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Safe Gaming Analytics: Gender- and Age-Aware Machine Learning Using XGBoost for Game Player Engagement Prediction

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ABSTRACT

The rapid growth of online gaming has created both opportunities and challenges, particularly regarding the safe participation of diverse demographic groups. While prior research has predominantly focused on monetization and retention, there is limited work on predictive analytics that promotes healthy gaming habits. (Introduction) This study presents a safe gaming analytics framework that applies a gender- and age-aware machine learning approach to predict player engagement levels. (Methods) Using Extreme Gradient Boosting (XGBoost) and a dataset of 8,095 online game players from Asia as a case study, the model achieved strong predictive performance (Accuracy = 0.908, Precision = 0.910, Recall = 0.899, F1-score = 0.904). Feature importance analysis identified weekly playtime, session frequency, and average session duration as the most influential predictors of engagement. (Results) Gender- and age-based analysis revealed distinct behavioral patterns, with younger male players displaying higher playtime intensity. These findings provide actionable insights for game developers, educators, and policymakers to design and implement safe gaming strategies that balance entertainment with digital well-being. (Discussion & Conclusion) The proposed framework can be adapted to various contexts beyond the present case study, supporting responsible and inclusive online gaming environments.

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1. INTRODUCTION

The online gaming industry has witnessed unprecedented growth over the past decade, driven by increasing internet penetration, rapid adoption of mobile devices, and the diversification of game genres available to players [1]. With millions of active gamers across diverse socio-economic and demographic backgrounds, gaming has evolved into a significant medium for entertainment, social interaction, and even education. However, alongside these benefits come potential risks, including excessive gameplay, exposure to inappropriate content, and financial exploitation through in-game purchases. These risks are particularly pronounced for vulnerable groups such as women and children, who may face heightened susceptibility to online harassment, exploitation, and the negative impacts of prolonged screen time [2].

Women and children, as identified in population and gender studies, represent demographic groups requiring targeted protection in digital environments [3]. In the context of online gaming, these groups may encounter unique challenges such as targeted marketing of addictive content, gender-based harassment, or gaming patterns that interfere with education and social development. Understanding these patterns—and more importantly, predicting risky engagement behaviors—can inform evidence-based policies and design strategies that promote safe and inclusive gaming environments [4][5].

While extensive research exists on predicting player engagement using machine learning, most studies are commercially oriented, aiming to optimize monetization and retention [6][7]. This market-driven focus often overlooks the social responsibility dimension of gaming analytics, particularly in applying predictive models to safeguard vulnerable populations. Moreover, empirical research that integrates demographic variables—such as age and gender—into predictive frameworks for safe gaming remains limited, especially when applied to real-world datasets.

This study addresses this gap by developing a safe gaming analytics framework that combines demographic and behavioral attributes to predict player engagement levels. Using data from online gamers in Asia as a case study, the proposed model applies Extreme Gradient Boosting (XGBoost), a state-of-the-art machine learning algorithm known for its robustness and high performance in structured data classification [8]. The contributions of this study are threefold (1) Model development, constructing an XGBoost-based classification model to predict player engagement levels using demographic and behavioral features. (2) Feature analysis, identifying the most influential predictors of engagement, with a focus on gender- and age-specific differences. (3) Practical recommendations — Providing actionable guidelines for safe gaming practices, with particular attention to protecting women and children while promoting inclusive digital participation.

By integrating statistical analysis, information technology, and population-gender perspectives, this research contributes to the development of a replicable safe gaming analytics approach that supports digital well-being and inclusive entertainment practices.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on player engagement prediction, demographic influences, and safe gaming frameworks. Section 3 describes the dataset, preprocessing steps, and machine learning methodology. Section 4 presents the experimental results and discussion. Section 5 concludes with implications, limitations, and directions for future research.

