective in distinguishing between the classes, as evidenced by their lower precision, recall, and F1-scores. This suggests that while these models are competent, they may struggle with the complexities or nuances present in the data that the ensemble methods could capture more effectively. The findings underscore the value of advanced classification methods in refining strategies and optimizing performance evaluations in diverse gaming environments.

IV. CONCLUSION

A. Limitations

There are limitations of this study, which include controlling the variables, age range, and honesty. All the participants had prior experience playing VVG; however, some participants had better skills than others. More skills would result in the players tackling situations better than those less skilled. Similarly, the participants would have different types of smartwatches, which could have affected their heart rates. Some participants used a smartwatch, while others manually checked their pulse due to the unavailability of the technology. However, most participants were given a smartwatch to measure their heart rates to counteract the unavailability. Also, this study mainly consisted of 16-23-year-olds. Due to the unequal age distribution, the data might have different results when conducted with a more age-inclusive sample. Since most players who play VVG are in this age range, resulting in a minimal sample for older ages. Another possible limitation could be the data itself. Furthermore, the low number of data points for each background condition limits the robustness of the analysis, making it difficult to draw strong conclusions from the results. Lastly, the players may not have filled out the surveys honestly. Some participants may not have concentrated on the whole video or filled out the survey questions to the best of their abilities.

B. Implications

It is essential to enhance the competitive players' experience while playing VVG competitively because VVG induces threatening amounts of mental stress to these players, as mentioned earlier. Cyberbullying, increased aggression amongst individuals, high amounts of stress caused, and the contribution of VVG to suicides are all factors that affect not only the competitive players but also the people around them and their loved ones [33]. Stress induced by VVG to competitive players sometimes even contributed to death and intense cyberbullying, which shows how playing VVG competitively could be a potential threat to society, and more solutions are needed to minimize its effects on the player's mental health. The findings from this study can be used to develop backgrounds for VVG, which allows competitive gaming to ensure that the players have a less stressful gaming environment. By doing so, the players will have lower stress and aggression levels, resulting in an improved social network and fewer chances of violent behavior towards their peers [34]. This ensures peace in the gaming society as it decreases cyberbullying and aggressive behaviors. Decreased bullying and cyberbullying also positively impact society and the individual's social life.

This study demonstrated that blander and emptier backgrounds reduce stress in most of competitive players. However, with most VVG, the players experience higher stress levels due to their backgrounds. The backgrounds are most focused on keeping the players entertained and not on the stress levels of the players. This study suggests that emptier backgrounds kept the players focused and entertained than the bright crowded backgrounds The effectiveness of classifiers such as the Voting Classifier, which achieved a 97% accuracy, demonstrates how machine learning models can effectively predict stress levels and support the development of better VVG environments. Consequently, VVG companies might benefit from integrating more straightforward backgrounds to offer a more balanced and stress-free gaming experience.

If more bland and empty backgrounds were implemented in a VVG, it would allow the players to have increased entertainment and welfare due to experiencing fewer stress levels. This would also enable the players to have better mental health, preventing teen suicides caused by VVG’s. This may increase the chances of the players having a better time gaming and decrease the money spent to buy VVG with exotic backgrounds and higher stress levels. Ultimately, if more VVG’s with blander backgrounds are released for competitive gamers, the gaming experience, as well as the welfare of the competitive players, will be increased.

V. Future Research

This study demonstrates the effects of different backgrounds on the stress levels of competitive VVG players. However, some VVG’s, predominantly violent horror or adventure, cannot have backgrounds that are bland or empty. These types of VVG’s usually have a lot of props in the background to keep the players engaged in the game. Future research into this field should include further investigation into whether bland crowder backgrounds or bright empty backgrounds are less successful in reducing stress, particularly with experienced competitive players. This would help decrease the stress levels in more narrow types of VVG’s. Incorporating machine learning models, such as the Voting Classifier with its 97% accuracy or the MLP with its 91% accuracy, could refine strategies for enhancing player experience by providing more precise predictions of stress levels based on background types. Future studies should leverage these models to better understand and design VVG environments that cater to diverse player needs and preferences.

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The authors declare that there is **no conflict of interest.**

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