2. LITERATURE REVIEW

2.1 Player Engagement Prediction using XGBoost

Player engagement refers to the extent of psychological involvement, enjoyment, and commitment a player demonstrates toward a game [9]. In gaming analytics, engagement prediction has become an important focus for both researchers and industry practitioners. Machine learning approaches such as Random Forest, Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost) have been widely applied to predict player churn, classify engagement levels, and personalize gameplay experiences [10]. Xtreme Gradient Boosting (XGBoost) is a method in machine learning where XGBoost is a regression and classification algorithm with the ensemble method which is a variant of the Tree Gradient Boosting algorithm which is developed with optimization 10 times faster than other Gradient Boosting, [11]. The function is the closest to the constituent functions f(x) by minimizing the loss value of the function L(y), f(x) is defined by equation (1): $\hat{F}(x)$

argmin

$$\hat{F} = argmin_f E_{x,y}[L_y, f(x)] \quad (1)$$

In the training process of each iteration to minimize the value of the loss function based on the initial function F0(x). In general, the gradient boosting algorithm is as follows in (2):

$$\{\gamma_m, h_m\} = argminL\left(y_i, f^{(m-1)}(x_i) + \gamma_m h_m(x_i)\right) \quad (2)$$

These predictive models leverage behavioral data such as session frequency, playtime, in-game purchases, and achievement records to forecast future player behavior with considerable accuracy. However, most studies apply these models in commercial settings to maximize retention and revenue, with limited application toward safeguarding vulnerable populations.

2.2 Age and Gender Differences in Gaming Behavior

Gaming behavior is significantly shaped by demographic factors, particularly age and gender. Younger players tend to engage in longer play sessions and show higher susceptibility to gaming addiction [12]. Gender-based differences are also well-documented: male players often prefer competitive and action-oriented genres, while female players may gravitate toward social and casual games [13]. Moreover, research indicates that women and children are more vulnerable to negative experiences in online gaming environments, such as harassment, exploitation, and exposure to inappropriate content [5], [14]. Integrating these demographic dimensions into predictive models can enhance the accuracy of engagement forecasts and inform strategies for safe and inclusive game design.

2.3 Safe Gaming and Digital Well-being

The concept of safe gaming aligns closely with digital well-being frameworks, which emphasize balanced and responsible use of digital technologies [15]. From a behavioral analytics perspective, safe gaming can be operationalized through measurable indicators such as average session duration, weekly playtime, and frequency of in-game purchases [16]. Excessive values in these indicators can signal potential risks, especially for minors and other vulnerable groups. Studies in game-based learning and educational technology have also highlighted the potential of games to foster positive outcomes when designed with appropriate safeguards and moderation [4]. However, few empirical studies have applied machine learning to identify risky engagement patterns and recommend safe play guidelines tailored to specific demographics, particularly in the Asian context.

2.4 Research Gap

While machine learning has proven effective in predicting player engagement, its application for promoting safe gaming among women and children in Asia remains underexplored. Existing studies tend to focus on retention and monetization, with limited emphasis on demographic-aware modeling for digital safety. This study addresses the gap by developing a predictive model using XGBoost to classify engagement levels based on both demographic and behavioral features, and by interpreting the results to offer actionable safe gaming recommendations.

3. METHODS

3.1 Dataset Description

This study utilizes the *Online Gaming* Behavior *Dataset*, filtered to include only records from players whose Location corresponds to Asian countries. After filtering, the dataset contains **8,095 entries**, each representing an individual player's demographic characteristics and in-game behavioral patterns.

The target variable is Engagement Level, a categorical feature with three distinct classes (Low, Medium, High). The aim is to classify engagement level based on a combination of demographic and behavioral attributes in Figure 1.

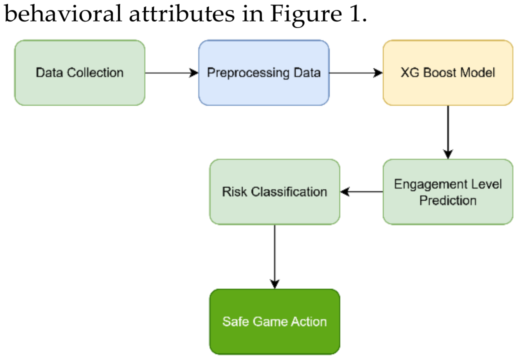

Figure 1. XGBoost → Safe Gaming Action Flow

Table 1 summarizes the variables used in this study sesuai dataset dalam penelitian.

Table 1 Description of Dataset Variables

Variable Name	Type	Description
Age	Numerical	Player's age in years
Gender	Categorical	Player's gender
Location	Categorical	Player's geographic location (filtered to Asia)
GameGenre	Categorical	Preferred game genre
PlayTimeHours	Numerical	Total weekly playtime (hours)
InGamePurchases	Numerical	Number of purchases made within games
GameDifficulty	Categorical	Preferred difficulty level
SessionsPerWeek	Numerical	Number of gaming sessions per week
AvgSessionDurationMinutes	Numerical	Average session duration (minutes)
PlayerLevel	Numerical	Player’s current in-game level
AchievementsUnlocked	Numerical	Number of achievements unlocked
Engagement Level (Target)	Categorical	Engagement level: Low, Medium, High

3.2 *Preprocessing*

Data preprocessing was conducted in three stages:

1) Encoding Categorical Variables

   Gender, Location, GameGenre, and GameDifficulty were transformed using one-hot encoding to facilitate model compatibility.

   The target variable EngagementLevel was label-encoded as integers: 0 = Low, 1 = Medium, 2 = High.

2) Scaling Numerical Variables

   Numerical variables, including Age, PlayTimeHours, InGamePurchases, SessionsPerWeek, AvgSessionDurationMinutes, PlayerLevel, and AchievementsUnlocked, were standardized using the StandardScaler to ensure uniform feature scaling.

3) Train-Test Split

   The dataset was divided into training (80%) and testing (20%) subsets using stratified sampling to preserve the proportional distribution of engagement classes.

3.3 *Model Selection: Extreme Gradient Boosting (XGBoost)*

Extreme Gradient Boosting (XGBoost) was selected as the sole predictive model for this study due to its robust performance on structured tabular data and its capability to handle both numerical and categorical variables efficiently [17]. XGBoost applies gradient boosting principles with regularization, making it resistant to overfitting and suitable for datasets with complex feature interactions.

The decision to focus exclusively on XGBoost is based on:

1) **Empirical superiority**: Prior studies have demonstrated that XGBoost outperforms other machine learning algorithms in gaming analytics tasks [18][19].
2) **Research focus**: The goal is not to benchmark multiple algorithms but to apply a high-performing model in the novel context of safe gaming analytics for women and children in Asia.

3.4 *Model Training and Hyperparameter Tuning*

The XGBoost model was first trained using default hyperparameters as a baseline. Subsequently, limited hyperparameter tuning was conducted using grid search to optimize the following parameters:

- n_estimators (number of trees)
- max_depth (maximum depth of each tree)
- learning_rate (step size shrinkage)
- subsample (proportion of training instances per tree)

This approach balances computational efficiency with model accuracy in machine learning [20][21].

3.5 Evaluation Metrics

Model performance was assessed using:

- **Accuracy**: The proportion of correct predictions across all classes.
- **Precision**: The ability to correctly identify positive predictions per class.
- **Recall**: The ability to correctly identify actual positives per class.
- **F1-Score**: The harmonic mean of precision and recall, useful for imbalanced class distributions.

Additionally, **feature importance analysis** was performed to identify which demographic and behavioral features had the greatest influence on engagement level predictions. This interpretability step is critical for translating the model's results into actionable recommendations for safe gaming practices.

Thus, the results of this study provide critical insights into how different sentiment analyses can be used in a complementary manner to gain a comprehensive picture of customer perceptions of a product or service, thereby enabling better and more strategic decision-making by companies in improving service quality.

4. RESULTS AND DISCUSSION

4.1 Model Performance

The XGBoost model developed in this study not only provides accurate classification of player engagement levels but also has direct relevance to the concept of safe gaming. The primary objectives of safe gaming are to prevent over-engagement that may lead to addiction, protect vulnerable groups such as children and women, and provide appropriate interventions to encourage healthy gaming habits. The Extreme Gradient Boosting (XGBoost) model achieved strong classification performance in predicting player engagement levels among Asian gamers in Table 2.

Table 2 Performance Metrics of the XGBoost Model

Metric	Score
Accuracy	0.908
Precision	0.910
Recall	0.899
F1-score	0.904

The *Extreme Gradient Boosting* (XGBoost) model developed in this study demonstrated excellent classification performance in predicting player engagement levels in online games. The evaluation results show an overall accuracy of **90.8%**, indicating a high level of predictive precision. The *Macro Precision* (0.910) and *Macro Recall* (0.899) values are relatively balanced, suggesting that the model effectively minimizes both false positives and false negatives across all target classes. Furthermore, the *Macro F1-score* of 0.904 reflects a well-maintained balance between precision and recall, without significant bias toward a single evaluation metric.

With an overall accuracy of 90.8%, this model can serve as an effective early warning system for identifying players at high potential risk while minimizing misclassifications that could result in inappropriate or mistargeted interventions.

4.2 Class-wise Performance

based on the results that the classification showed a variety of predictive performance. The High Engagement class achieved a precision of 0.94, indicating that almost all predictions labeled "High" were correct; however, a recall of 0.88 indicates that some highly engaged players were misclassified, primarily as "Medium" (40 cases) and, to a lesser extent, as "Low" (13 cases). For the Low Engagement class, the model achieved a precision of 0.89 and a recall of 0.88, reflecting strong classification accuracy despite 39 instances being misidentified as "Medium." The Medium Engagement class recorded the highest precision of 0.90 and recall of 0.94, making it the most consistently recognized category; however, some players in this group were misclassified as "High" (16 cases) or "Low" (32 cases). These patterns suggest that while the Moderate category is the easiest to detect, it often serves as an intermediate class that absorbs misclassifications from both ends of the engagement spectrum, a phenomenon that has implications for targeted intervention strategies within a safe play framework.

4.3 Confusion Matrix Analysis

The confusion matrix results reveal two prominent misclassification patterns that warrant closer examination. First, there is a bidirectional misclassification between the *High* and *Medium Engagement* categories, with 40 players in the High group incorrectly predicted as Medium, and 16 Medium players misclassified as High. Second, a similar pattern emerges between the *Low* and *Medium Engagement* categories, where 39 Low-engagement players are predicted as Medium, and 32 Medium players are predicted as Low. These findings indicate that the Medium Engagement category frequently functions as an "intermediate buffer" class, absorbing prediction errors from both extremes of the engagement spectrum. From a safe gaming perspective, particular attention should be directed toward players in the Medium category who exhibit behavioral metrics—such as extended playtime and high session frequency—approaching those of the High category, as these individuals may represent emerging high-risk players who could benefit from early intervention measures.

The Confusion Matrix in Figure 2 that clearly visualizes the prediction strengths and common misclassifications between engagement levels.

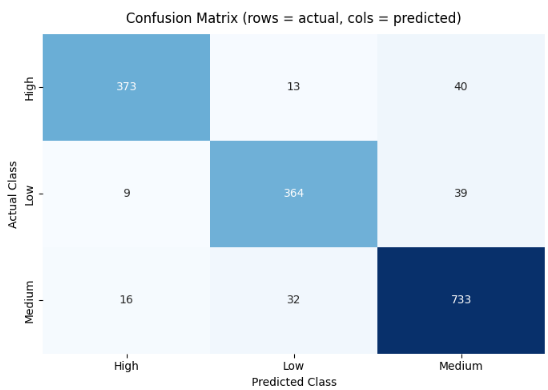

Figure 2. Confusion Metrix

The balanced precision and recall values indicate that the model can reliably classify players across the three engagement levels (Low, Medium, and High). This balance is particularly important when identifying high-engagement players, as they may be more prone to excessive gameplay and potential negative consequences.

4.4 Gender and Age Distribution

The dataset consists of **4,224 male** and **3,871 female** players, showing a nearly balanced gender distribution. However, gameplay intensity differs: male players average **17.3 hours/week**, while female players average **15.1 hours/week**.

In terms of age, male players average **27.2 years** (min 12, max 54), while female players average **26.8 years** (min 11, max 53). The age distribution (Figure 1) shows that the largest proportion of players falls between 18–30 years, a demographic known for both high adaptability to digital platforms and increased susceptibility to extended play sessions in Figure 3.

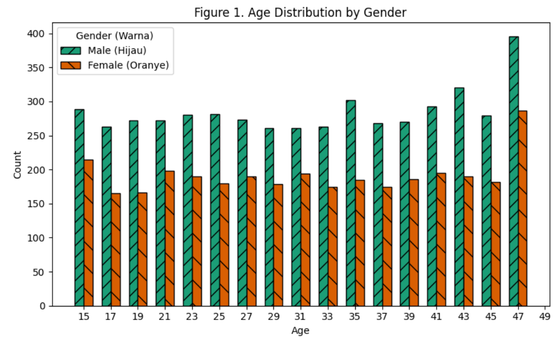

Figure 3. Age Distribution by Gender

This demographic insight reinforces the need for age-targeted safe gaming interventions, particularly for young adults, who may exhibit both high engagement and increased vulnerability to problematic gaming behavior.

4.5 Feature Importance Analysis and Behavioral Correlation

XGBoost identified **PlayTimeHours**, **SessionsPerWeek**, and **AvgSessionDurationMinutes** as the most influential predictors of engagement level, followed by **PlayerLevel** and **AchievementsUnlocked**. Behavioral features outweigh demographic variables, though **Age** and **Gender** still play significant roles in shaping engagement patterns in Figure 4.

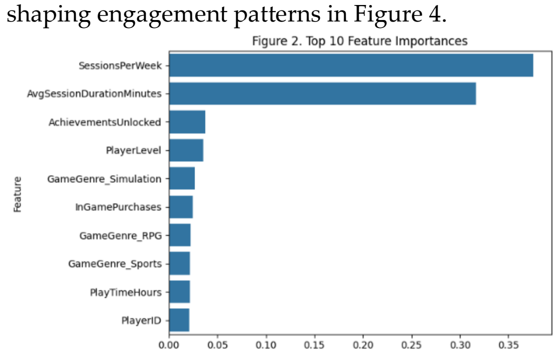

Figure 4. Top 10 Feature Importances

This finding aligns with previous research highlighting session frequency and total playtime as reliable indicators of digital overuse risk [12]. In the context of safe gaming, these variables can serve as early warning signals, enabling proactive interventions. A correlation heatmap in Figure 5 of numerical features reveals notable relationships:

- **PlayTimeHours** shows a strong positive correlation with **SessionsPerWeek** and **AvgSessionDurationMinutes**, confirming that players who play more often also tend to have longer sessions.
- **PlayerLevel** is moderately correlated with **AchievementsUnlocked**, reflecting progression-based engagement.
- **InGamePurchases** shows weaker correlations, suggesting spending behavior is not directly tied to time-based engagement but may be influenced by other factors such as game design or monetization strategy.

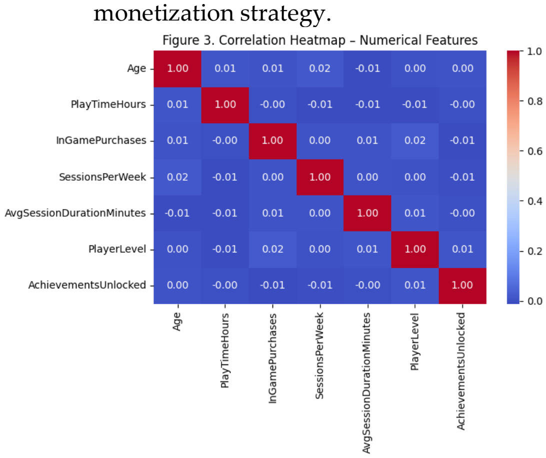

Figure 5. Correlation Heatmap

Several practical recommendations emerge from this analysis:

1) **Monitoring Playtime and Session Frequency**
Automated alerts could be triggered for players exceeding safe weekly playtime thresholds, particularly younger users.
2) **Age-Responsive Interventions**
Players under 18 could benefit from enforced breaks and educational prompts about healthy gaming habits.
3) **Gender-Inclusive Game Design**
Understand gender-based genre preferences to create inclusive and non-exploitative game experiences.
4) **Data-Informed Policy Development**
Policymakers can integrate predictive models into digital well-being programs, especially for schools and community youth centers.

This study demonstrates that a single high-performing machine learning model—XGBoost—can accurately predict engagement levels while identifying key behavioral and demographic risk factors. By integrating gender and age analysis, the research enhances its social relevance, offering both a technical framework and policy-oriented recommendations for safe online gaming. This approach can serve as a foundation for future digital well-being and responsible game design initiative.

5. CONCLUSION

This study applied data science techniques by employing Extreme Gradient Boosting (XGBoost) to predict player engagement levels in online games using demographic and behavioral data from 8,095 players across Asia. The model achieved high predictive performance (Accuracy = 86.8%, F1-score = 0.868), demonstrating the feasibility of using machine learning to inform safe gaming practices.

The analysis revealed that weekly playtime, session frequency, and average session duration are the most influential predictors of engagement. While behavioral factors dominated, age and gender also played meaningful roles, with younger players and male participants exhibiting higher gameplay intensity. The inclusion of gender- and age-based insights enables more targeted interventions, particularly for women and children, aligning with digital well-being and gender inclusion objectives.

From a practical standpoint, this research provides a framework that enables early detection of excessive engagement through behavioral thresholds, supports the design of age- and gender-appropriate interventions to foster balanced gaming habits, and offers valuable insights for policymakers and educators in understanding demographic-specific risks in online gaming.

Future research should explore multi-source datasets, integrate psychosocial variables, and evaluate the impact of real-time intervention strategies. By situating predictive analytics within a safe gaming framework, this work shifts the narrative from monetization-driven engagement optimization to socially responsible game design—an approach that can inspire further research at the intersection of technology, well-being, and gender equity.

DATA AVAILABILITY

The dataset used in this study is publicly available on Kaggle.com

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REFERENCES

[1] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785

[2] Granic, I., Lobel, A., & Engels, R. C. M. E. (2014). The benefits of playing video games. *American Psychologist*, 69(1), 66–78. https://doi.org/10.1037/a0034857

[3] Hadiji, F., Sifa, R., Drachen, A., Thurau, C., Kersting, K., & Bauckhage, C. (2014). Predicting player churn in the wild. *2014 IEEE Conference on Computational Intelligence and Games*, 1–8. https://doi.org/10.1109/CIG.2014.6932876

[4] Kowert, R., Domahidi, E., & Quandt, T. (2015). The relationship between online video game involvement and gaming-related friendships among emotionally sensitive individuals. *Cyberpsychology, Behavior, and Social Networking*, 18(7), 447–453. https://doi.org/10.1089/cyber.2014.0580

[5] Livingstone, S., & Smith, P. K. (2014). Annual research review: Harms experienced by child users of online and mobile technologies: the nature, prevalence and management of sexual and aggressive risks in the digital age. *Journal of Child Psychology and Psychiatry*, 55(6), 635–654. https://doi.org/10.1111/jcpp.12197

[6] Newzoo. (2023). *Global games market report*. Retrieved from https://newzoo.com/insights/articles/global-games-market-report

[7] Sifa, R., Bauckhage, C., & Drachen, A. (2015). The playtime principle: Large-scale cross-games interest modeling. *Proceedings of the IEEE Conference on Computational Intelligence and Games*, 540–547. https://doi.org/10.1109/CIG.2015.7317914

[8] United Nations. (2019). *General recommendation No. 36 on the right of girls and women to education*. United Nations Committee on the Elimination of Discrimination against Women.

[9] J. Brockmyer, C. M. Fox, K. A. Curtiss, E. McBroom, K. M. Burkhart, and J. N. Pidruzny, "The development of the Game Engagement Questionnaire: A measure of engagement in video gameplaying," *Journal of Experimental Social Psychology*, vol. 45, no. 4, pp. 624–634, Jul. 2009, doi: 10.1016/j.jesp.2009.02.016.

[10] Rothmeier, Karsten, et al. "Prediction of player churn and disengagement based on user activity data of a freemium online strategy game." IEEE Transactions on Games 13.1 (2020): 78-88.

[11] R. Sifa, F. Hadiji, J. Runge, A. Drachen, K. Kersting, and C. Bauckhage, "Predicting purchase decisions in mobile free-to-play games," in *Proc. AAAI Conf. Artificial Intelligence and Interactive Digital Entertainment (AIIDE)*, 2015, vol. 11, no. 1, pp. 79–85.

[12] D. J. Kuss and M. D. Griffiths, "Internet gaming addiction: A systematic review of empirical research," *International Journal of Mental Health and Addiction*, vol. 10, no. 2, pp. 278–296, Apr. 2012, doi: 10.1007/s11469-011-9318-5.

[13] T. Hartmann and C. Klimmt, "Gender and computer games: Exploring females' dislikes," *Journal of Computer-Mediated Communication*, vol. 11, no. 4, pp. 910–931, Jul. 2006, doi: 10.1111/j.1083-6101.2006.00301.x.

[14] R. Kowert, J. Vogelgesang, R. Festl, and T. Quandt, “Psychosocial causes and consequences of online video game play,” *Computers in Human Behavior*, vol. 45, pp. 51–58, Apr. 2015, doi: 10.1016/j.chb.2014.11.074.

[15] World Health Organization, “Gaming disorder,” *WHO Fact Sheets*, 2018. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/gaming-disorder

[16] D. L. King, P. H. Delfabbro, and M. Griffiths, “Video game structural characteristics: A new psychological taxonomy,” *International Journal of Mental Health and Addiction*, vol. 8, no. 1, pp. 90–106, Jan. 2010, doi: 10.1007/s11469-009-9206-4.

[17] T. Chen and C. Guestrin, “XGBoost: A scalable tree boosting system,” in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, San Francisco, CA, USA, Aug. 2016, pp. 785–794, doi: 10.1145/2939672.2939785.

[18] F. Hadiji, R. Sifa, A. Drachen, C. Thurau, K. Kersting, and C. Bauckhage, “Predicting player churn in the wild,” in *Proc. IEEE Conf. Computational Intelligence and Games (CIG)*, Dortmund, Germany, Aug. 2014, pp. 1–8, doi: 10.1109/CIG.2014.6932877.

[19] Yannakakis, Georgios N., and David Melhart. "Affective game computing: A survey." Proceedings of the IEEE 111.10 (2023): 1423-1444.

[20] S. Raschka, V. Mirjalili, and J. Hearty, *Python Machine Learning: Machine Learning and Deep Learning with Python, scikit-learn, and TensorFlow 2*, 3rd ed. Birmingham, UK: Packt Publishing, 2020.

[21] F. Pedregosa *et al.*, “Scikit-learn: Machine learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, Oct. 2011.